THE HONG KONG POLYTECHNIC UNIVERSITY
香港理工大學
Pao Yue-kong Library
包玉剛圖書館

Copyright Undertaking

This thesis is protected by copyright, with all rights reserved.

By reading and using the thesis, the reader understands and agrees to the following terms:

1. The reader will abide by the rules and legal ordinances governing copyright regarding the use of the thesis.
2. The reader will use the thesis for the purpose of research or private study only and not for distribution or further reproduction or any other purpose.
3. The reader agrees to indemnify and hold the University harmless from and against any loss, damage, cost, liability or expenses arising from copyright infringement or unauthorized usage.

IMPORTANT

If you have reasons to believe that any materials in this thesis are deemed not suitable to be distributed in this form, or a copyright owner having difficulty with the material being included in our database, please contact lbsys@polyu.edu.hk providing details. The Library will look into your claim and consider taking remedial action upon receipt of the written requests.

Pao Yue-kong Library, The Hong Kong Polytechnic University, Hung Hom, Kowloon, Hong Kong

http://www.lib.polyu.edu.hk

SMART TOOL-BASED QUALITY MANAGEMENT SYSTEM FOR ON-SITE TRACEABILITY

XINCONG YANG

PhD

The Hong Kong Polytechnic University

This programme is jointly offered by The Hong Kong Polytechnic University and Harbin Institute of Technology

2020

The Hong Kong Polytechnic University

Department of Building and Real Estate

Harbin Institute of Technology

School of Civil Engineering

Smart Tool-based Quality Management System for On-site Traceability

Xincong YANG

A thesis submitted in partial fulfilment of the requirements for the degree of Doctor of Philosophy

April 2019

CERTIFICATE OF ORIGINALITY

I hereby declare that this thesis is my own work and that, to the best of my knowledge and belief, it reproduces no material previously published or written, nor material that has been accepted for the award of any other degree or diploma, except where due acknowledgement has been made in the text.

___________________________________ (Signed)

_____ Xincong Yang _________(Name of student)

ABSTRACT

Quality plays a significant role in the construction industry in that it not only affects consumers' satisfaction but also pertains to the lives and safety of people. To ensure the construction quality in the past decades, researchers proposed various approaches to monitor and manage the on-site activities, including wearable devices with activity recognition, surveillance cameras with computer vision, etc. However, the sensor-based methods were intrusive because the deployment added labor workloads, reduced labor productivity, and weakened the ability in handling daily construction activities; meanwhile the camera-based methods were seriously affected by the none-line-of-light effects, poor light illumination, and exposed environment. In addition, these approaches both contributed to the privacy issues at the construction sites, which resulted in a lack of independence and the depression of manpower. It was concluded that there was no efficient and effective way to record and recognize the on-site construction activities. A possible non-intrusive approach to recording the on-site events is suggested by considering the kinematic motions of construction tools used in construction tasks. As is well known, the way human beings make and use tools is perhaps what sets us apart more than anything else, employees in modern architecture, engineering and construction industry are always carrying out their behaviors with the assistance of valuable hand or power tools. This study therefore proposes a novel method that record and recognize the on-site construction processes by collecting the motion data of the equipped tools, which possibly facilitates the management of construction quality within the expectation of privacy to be legally permissible. A wireless tool tracking gadget using micro-electro-mechanical-system inertial measurement unit is presented. The prototype is capable of capturing the direct motion data, consisting of acceleration, angular velocity, and magnetic field, as well as the indirect kinematic data, including displacement, velocity, rotation angle, etc. A model for the on-site process reconstruction and activity recognition is then presented, which also enables one to obtain the construction activity indicators for the quality control and management, such as work time and orthogonality. A model for the traceability along the construction process is also presented, which is based on Bayesian Networks that has the capability of tracking forward and backward by probability delivery and belief backpropagation. These models were tested in steel rebar connection and concrete consolidation experiments, and led to satisfactory results, showing the effectiveness and efficiency of the proposed method that makes the on-site activity monitoring smarter and allows for traceability along the construction processes.

Key Words: construction tracking, activity recognition, construction tools, on-site traceability

PUBLICATIONS

Refereed Journal Articles

[1] Yang, X., Li, H., Huang, T., Zhai, X., Wang, F., & Wang, C. (2018). Computer-Aided Optimization of Surveillance Cameras Placement on Construction Sites. Computer-Aided Civil and Infrastructure Engineering, 33(12), 1110-1126. doi:10.1111/mice.12385

[2] Yang, X., Li, H., Yu, Y., Luo, X., Huang, T., & Yang, X. (2018). Automatic Pixel-Level Crack Detection and Measurement Using Fully Convolutional Network. Computer-Aided Civil and Infrastructure Engineering, 33(12), 1090-1109. doi:10.1111/mice.12412

[3] Yang, X., Luo, X., Li, H., Luo, X., & Guo, H. (2017). Location-based measurement and visualization for interdependence network on construction sites. Advanced Engineering Informatics, 34, 36-45. doi:10.1016/j.aei.2017.09.003

[4] Yang, X., Yu, Y., Li, H., Luo, X., & Wang, F. (2017). Motion-based analysis for construction workers using biomechanical methods. Front. Eng, 4(1), 84-91. doi:10.15302/j-fem-2017004

[5] Li, H., Yang, X., Skitmore, M., Wang, F., & Forsythe, P. (2017). Automated classification of construction site hazard zones by crowd-sourced integrated density maps. Automation in Construction, 81, 328-339. doi:10.1016/j.autcon.2017.04.007

[6] Li, H., Yang, X., Wang, F., Rose, T., Chan, G., & Dong, S. (2016). Stochastic

state sequence model to predict construction site safety states through Real-Time Location Systems. Safety Science, 84, 78-87. doi:10.1016/j.ssci.2015.11.025

[7] Yu, Y., Li, H., Yang, X., Kong, L., Luo, X., & Wong, A. Y. L. (2019). An automatic and non-invasive physical fatigue assessment method for construction workers. Automation in Construction, 103, 1-12. doi:10.1016/j.autcon.2019.02.020

[8] Cao, D., Li, H., Wang, G., Luo, X., Yang, X., & Tan, D. (2017). Dynamics of Project-Based Collaborative Networks for BIM Implementation: Analysis Based on Stochastic Actor-Oriented Models. Journal of Management in Engineering, 33(3), 04016055. doi:10.1061/(ASCE)ME.1943-5479.0000503

[9] Luo, X., Li, H., Cao, D., Yu, Y., Yang, X., & Huang, T. (2018). Towards efficient and objective work sampling: Recognizing workers' activities in site surveillance videos with two-stream convolutional networks. Automation in Construction, 94, 360-370. doi:10.1016/j.autcon.2018.07.011

[10] Luo, X., Li, H., Dai, F., Cao, D., Yang, X., & Guo, H. (2017). Hierarchical Bayesian Model of Worker Response to Proximity Warnings of Construction Safety Hazards: Toward Constant Review of Safety Risk Control Measures. Journal of Construction Engineering and Management, 143(6), 04017006. doi:10.1061/(ASCE)CO.1943-7862.0001277

[11] Yang, X., Wang, F., Yang, X., & Zhou, Q. (2017). Fractal dimension in concrete and implementation for meso-simulation. Construction and Building Materials, 143, 464-472. doi:10.1016/j.conbuildmat.2017.03.157

[12] Yang, X., Wang, F., Yang, X., Zhu, F., & Chi, B. (2017). Quantity and shape modification for random-fractal-based 3D concrete meso-simulation. Powder

Technology, 320, 161-178. doi:10.1016/j.powtec.2017.07.031

Conference Publications

[1] Yang, X., Li, H., Wang, F., Luo, X., & Cao, D. (2018). Using Switching State-Space Model to Identify Work States Based on Movement Data. Paper presented at the Proceedings of the 21st International Symposium on Advancement of Construction Management and Real Estate, Hong Kong.

[2] Yang, X., Wang, F., Li, H., Yu, Y., Luo, X., & Zhai, X. (2019). A Low-Cost and Smart IMU Tool for Tracking Construction Activities. Paper presented at the 2019 Proceedings of the 36th ISARC, Banff, Alberta, Canada.

ACKNOWLEDGEMENTS

Fortunately, this dissertation was accomplished in the end of my PhD, and unfortunately, I found that improvements could always be developed if more time offered. Although this thesis was imperfect, it's still worth my time and it is also the end of a long study in my life. I would like to thank all people who have helped and inspired me to make this dissertation possible.

First and foremost, I want to thank my chief supervisor, Prof. Heng Li, for the patient guidance, encouragement, and support throughout my time as his student. I have been extremely lucky to have a supervisor who cares about my work so much. Prof. Li is always visionary beyond the era, who has been a tremendous mentor for me. I would also like to thank my co-supervisors Prof. Ximei Zhai and Prof. Fenglai Wang in Harbin Institute of Technology. They have supported my study with patience and encouragement whilst allowed me to explore the research freely.

Moreover, I am delighted to have Prof. Tarek Zayed as the Chair of BoE, who made great efforts to organize my viva voce. I also would like to express my special gratitude to the external examiners, Prof. Song Wu from University of Huddersfield, and Dr. Wei Pan from The University of Hong Kong. Their expertise and experience broaden my perspective and nourish my intellectual maturity. I gratefully acknowledge them for their valuable guidance, comments, and suggestions that would significantly improve the quality of my thesis and the construction industry.

Last but not least, many thanks go to the friends and colleagues in the Sclab and BRE for your incredible help and support throughout my life in PolyU. I would also like to express my gratitude to Ms. Chloe Shing and Ms. Irene PANG in General Office for all their hard work to ensure the efficient and smooth proceeding of my Ph.D. study.

TABLE OF CONTENTS

LIST OF FIGURES

LIST OF TABLES

LIST OF ABBREVIATIONS

QA	Quality Assurance
QC	Quality Control
TQM	Total Quality Management
CoQ	Cost of Quality
GPS	Global Positioning System
RFID	Radio Frequency Identification
UWB	Ultra Wide Band
UHF	Ultra High Frequency
BLE	Bluetooth Low Energy
CV	Computer Vision
LiDAR	Light Detection And Ranging
PTZ	Piezoelectric sensing
GPR	Ground Penetrating Radar
InSAR	Interferometric Synthetic-Aperture Radar
3M	Men, Machines and Materials
ISO	International Organization for Standardization
GS1	Global Language of Business
BIM	Building Information Modelling
NFC	Near-Field Communication

MEMS	Micro-Electro-Mechanical System
IMU	Inertial Measurement Unit
QN	Quantization Noise
RW	Random Walk/White Noise
CN	Correlated Noise
SN	Sinusoidal Noise
BI	Bias Instability
RRW	Rate Random Walk
RR	Rare Ramp
AVAR	Allan VARiance
ADEV	Allan DEViation
PSD	Power Spectral Density
EKF	Extended Kalman Filter
ZUPT	Zero velocity UPdaTe
INS	Inertial Navigation System
HMM	Hidden Markov Model
SVM	Support Vector Machines
DTW	Dynamic Time Warping
MEMM	Maximum-Entropy Markov Model
KNN	K-Nearest Neighbor
ANN	Artificial Neural Network
RF	Random Forest

FFT	Fast Fourier Transform
BN	Bayesian Network
DAG	Directed Acyclic Graph
CPT	Conditional Probability Table
HVAC	Heating, Ventilation and Air Conditioning
AHRS	Attitude and Heading Reference System
IBC	International Building Code
ACI	America Concrete Institute
ML	Machine Learning
SVM	Support Vector Machine
AoE	Area of Effect
VPM	Vibrations Per Minute

LIST OF SYMBOLS

E_t	Translational/kinetic work/energy	$\mathrm{kg \cdot m^2 \cdot s^{-2}}$
E_r	Rotational/angular kinetic work/energy	$\mathrm{kg \cdot m^2 \cdot s^{-2}}$
E_k	Total kinetic energy	$\mathrm{kg \cdot m^2 \cdot s^{-2}}$
F	Force	N
m	Mass	kg
s	Displacement	m
v	Velocity	$\mathrm{m \cdot s^{-1}}$
a	Acceleration	$\mathrm{m \cdot s^{-2}}$
I	Moment of inertia	$\mathrm{kg \cdot m^2}$
τ	Torque	$\mathrm{N \cdot m}$
r	Angle/Rotation	rad
ω	Angular rate/velocity	$\mathrm{rad \cdot s^{-1}}$
α	Angular acceleration	$\mathrm{rad \cdot s^{-2}}$
h	Magnetic field	mG
$\sigma_y^2(\tau_o)$	Allan Variance	
$\sigma_y(\tau_o)$	Allan Deviation	
N	Total number of samples	
τ_o	Observation period	s
σ_{QN}^2	Variance of quantization noise	

σ_{RW}^2	Variance of random walk/white noise	
σ_{CN}^2	Variance of correlated noise	
σ_{SN}^2	Variance of Sinusoidal noise	
σ_{BI}^2	Variance of bias instability	
σ_{RRW}^2	Variance of rate random walk	
σ_{RR}^2	Variance of rate ramp	
f	Frequency	Hz
$\boldsymbol{Trans}$	Translation matrix	
$\boldsymbol{Rot}$	Rotation matrix	
ϕ	Roll angle around x-axis	rad
θ	Pitch angle around y-axis	rad
ψ	Yaw angle around z-axis	rad
R_N	Normal radius of Earth	km
R_M	Meridian radius of Earth	km
φ	Geodetic latitude	
$\boldsymbol{A}$	Transition matrix	
$\boldsymbol{B}$	Noise control matrix	
$\boldsymbol{w}$	Process noise vector	
$\boldsymbol{Q}$	Process noise covariance	
$\boldsymbol{H}$	Observation matrix	
$\boldsymbol{v}$	Observation noise vector	
$\boldsymbol{R}$	Measurement noise covariance	

$\boldsymbol{x}$	Actual/true state vector
$\boldsymbol{z}$	Observed/measurement state vector
$f(\cdot)$	Non-linear transition function
$g(\cdot)$	Non-linear measurement function
$\boldsymbol{A}_t$	Jacobian matrix of transition function to x
$\boldsymbol{W}_t$	Jacobian matrix of transition function to w
$\boldsymbol{V}_t$	Jacobian matrix of measurement function to v
x	Magnitude of state data
w	Window size for local variance
$G(\cdot)$	Graph model
V	Set of graph vertices
E	Set of graph edges
v_r	Radial velocity
Ω	Damping coefficient of the fresh concrete

LIST OF PHYSICAL CONSTANTS

R_E	Earth's equatorial radius/semi-major axis	6,378.1370	km
e_E	Earth's eccentricity	0.08181919	
g_E	Gravity constant	9.78032677	$\mathrm{m \cdot s^{-2}}$
ω_{IE}	Constant angular velocity of Earth	7.2921159e^{-7}	$\mathrm{rad \cdot s^{-1}}$

CHAPTER 1 INTRODUCTION

1.1 Background to the problem

The quality of a product is based on how well the product does, what it was designed to do, and how well it holds up over time, it is defined as delivering a customer's service or product without a defect being present (Juran and Godfrey 1999). The importance of product quality cannot be overemphasized because it builds trust between producers and customers and provides them with a higher return on their investment along with a more comfortable lifestyle. High quality ensures higher satisfaction and a greater chance of continued partnership, whereas poor quality ruins the reputation of the manufacturer and destroys its relationship within the industry (Hallak 2006).

Not as a degree of goodness or excellence in manufacture industry, in the construction industry, quality can be briefly described as conformance to project plans and specifications (Kubal 1994). But the terminology of quality is intrinsically a comprehensive and complicated definition that the client should take a number of aspects into consideration, including funding, time, corporate policies, requirements of business and stakeholders, the views of external organizations (such as local planning authority and design council), local and national legislation. The basic elements of quality in construction are composed of design quality, construction materials quality, and on-site conformance quality. The quality of design primarily refers to the ability to satisfy given requirements of the standards, users, functionally efficient system, and economical maintainable system (Davis, Ledbetter, and Burati 1989); and the quality of construction materials is related to the satisfaction of materials and equipment requirements in the specification, consisting of all engineered, fabricated and bulk materials provided by vendors and subcontractors (Stukhart 1989); and the quality of conformance is the degree to which the constructed facility conformed the design and construction specification (Nandakumar, Datar, and Akella 1993).

Although the quality in construction industry has many meanings, the overall management of it is a 'bottom-line' issue. It has become a crucial cog in modern systems, not only playing a significant role in the success of a building project but also pertaining to the lives and safety of the public. Good construction quality is a win-win situation; otherwise, all stake holders lose when a defective project is undertaken.

For example, in June 2018, the newly constructed underground platforms at MTR corporation's Hung Hom station have confirmed the suspicions of faulty work. Thousands of steel rebars were cut prior to being connected to screw couplers embedded in the concrete components (see Figure 1-1). The public were worried that there might be safety issues in twenty or thirty years. Till almost half a year later, the problematic couplers have been identified with unnecessary and unreasonable cost, manpower, and time (Cheng 2018).

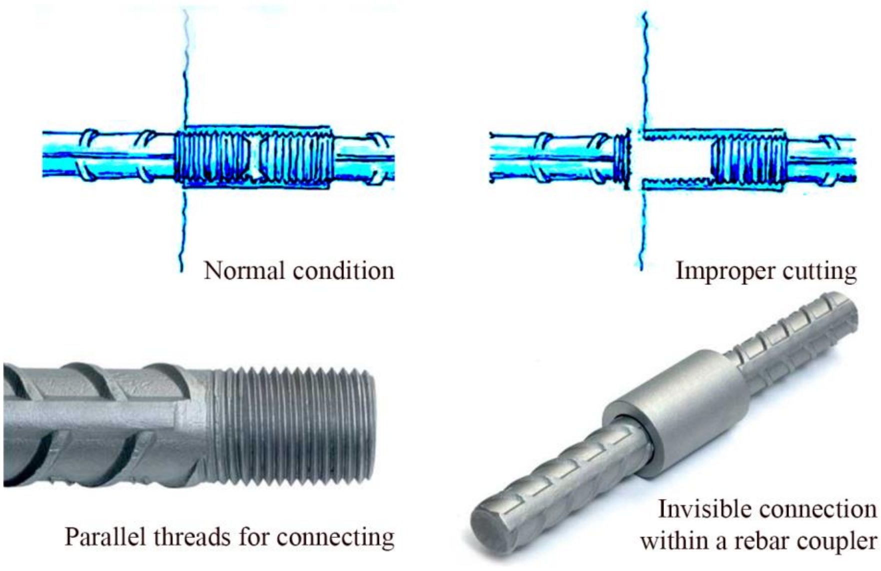

Figure 1-1 Cutting steel rebars before being connected to couplers

The modern construction industry faces ongoing challenges, such as increasing project requirements and growing building complexities, but with stringent regulations and tight deadlines. Under this situation, it can be seen from the sample that the construction quality has caused a bottleneck in the overall performance of a project in that the defective construction work, re-work, remedial work, and overall poor quality of building products account for roughly 4% - 6% of the contract price on average, as well as 7% - 8% of the delay in work time (Josephson and Hammarlund 1999, Josephson, Larsson, and Li 2002).

While the importance of quality in the construction industry as a project key point is clear, arguments exist over the proper approach to achieve quality goals. In the response to the growing concern about quality, academic researchers and construction institutes continuously pursue a major effort in the development of construction in engineering. However, regardless of quality assurance/quality control (QA/QC) programs, the application and benefits of them are neither fully understood nor effectively utilized in the planning, design, and construction phases of engineered projects (Tang et al. 2005). In spite of the significance of the quality issue in engineered projects, an extensive review of the literature has revealed no effective and efficient system in the construction industry for the tracking and tracing of quality related activities. That's one of the most crucial reasons accounting for the quality issues, just like the sample of improper rebar cutting. Therefore, the obvious question is, "Why are there no systems to track and trace quality-related activities in the construction industry?"

After all, the concept of traceability for quality is not new and has been used in a number of industries for a long time. For example, the ability of tracking and tracing enables the medicine industry to shore up quality safety and shift out counterfeit drugs; the food industry to validate raw product processes for quality safety; and the manufacturing industry to maintain quality visibility as products move throughout the supply chain. The authors believe that a major reason that such system do not exist in the construction industry is the nature of the construction process. Drug, food or general manufacturing normally involves a steady-state process of assembly-line that the production procedures have been designed, constructed and optimized at stable status; meanwhile the construction industry involves single, unique projects with various changes occurring during the design and construction phases. It might be concluded that the concepts of manufacturing-oriented quality tracking and tracing do not apply to the construction industry because of the fundamental difference and continuous variability.

How do the quality managers and supervisors make intelligent decision about the mechanisms, extent and performance of their quality management efforts if they are not aware of the quality-related activities happened in engineered construction projects? How do they address the quality-related issues and prevent the negative effects if they do not know the relationship between quality-related activities and the quality defects? A quantitative method is needed to track and trace the construction activities in an effective and efficient manner. This is not limited to the engineered construction; every segment of the construction industry can benefit from quantitative record and analysis of the quality-related activities. It not only produces an overwhelming amount of data to validate the raw construction processes, yet along the man hours associated with keeping the data captured organized and useable, it also tracks and traces the construction accountability when coupled with detail assignments. Further, the tracking and tracing method has become a vital tool for all participants, across all stages to gain greater control over construction quality, respond to higher demands and rebuild the confidence of the public.

1.2 Problem description

To achieve the construction quality goals, researcher have proposed a series of methods using the state-of-the-art electrical technologies to enhance the control and management of the construction processes. For example, the wearable devices, containing watches, insoles, helmets, etc., are introduced at the construction sites to capture the construction activities. However, these devices are always intrusive that the normal construction activities are disrupted because the inconvenient and complex data collections. In addition, the workers who are wearing the devices feel their personal privacy are offended by the inspectors that do harm to the beliefs between construction employees and employers. On the other side, contractors install surveillance cameras around the construction sites to monitor the construction process in a visual and timely manner. However, the cameras are tremendously affected by the none-line-of-sight effects, which means that the ambient occlusions and illumination made a significant contribution to the performance of the monitoring. Moreover, privacy issues also rise as the personal identities are recorded by the cameras.

Rather, by having a well-functioning traceability system in other industries, such as food and drug industries, stake holders can demonstrate their own compliance with regulations, and retrieve detailed production to identify the potential problems and take corresponding corrective actions. Increased traceability can thus increase the control level and management strategy by learning lessons from history. In addition, it provides the proof of product authenticity as well.

Also, in the construction industry, every participant is eager to improve the traceability and transparency for a better building quality. It is therefore of interests to introduce the traceability concept to the conventional construction management and find a new way to monitor and improve the current construction process without privacy and intrusion issues.

1.3 Research aim and objectives

Since the quality issue has become the bottleneck in current construction industry and the traceability system has revolutionize the quality management in many other industries, this research therefore aims to improve the construction quality by introducing and increasing its traceability by a non-intrusive means.

The objectives of this research are three-folded as follows:

- to propose a new data collection and select suitable techniques for a prototype to track, monitor and control most of the construction processes without privacy and intrusion issues.
- to review the literature of inertial navigation and develop data models to analyze the collected data and generate associated quality variables for compliance with existing regulations.
- to present a framework to combine the data collection and data models, build up a traceable quality model for tracing backwards and forwards, test and validate the prototype and models in practical applications..

1.4 Research questions

In order to fulfill the above research aims and objectives, there are three important areas to study. At first, a feasible solution to replace the conventional construction tracking methods through wearable devices and surveillance cameras needs to be figured out. Such data collection with advanced techniques should not bring interruptions or offences into the normal construction activities and provide reliable and timely information on the construction process at the same time. Secondly, mathematical models to simulate and retrieve the next and the past construction activities need to be established, the input of which is the collected data by an ideal tracking system and the output is the process variables that can be compared with existing regulations. Thirdly, an integrated framework that combines the data collection and data analysis requires to be built up to form a structural quality chain, which works like a traceability chain in other industries, providing a solid proof for stake holders to trace forward and backward in life-cycle quality management. These three areas of investigation are formulated into the following three research questions:

- How to collect the construction activities/processes data through the advanced techniques without privacy and intrusion issues?
- How to analyze certain construction activities and evaluate their quality to determine whether they are conformity with the construction regulations relying on the collected data?
- How to combine the non-intrusive data collection and the smart data analysis model to automatically generate a traceable structure framework for quality evaluation and root cause analysis?

1.5 Outline of the report

This thesis is composed of 11 chapters. Each chapter is briefly described in the following paragraphs to guide the reader.

- Chapter 1 – the introduction chapter presents the background and problem description to the research area. The research aim and objectives, the research questions and the research outline are introduced subsequently.
- Chapter 2 – the literature review chapter introduces the background and associated concepts to provide a foundation of the research, containing the development of quality management in the construction industry, the traceability implementations in other industries, and the traceability implications to the construction industry.
- Chapter 3 – the methodology chapter describes the chosen research approaches for data collection, data analysis, and the principles for technique selection. This chapter ends with a discussion on the validation and reliability of these research approaches.
- Chapter 4 – the data collection chapter represents the proposed new method for data collection, discusses its pros and cons, analyses its potential noises and proposes models for specific construction applications.
- Chapter 5 – this chapter introduces the proposed data model following the order of data processing, data fusion, data segmentation and feature extraction.
- Chapter 6 – the theoretical traceability chain chapter represents the establishment of the construction traceability chain, and the quantitative methods to trace forward and backward along the network.
- Chapter 7 – the prototype chapter systematically introduces the smart construction tool gadget with respect to system framework, instruments and devises, and data visualization/
- Chapter 8 & 9 – the experiment chapters show the implementation of the developed prototype and proposed methods on the rebar connection task by an

adjustable wrench and the concrete consolidation tasks by an internal concrete vibrator.

- Chapter 10 – the discussion chapter discusses the validity of the experiment results, the generalization and the limitations of this research.
- Chapter 11 – the conclusion chapter presents the answers to the research questions, explains the contributions of this research, and suggests the future research recommendations.

CHAPTER 2 LITERATURE REVIEW

This chapter presents the research background based on published papers on the subjects of 1) quality in the construction industry; 2) the traceability applications for quality in other industries; 3) and the requirements on traceability within the construction industry. It provides a systematic literature review of quality-relevant studies between 1911 and 2019, complemented with comments of the author. The author's opinion result from his perception and understanding of the development of quality in both the construction industry and other manufacture sectors.

In Section 2.1, the general view of quality in the construction industry is drawn along the development timeline, including inspection, quality control, quality assurance, total quality management, and modern automated quality technologies. Section 2.2 refers to the commercial applications of traceability in manufacture sectors for quality and safety control and assurance, especially in the food traceability and drug traceability. Section 2.3 is devoted to the rigid demand of traceability concept for quality management in the construction industry. The overall structure of this section is described in Figure 2-1.

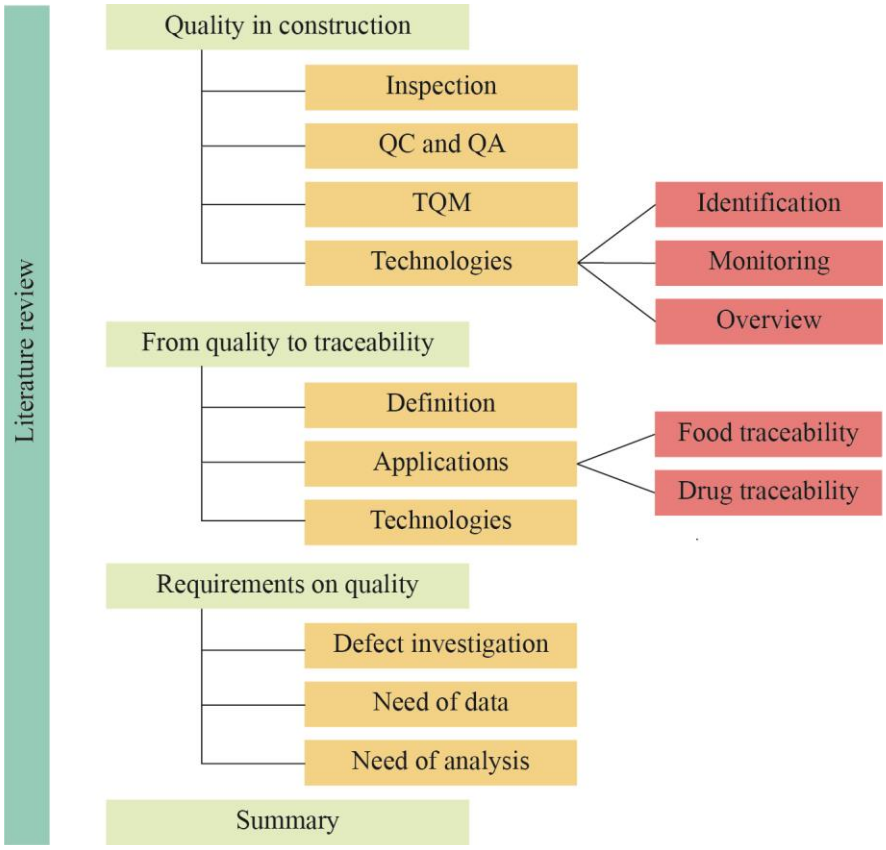

Figure 2-1 Structure of literature review chapter

2.1 Quality in the construction industry

Quality is defined as *the degree to which a set of inherent characteristics fulfills requirements*, where the degree refers to *a level to which a product or service satisfies*, termed as excellent, good or poor quality; and the inherent characteristics are *those features that are a part of the product and are responsible to achieve satisfaction*; and the requirements represents *the needs of customers, organizations and other interested parties, including regulatory bodies, community, and environment*, as well as *the expectations that may be stated, generally implied or obligatory* (International Organization for Standardization 2015). Drawn upon from the general definition, construction quality is defined as *the conformity of building products to the customer requirements and public regulations, as documented by plans, specifications, contracts, and applicable code and standards* (Harris and McCaffer 2013).

With respect to process perspective, construction consists of constructing, altering, erecting, assembling, installing, repairing, and demolishing building, infrastructure, civil engineering, and other similar structures. The outputs of construction are large, heavy, durable, immobile, unique, complex and expensive, such as houses, departments, bridges, and roads. The inputs of construction are discontinuous, uncertain, and in various sizes and types. The locations and resources change over the stages of construction process. Till now, the construction is still labor-intensive with low productivity because of these characteristics and a number of construction projects suffer from overruns in cost and time (McKinsey Global Institute 2017). Therefore, to simplify and make the lessons from manufacturing feasible, quality in the construction industry can be defined as the attainment of acceptable levels of performance from construction activities, in terms that the quality of construction is achieved when the related activities meets or exceeds the requirements of the client and the desired specifications (Mishra 2017). Achieving excellent quality in the construction industry in the long run is not easy and has become an open challenge since the characteristics of construction are tough issues. Quality management therefore has been one of the vital project objectives from an early age.

Quality management is defined as *the process of identifying and administering the activities need to achieve the quality objectives of an organization* (Tang et al. 2005). It is composed of *a series of management functions that determine the quality policy, objectives and responsibilities, and implement them by means such as quality planning, quality control, quality assurance, and quality improvement with the quality system* (International Organization for Standardization 2015).

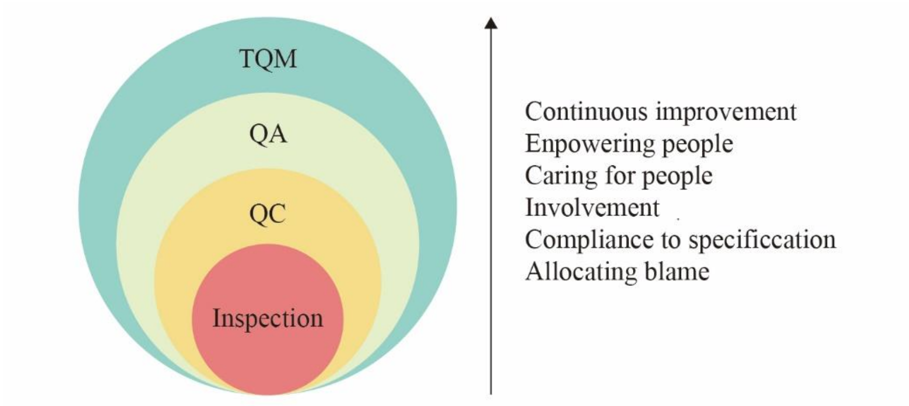

Figure 2-2 Four stages of quality management

In the development of quality management, there exist four stages: inspection, quality control, quality assurance, and total quality management (Tang et al. 2005). As shown in Figure 2-2, inspection and quality control (QC) operate through detection, which aim to identify problems that have occurred; meanwhile quality assurance (QA) and total quality management (TQM) work in prevention mode, which aim to reduce and avoid potential problems occurring. These approaches are reviewed in the following sections.

2.1.1 Inspection

The use of quality inspection to assure conformity to specific requirements dates back to the Middle Ages. Craft guilds established standards to safeguard their reputation in ancient European, and royal courts published technical treatises (a unified set of architectural standards) for builders, architects, craftsmen and governments to building coherence and safe use (Guo 1998). Based on these standards, quality inspection is performed at three levels: self-inspection, internal-inspection, and external-inspection. Self-inspection refers to each craftsman exclusively inspecting the quality of his own work; internal-inspection occurs when several craftsmen perform similar tasks of which a skilled foreman is in charge of inspecting; and external-inspection represents a third-part, such as communities and governments, performing inspections.

Although the early years of low-volume manufacturing and construction, manual inspection of products and projects and arbitrary review of worker output sufficed. However, as organizations and production yields became larger and more complicated, the need for better quality and less manpower through more effective and efficient operations became evident.

2.1.2 Quality control and quality assurance

In the beginning of 20th century, the concept of quality management took a huge leap forward with the advent of statistics (Taylor 1911). Quality control has been formalized as a distinct function conducted by inspectors who are not directly involved in the production process. After ten years, quality control has been developed to be proactive rather than strictly relying on measurements and inspections of the final product (Shewhart and Deming 1986, Shewhart 1931). To enhance the role and involvement of management for high quality, Plan-Do-Study-Act (PDSA) cycle was proposed and became a popular methodology for pretesting and perfecting before implementation. From a customer viewpoint, the quality trilogy (quality planning, control and improvement,) was established and served as the important quality initiatives (Juran and Godfrey 1999). Taking the cost of corrective actions into consideration, quality assurance was then derived from quality control that more quality actions were performed earlier in the product process. Although these terms "quality assurance" and "quality control" are often used interchangeably, it is remarkable to compare these approaches to ensure the quality of a product or service since the costs of them are distinctly different in the construction industry.

As Table 2-1 lists, QA is defined as *a part of quality management focused on providing confidence that quality requirements will be fulfilled*; meanwhile QC is defined as *a part of quality management focused on fulfilling quality requirements* (International Organization for Standardization 2015). In short, QA is a strategy for prevention that demonstrates on planning, documenting, and agreeing on a set of necessary guidelines; and QC is a strategy for detection that demonstrates on determining the level of conformance to desired quality.

In the 1970s, the automobile and electronic products of Japanese industry popularized around the world that quality movement was established for higher quality with lower costs. Taking note of Japanese success, the quality management has grown and expanded through a milestone named total quality management.

Table 2-1 The differences between quality assurance and quality control

	Quality assurance	**Quality control**
Focus	QA aims to prevent defects with focus on the product process. It is a proactive process	QC aims to identify and correct defects with focus on the final product. It is a reactive process
Goal	The goal of QA is to improve the development process to avoid the appearance of defects when the product is being developed	The goal of QC is to identify the defects to improve the final product after the product is developed
Orientation	QA is process oriented	QC is product oriented.
Example	Verification	Validation and testing
Activity	Periodic performance audits and continuous monitoring of the process	Conformity with regulations and requirements
Responsibility	Everyone involved in production	Testers and inspectors

2.1.3 Total quality management

Total quality management (TQM) refers to *a management process directed at establishing organized and continuous process improvement activities, involving everyone in the organization in a totally integrated effort towards improving performance at every level* (Aly, Maytubby, and Elshennawy 1990). The definition is based on the belief that an organization can build a long-term success by having all member focus on improving quality.

To achieve the long-term success in quality, a series of pathways have to be accomplished to instill a discipline of quality into the culture of organization and the development of production (Kanji 1990). These principles and actions are listed in Table 2-2.

Table 2-2 Principles and actions for the development of the total quality management

Principles	**Actions**
Approach	Management-led
Scope	Company wide
Scale	Everyone is responsible for quality
Philosophy	Zero detection
Standard	Right first time
Control	Cost of quality
Theme	Continuous improvement

To apply the systematic concept to practical projects, awareness of the additional benefits and costs of these quality development programs in the design and construction of engineered projects are needed.

2.1.4 Cost of quality

Cost of quality (CoQ) is usually understood as *the sum of conformance and non-conformance costs, where the cost of conformance is the price paid for prevention of poor quality (for example, inspection and quality appraisal), and cost of non-conformance is the cost of poor quality caused by product and service failure (for example, rework and returns)* (Schiffauerova and Thomson 2006). There exist a number of CoQ models and the widely acceptable categorization of CoQ contains prevention, appraisal and failure costs. Prevention costs are associated with actions taken to ensure the desired quality; appraisal costs are related to measuring the level of quality attained by the process; and failure costs are incurred to correct quality in product and services prior to delivering to consumers (Armand V. Feigenbaum 2004). The basic suppositions of these models are that investment in prevention and appraisal activities will reduce failure costs, and that further investment in prevention activities will reduce appraisal costs (Porter and Rayner 1992). Because the cost variables are negatively correlated, the objective of stake holders therefore is to find the minimum value of the total CoQ. From this traditional view, an optimum CoQ locates at a certain quality level where the increasing cost of prevention and appraisal exceeds the decreasing cost of failure, in terms that the costs of prevention plus appraisal outweighs the benefits of them in spite of increasing or decreasing the level of quality. However, the concept has been challenged from the modern view of CoQ. It is clarified that the optimum quality level equals or approximates to zero defects (Plunkett and Dale 1988). These views can be reconciled that the classic model works in time-constrained condition whilst the modern model prevails under infinite time horizon (Schiffauerova and Thomson 2006).

Since the time of a construction project is extremely long and the contractor usually earn profits that are unappreciated in conventional contracts, such as a reduction of expenses associated with inventory, rework, scraps and warranty (Jang and

Skibniewski 2009a). Besides, owners are likely to pay an extra premium, and government may hand out awards for high-quality buildings. With respect to modern model, these motivations have driven quality management to be one of the most competitive attributes in the construction industry (Crosby 1983). Since the goal of construction quality is zero defects, various state-of-the-art technologies are utilized to enhance the quality management over different periods.

2.1.5 Technologies for construction quality

To support quality decision-making process, advanced technologies for timely detection of construction discrepancies are becoming more and more significant. The associated technologies are categorized into detection, monitoring systems and management-enhancing tools by purpose. Defect identification is the crucial procedure for quality control; process monitoring is the approach for quality assurance; and management-enhancing technologies provide great help in quality decision making.

2.1.5.1 Technologies for defect identification

To achieve an objective and quantitative identification of construction defects, automated detection technologies are adopted and becoming a tireless inspector for building products. With the advent of low-cost and tiny sensors and artificial intelligence (AI), as listed in Table 2-3, more and more cutting-edge technologies are introduced for defect identification anytime and anywhere.

Table 2-3 Advanced technologies for construction defect identification

Technology	Defect identification	References
Computer vision (CV)	Cracks, joint displacement, holes, erosion,	(Moselhi and Shehab-Eldeen 1999, Zhu and Brilakis 2008, Koch et al. 2015)
Laser scan	Geometrical deviations	(Yue et al. 2006)
Light detection and ranging (LiDAR)	Reinforcement corrosion, surface erosions, structural damages	(Wang et al. 2015, Li and Liu 2019, Chen, Chung, and Park 2013)
Piezoelectric sensing (PZT)	Cracks, corrosion	(Zhao et al. 2007, Tua, Quek, and Wang 2004, Chen, Chung, and Park 2013)
Ultrasonic/ultrasound + Frequency tomography	Wood and concrete defects	(Wenyong et al. 2006, Van Leeuwen, Nahant, and Paez 2011)
Pulse phase thermography	Honeycombing	(Van Leeuwen, Nahant, and Paez 2011)
Acoustic laser/emission	Concrete defects, brick masonry defects	(Yu et al. 2016, Labres et al. 2018)
Ground penetrating radar (GPR)	Tunnel defects, road surface defects, leakage	(Zhang, Xie, and Huang 2010, Saarenketo and Scullion 2000, Lai, Kind, and Wiggenhauser 2011, Hunaidi and Giamou 1998)
Impact echo	Concrete and masonry defects	(Sansalone and Streett 1997, Sansalone and Carino 1988, Pratt and Sansalone 1992)
Infrared thermography	Concrete spalling, render lamination	(Titman 2001, Taylor, Counsell, and Gill 2014)
Sub-terahertz imaging	Block defects	(Oyama et al. 2009)
Interferometric synthetic-aperture radar (InSAR)	Building deformations	(Pieraccini et al. 2002)
X-Ray	Welding defects, moisture	(Zhang, Xu, and Ge 2004, Pease, Scheffler, and Janssen 2012)

2.1.5.2 Technologies for process monitoring

On-time feedback is critical for quality management in the construction industry that if any construction defects or discrepancies are determined, taking corrective actions in a timely manner not only mitigates the negative impacts on quality, but also save time and cost of rework (Omar and Nehdi 2016). A huge body of researchers, therefore, conducted research and proposed diverse automated approaches to process monitoring, and the related technologies were summarized in Table 2-4. It can be seen that given a demand of a certain level of data accuracy, sampling frequency, and budget, there is an abundance of technologies available to collect data from the on-site work flow; while, it is still worth treating the privacy and intrusion issues.

Table 2-4 Advanced technologies for on-site process monitoring

Technology	**Data**	**Objectives**	**References**
Global positioning system (GPS)	Location	Materials, equipment	(Pradhananga and Teizer 2013, Li et al. 2005, Caldas, Torrent, and Haas 2006)
Radio frequency identification (RFID)	Location, identification	Materials, manpower, vehicles, machinery	(Song et al. 2005, Razavi and Moselhi 2012, Lu et al. 2007, Lu, Huang, and Li 2011)
Ultra wide band (UWB)	Location, pose	Materials, crane	(Zhang, Hammad, and Rodriguez 2011, Shahi et al. 2012, Cheng et al. 2011)
Ultra high frequency (UHF)	Location, identification	On-site staffs, materials, machines	(Yang et al. 2012, Tarng and Perng 1997, Hubbard et al. 2015)
Bluetooth low energy (BLE)	Noise, location, connection	Manpower, environment, harness	(Park, Kim, and Cho 2016, Hughes, Yan, and Soga 2015, Gomez-de-Gabriel et al. 2019)
Computer vision (CV)	Location, geometry, identification, pose	Manpower, vehicles, building elements, equipment	(Son, Kim, and Choi 2010, Seo et al. 2015, Park, Koch, and Brilakis 2011, Liu, Eybpoosh, and Akinci 2012, Li and Lee 2011, Ibrahim et al. 2009, Azar 2015)
Laser scan	Geometry, pose	Building elements, manpower	(Su, Hashash, and Liu 2006, Gordon et al. 2003, Cheok et al. 2001, Bosche, Haas, and Akinci 2009)
Ultra sound	Location	Materials,	(Jang and Skibniewski 2009b, Jang and Skibniewski 2008)
Infrared thermography	Temperature	Asphalt	(Cho et al. 2011)
Wearable devices	Temperature, physiological indicators, EEG, EMG	Manpower	(Wang et al. 2017, Jebelli, Hwang, and Lee 2017, Guo et al. 2017, Cheng et al. 2012, Awolusi, Marks, and Hallowell 2018, Aryal, Ghahramani, and Becerik-Gerber 2017)

2.1.5.3 Overview of methods for quality data acquisition

The mentioned technologies have proven their ability to identify defects and monitor process for construction quality. In short, the technologies for defect identification and quality control are divided into destructive and non-destructive methods. Non-destructive methods are generally vision-based while destructive methods are sensor-based as the sensing gadgets have to be attached on the body of men, machines or materials (3M), or embedded in building blocks. With a dynamic respect to quality management, the entire construction process is likely to be recorded to obtain a whole picture of the building project. The technologies therefore have the capability of quick response, low-cost, easy-handling and continuous data acquisition. Table 2-5 summarizes the existing vision-based and sensor-based technologies to capture the on-site quality activities.

Table 2-5 Summary of methods for construction quality data acquisition

Method	Advantages	Limitations
Vision-based methods	• Direct visualization • Easy interpretation • Wealth information • Multi-task	• Subjective and labor consuming • Complicated algorithms • Qualitative results • Time consuming and time delay • Tag/anchor required
Sensor-based methods	• Real-time response • Portable and wireless • Low cost • High accuracy	• Intrusion • Destruction • Complicated data processing • Single task • Charge required

However, recent survey in practical projects reveals that although most of respondents are using advanced technologies for quality management, a number of on-site staffs present positive attitudes against the tracking technologies (Schiff et al. 2009). Since the vision-based methods and sensor-based methods are capable of identify ones' identity through face recognition and personal unique characteristics, employees feel offended that their privacy has been invaded.

In short, although the effective and efficient quality management tools have brought significant improvement in manufacturing industry, in the construction industry, the quality principles, actions and technologies raise the issue of defining the real quality need and determining if it has been met, as well as the privacy concern that the normal construction activities are intruded, the harmony employee-employer relationship is broken, and positive workplace culture is negatively affected.

2.2 From quality to traceability

During the past decades, the concept of traceability is formalized and applied to achieve the quality goal. A proven track and trace framework is now essential in all industries that it has been considered as a new era of production and distribution compliance. Today, a full end-to-end traceability means creating the physical and operational conditions necessary for enforcing quality assurance and quality control, in terms that using available technology to seamlessly integrate traceable data, yield an error proof, and ensure the error can be effortless accessed and take proactive actions in real-time.

2.2.1 Definitions and framework of traceability

Traceability literately refers to the ability to trace all processes from procurement of raw materials to production, consumption and disposal to clarify when and where the products was produced by whom. The ISO has defined traceability as *the ability to trace the history, application, use and location of an item or its characteristics through recorded identification data* (International Organization for Standardization 2015). As Figure 2-3 describes, traceability enables access to relevant product data so that analysis and decisions are conducted in an effective and transparent way where the sharing, use, and reuse of the traceability data enhance the entire industry security and quality.

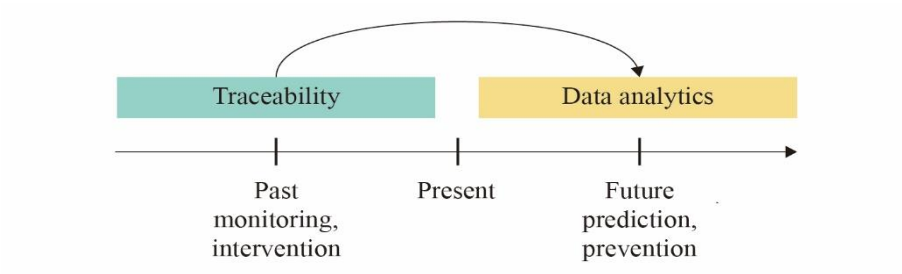

Figure 2-3 Four stages of quality management

The general framework for the development of a traceability system contains identification, data capture and data sharing, in terms that these needs are required to be addressed:

- Unique identification of products, locations, and associated 3M
- Labelling products with a certain singularity (class-, batch-, or instance-level)
- Capturing and recording traceability data
- Enabling access to the data

The traceability data includes information that spans five important dimensions: who, what, where, when and why, and provide valuable contexts to various applications.

- Who are involved?
- What are the primary and related objects to be recorded?
- Where did the event take place?
- When did the movements or events occur?
- Why did the movements or events occur at a specific time and a specific place?

2.2.2 Traceability in industry sectors

The developments and the state-of-the-art applications of track and trace systems in diverse industries are listed below:

2.2.2.1 Food traceability

Quality issues in food industry contain conscious food fraud and inadvertent contamination in spite of the existing high standards of hygiene and measures for quality. Food traceability is believed as a safety solution to enhance the capability of addressing the quality breaks and recalling problematic food products (Creydt and Fischer 2019). The terminology of traceability has appeared recently but the idea was already used for a long time since the mad cow crisis in 1996. It is defined as the ability to discern, identify and follow the movement of a food or substance intended to be or expected to be incorporated into a food, through all stages of production, processing and distribution. It adds value to the overall quality management system in six significant aspects.

- Product traceability – which locates the physical position of a food at any stage in the supply chain to facilitate the dissemination of information to customers, regulators and production stake holders.
- Process traceability – which ascertains the type and sequence of activities that have impacts on the food quality during the growing, harvest, producing and distributing operations.
- Genetic traceability – which determines the genetic constitute of the food, particularly for the genetically modified organisms and materials.
- Inputs traceability – which determines the chemical inputs of the food, including fertilizer, chemical sprays, feed, additives, and the presence of the other chemicals used for the preservation or transformation.
- Disease and pest traceability – which determines the epidemiology of pest, and the biotic hazards such as bacteria, viruses and other emerging pathogens that may contaminate food.
- Measurement traceability – which combines the individual measurement results through an unbroken chain of calibrations to the reference standards of acceptance.

In implementing the traceability in the routine quality management system, the above six aspects have to be addressed to generate sufficient data for the reliable evaluation and take corrective actions for the food quality concerns. The strength of food traceability lies in preventing the incidence of food safety hazards, and reducing the enormity and impact of such incidents by facilitating the identification of unacceptable products and batches, specifying what occurred, when and where it occurred.

Above all, food traceability has been an important requirement in food law around the world, which obliges the business to be able to identify at least the immediate supplier and the immediate subsequent recipient, and achieve a high-level food quality and safety.

2.2.2.2 Drug traceability

Drug traceability, also named pharmaceutical traceability, is defined as the process that enables one to see the movement of prescription drugs or medical devices across the supply chain, trace backwards to identify the history of the transfers and locations of a product from the point of manufacture onwards, and track forwards to predict the intended route of the product towards the point of care. The introduction of traceability concept into the drug industry not only captures benefits to improve patient safety and drug quality, it also enhances the ability to rapidly identify and isolate issues, reduce supply disruptions, and lead to an effective recall process. In practice, four types of events are captured and recorded when monitoring the movements and whereabouts of products are:

- When products are impacted?
- When did this time-stamped event occur?
- Where is the product at a specific time?
- Which process steps are related to the observation?

To answer the above questions, serialization, track and trace, and verification are the three underpinnings to achieve drug traceability,

- Serialization – which assigns a unique identity on a product at a certain level of granularity (item, batch, case or pallet level), indicating what events occur when drugs are produced, distributed and dispensed.
- Track and trace – which captures the information from a forward view to show where is a product right now and from a historical view to present where has a product been. With the track and trace framework, one can understand the changes of ownership of a drug product and go back in time to a certain point even if the product has not change hands.
- Verification – which verifies the information, such as ownership and movement by serial number and transaction history, about the products at one or more places in the supply chain.

In short, drug traceability has brought both a challenge and an opportunity. Although the industry may be overwhelmed with the legislation, the end-to-end implementation of serialization and track-and-trace solutions, and the smart use of the rich data, provide unparalleled changes to improve control over supply chain, increase quality, safety, transparency, and reliability, as well as boost consumer confidence and brand image.

Traceability has become a critical requirement for today's industrial business to reduce risks and stay competitive. Apart from high regulated industries, such as food and drug industries, traceability is also a vital tool for all manufacturers, across all domains, containing aerospace, automation, and instrument industries. It provides a centralized repository and process framework to collect and store all necessary product genealogy and traceability data from both internal and external systems and chain partners. General manufacturers can benefit from faster identification, isolation and containment of potential product defects across the production network, and ensure consistently higher product quality through lean data governance and standardization of key product and process data.

2.2.3 Technologies for traceability

Modern industry is becoming knowledge-intensive and information-driven. Technology innovations are introduced to facilitate the manufacturers to meet the higher regulations and consumer demands. In general, the technologies consist of identification technology, advanced measurements, and computer information programs.

- Product identification technology – which attaches a tag with identity to the basic raw products in order to consistently track the locations. The identity is composed of a series of numbers and alphabets, which codifies specific information, such as date and resources. The forms of the carrier are various, containing Ear-Tag (used in the livestock industry), Bar-Code, QR-Code, DataMatrix, RFID tags for the agriculture, seafood, and pharmaceutical industry. Advancements in material science have greatly led the development of electrical tags that are resistant to tear and wear, and which can withstand harsh environmental conditions, with chips and handheld scanners for reading, storing and transmitting traceability information.

- Quality measurement technology – which measures and analyses the quality attributes and relevant status of products by specific instruments and procedures. The specifications include physical properties, such as size, mass, dimensions, color and flavor; mechanical properties, such as hardness and density; and chemical properties, such as acidity, etc.
- Information technology – which is an integration of algorithms, programs, a central control system that links the traceability information with a local or cloud database at the company, national, and international level. At present, the blockchain technology is receiving increased attention as a popular one of distributed ledger technologies. Blockchain allows information transactions to be performed independently without a central entity. The basis is a digital logbook, named "block", which records a timestamp and an indication of previous block, thus the blocks are linked together and secured against manipulations. First attempts have been made to present the strength of blockchain that it is possible to trace along the entire supply chain within a few seconds.

By enforcing the use of the advanced technologies to tighten up and standardize the production and distribution, managers and supervisors can determine the authenticity, identity and whereabouts of a particular defect anytime and anywhere.

2.3 Requirements on traceability within the construction industry

Present construction projects are time- and labor-consuming that the construction industry is still labor-intensive with fluctuating productivity rather than a significant improvement in the manufacturing industry. Novel and cutting-edge concept and technologies have not been introduced to this conventional domain due to the following natures of the construction industry:

- Uniqueness – construction projects are commonly unique, and the construction process and building product is single-order and single-production.
- Dynamics – construction sites are changing all the time because new physical spaces are built along the construction process, while the factory or plant for general production is fixed and ordered.
- Numerous participants – owners, designers, engineers, contractors, subcontractors, material suppliers, inspectors, consultants, governments, communities, etc. are involved, the network of cooperation and the vision of responsibilities are neither simple nor clear.
- Long life-cycle and enormous expense – construction projects always last for a long time and overrun a huge budget (see Figure 2-4).

Because of the above natures, quality management concepts and frameworks from manufacturing have not been widely adopted as an effective and efficient tool to ensure the quality in the construction industry, such as traceability concept and industry 4.0. Therefore, construction defects issue a number of open challenges for quality management.

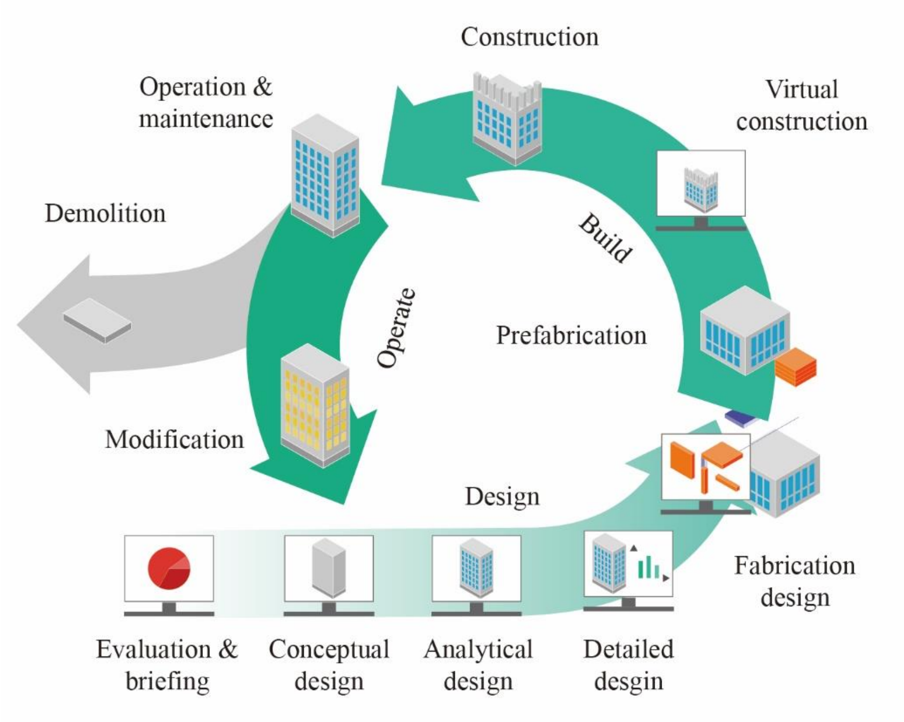

Figure 2-4 Life-cycle of a building project

2.3.1 Investigation of construction defects

A defect is generally understood as unnecessary rework that is required to be conducted more than once because the process was incorrectly implemented the first time, that is to say, construction defects are physical phenomena that need to be corrected, and the correcting process is unnecessary rework. In this study, the terms such as defect, fault, failure, and error are used interchangeably to describe building imperfections.

Based on severity, construction defects can be categorized into technical, aesthetic, and functional classes (Georgiou, Love, and Smith 1999). Technical defects indicate a loss of structural capacity, such as a loose connection of reinforcement bars; aesthetic defects refer to an unexpected appearance of building components, for example, a honeycomb surface of concrete panels; and functional defects indicate a failure to function or work as intended.

Researchers investigated on the causes of three defects and summarized the following roots:

- unreasonable designs – include inappropriate specifications of the materials, layout, and integration between them.
- poor workmanship – includes poor installation methods, poor handling of materials and poor planning
- unqualified materials – refer to the materials that do not perform up to their required standards.
- improper maintenance – represents the irregular or nonexistence of maintenance at the occupancy stage.

The failure mechanism of construction defects is complicated since any defect can have more than one root or cause. In addition, the defects can be found in any building elements. It is therefore a tedious task for inspectors to identify these defects and their causes for such a large product like a construction project.

To prevent future defects, the preliminary causal model of construction defects was proposed based on the Swiss cheese model for safety accidents in which the hierarchy structures were similar but the factors were replaced. This model illustrates the consensus that the correction or elimination of root causes or causal paths should prevent quality defects from occurring, although a vague understanding of the mechanics and their complex correlations between causal factors has limited the value of a root causal analysis.

2.3.2 The need for traceability data

To address the construction defects, monitoring on-site activities and operations of manpower, machinery and material is important, because it enables the construction process to be controlled with a high-resolution visibility. Timely reports on shifts and workers involved in the defective building product and process can be captured before the product is covered by the following materials. Traceability data therefore provides a solid chain of custody for tracking and tracing the on-site construction activities.

Traceability data is the integration of the concerning information, which creates a hierarchy network like a family tree, illustrating the parent-child relationship of each movement or operation of an individual worker or shift. This genealogy with related information – movements, operations, identities building component details and on-site environment, etc. – guides documentation both backwards and forwards (upstream and downstream) from any item in question to its ultimate source or disposition.

Each time a traceability relevant task is executed on a construction sites, traceability data is generated that spans five dimensions as mentioned in the previous section.

- It is valuable to distinguish the person who involved in the creating, handling, operating of the objects moving on the construction sites, providing a clear vision of responsibility.

- Uniquely identifying objects or procedures that move and flow over time is critical, such as displacement, velocity, angular velocity, rotation, etc. Also, they may include other physical, kinematic, and physiological indicators and documents.
- Accurate identified locations are critical to understanding the construction tasks that individual workers are assigned, executed, and accepted across stages. The area-restricted nature of construction projects makes the traceability data a validation between as-built and as-plan models.
- The date, time and timestamp when a specific event occurs can draw a timeline of a building component's life-cycle.
- With a respect to systematic thinking, traceability data provides the construction context around the events that have occurred. Based on data analysis or data mining techniques, reversible and irreversible damages are identified so that corrective actions and eliminations are determined prior to passing to the next procedure or customer.

2.3.3 The need for traceability analysis

Given traceability data for the purpose of construction quality, traceability system needs to support a multitude of relevant applications, from regulations to sustainability, productivity, consumer trust, health and safety, and multiple cases, from foundation to structure, walls, beams, columns, slabs, etc.

The legislative requirements of construction projects contain regulations on geometrical indicators and process parameter as below:

- Geometrical indicators are generated from the comparison between as-built and as-plan models, particularly from the geometrical shape deviations (polygonal, rectangular, circular, etc.). As a typical method of quality control, the geometry control need to be accounted from conceptual design throughout the production and final installation and erection (Zhang et al. 2011, Schwabe, König, and Teizer 2016).

- Process parameters refer to the variables under control across the construction stages. Process control is to continuously inspect the project progress, assess the project health, and make recommendations in response to anticipated construction defects, which assure the quality of final products from a process-oriented perspective (Srewil and Scherer 2013).

To couple the virtual models (such as BIM) and physical construction for the regulation compliance, it is obvious to mine and analysis the traceability data to obtain the control variables of geometry and process.

2.4 Summary

This chapter reviews the literature about the quality in construction industry and presents a systematic view of the development of traceability framework in other industries. The main findings are summarized as follows:

- There have been marked evolutions for the quality management in the construction industry along with the development of it in general industries. In addition, with the advances in sensor-based and vision-based technologies, the ability to identify the product defects and monitor the construction processes has become easier, more convenient and more automated to implement.

- Although sensor-based and vision-vision based destructive and non-destructive methods have proven their capability of defect identification and process monitoring, there are severe limitations on using them in construction projects, such as intrusion and privacy issues.
- An end-to-end traceability system has been considered as a novel era of production and distribution and a necessary tool for quality and safety management in diver manufacturing sectors. The traceability data consisting of who, what, where, when and why provide valuable contexts to various applications.
- The investigation of construction defects shows the open challenge of the vague understanding of the failure mechanism due to various and correlated factors. Traceability data and traceability analysis provides a high-resolution visibility to enhance quality in the construction industry.

CHAPTER 3 METHODOLOGY

In this chapter, the research strategy is scientifically motivated and the research methodological approach is represented here in three parts: 1) methods of data collection; 2) methods of data analysis; 3) evaluation and justification of methodological choices.

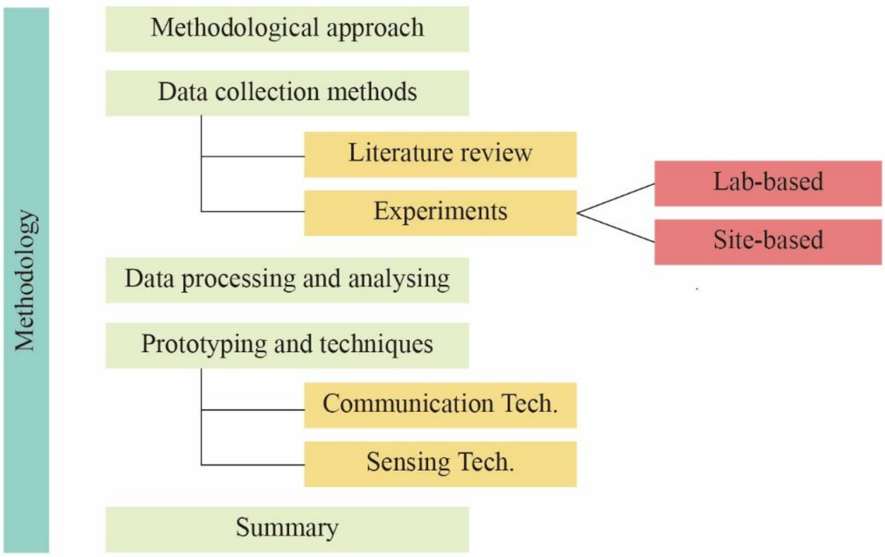

Figure 3-1 Structure of methodology chapter

The beginning Section 3.1 introduces the methodological approach for this study from a systematical view, followed by detail introduction of specific methods. Section 3.2 presents the data collection methods, containing literature review, lab- and site-based experiments. Section 3.3 then describes the data processing and analyzing methods for the collected data. To test the concept of the proposed traceability concept, Section 3.4 shows the prototyping research method and the technique selection criteria at the construction sites, particularly for the wireless communication and sensing techniques. The overall structure of this section is shown in Figure 3-1.

3.1 Methodological approach

The purpose of this thesis is to create a traceability system to track and trace the quality-related construction activities in an efficient and effective way, and to quantitatively identify the quality issues and prevent the negative impacts for the decision making process of the on-site quality management. To address the practical problem of construction quality, quantitative methods are adopted in this study and enable the authors to measure, categorize, identify activity patterns and make generalizations.

Since the data collection and analysis proposed is not a standard methodology for construction quality management, these methods are evaluated and justified by classic representative samples. The valid research is designed carefully in which the variables are controlled and records are accessible that can be replicated by other researchers, so that knowledge and prototype about the traceability concept and system for construction quality can be generalized to other fields. The systematic view explains the justification and connection between the research objectives and research method is show in Figure 3-2.

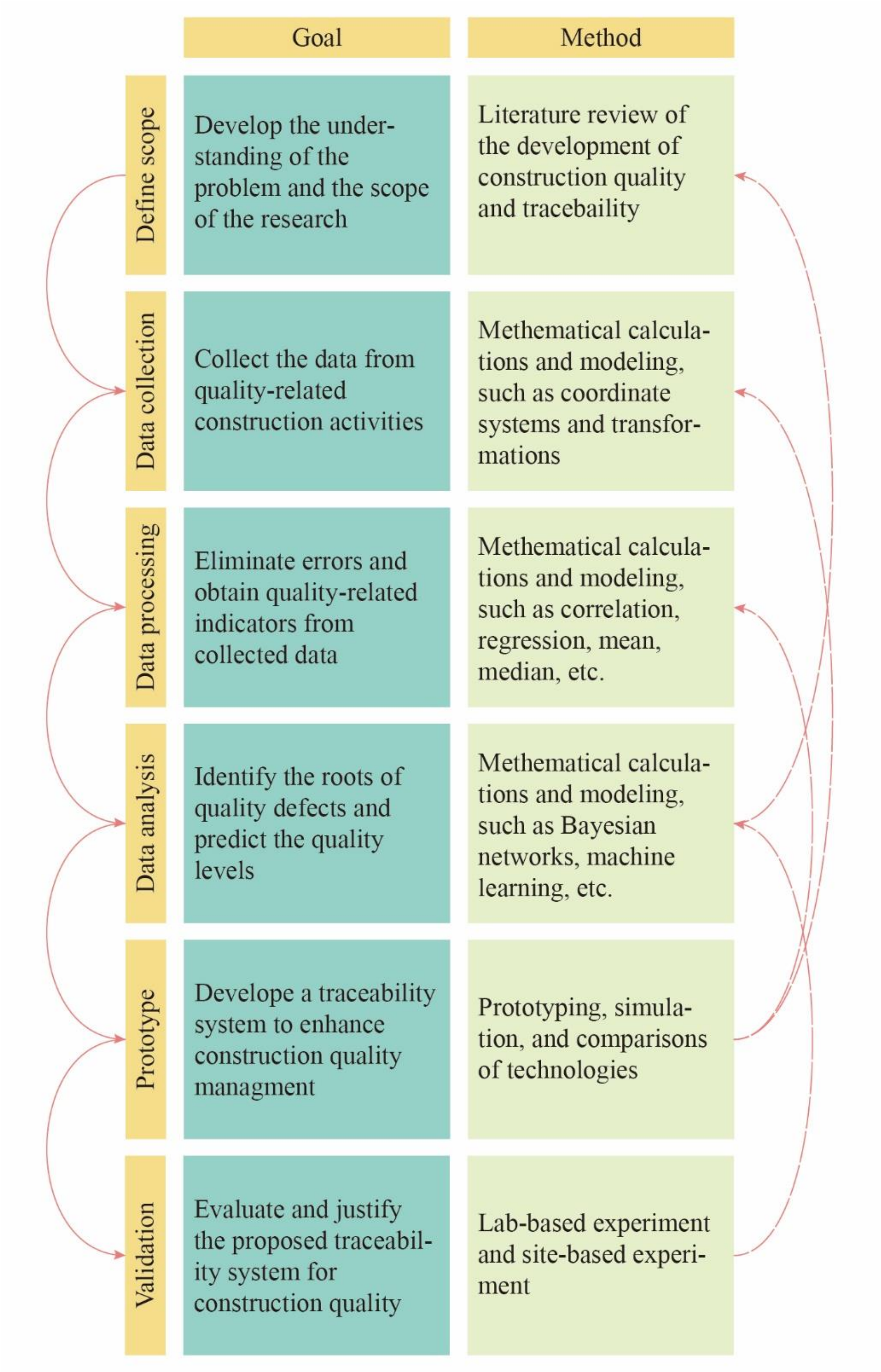

Figure 3-2 The research process of this study

3.2 Data collection methods

Multiple sources of data are involved in this research, containing literature documents, lab-based and site-based experiment data. The experiment data is collected by sensors and surveillance cameras that different sources of evidence are likely to increase the verification of this study. The literature review and two experiments are introduced in depth as follows:

3.2.1 Literature review

Literature review is initiated by searching the relevant background knowledge for a specific topic, including substantive findings, theoretical and methodological contributions. Most of the data come from academic journals and books, such as Automation in Construction and Advanced Engineering Informatics. The others are from construction quality and traceability standards of Hong Kong, U.K., U.S., Canada and China.

To establish the background of this research, construction defect reports and news are collected from internet as the motivation of this research; relevant literatures are reviewed within the areas of quality in the construction industry, traceability applications in manufacturing sectors, and requirements of traceability for on-site quality. The key words consist of inspection, quality control, quality assurance, total quality management, food traceability, drug traceability and construction defects.

3.2.2 Experimental methods

Conducting experiments are the main method of inquiry in science. An experiment is an investigation in which a hypothesis or prototype is scientifically tested. Experimental methods are objective that the views and experience of the researchers have no impacts on the test results, leading to more valid and less bias. In this research, two kinds of experiments are carried out, lab experiment and field experiment.

3.2.2.1 Lab-based experiment

A laboratory experiment is a test under the condition that relevant variables are highly controlled and accurate measurements are available. The lab experiment is taken place in the Smart Construction Laboratory in the Department of Building and Real Estate in The Hong Kong Polytechnic University.

Three participants are assigned to drive a nut into a bolt and loosen them apart for ten times. They adjusted the wrench and checked it to make sure the jaw opened a bit more than the size of a nut or bolt, and hence slipped the open jaw over clockwise to tighten until the nut is tight, and then turned the wrench in an anti-clockwise direction to loosen the nut until it was easy to remove.

3.2.2.2 Site-based experiment

Site-based experiment is done at an actual construction site by employed workers where the environmental variables are nearly under control in real-life setting. The field experiment is conducted in the School of Civil Engineering in Harbin Institute of Technology.

Three workers are required to consolidate the fresh and pouring concrete with an internal concrete vibrator, which forces the air bubbles within the concrete to raise into the open air to achieve even and quality. Concrete consolidation is not exactly necessary for small building blocks but is essential for large and load-bearing structures.

3.3 Data processing and analyzing methods

Data processing and data analysis always start in parallel with the data collection in experiments. Data processing is to prepare the data before analyzing, containing checking for missing data, removing outliers, transforming variables, etc., in short, it is technically manipulated to produce useful information from the raw data. In this research, multiple process models are adopted, such as time series models, stochastic process models, etc.; machine learning and artificial intelligence algorithms are also used to generate and interpret an output.

Table 3-1 Mathematical model types in this research

Type	Characteristics	System identification
White-box	Physical governing laws with known parameters	Linear and non-linear differential equations
Grey-box	Physical governing laws with partial known model structure and parameters	Linear and non-linear differential equations, state-space models, transfer and observe functions or fuzzy models with parameter estimation
Black-box	Unknown model structure and parameters	Artificial neural networks, support vector machines

Data analysis refers to the process of discovering useful information from processed data for decision making process. As listed in Table 3-1, white-box (theoretical), black-box (experimental), and their combination grey-box models are used for both data processing and analyzing processes. For example, white-box models are used for known pattern recognition and signal processing, like local variance; black-box models are apt to unknown pattern recognition; grey-box models are adopted for the root analysis of construction defects because the mechanism and relevant factors are partly known and unknown according to current knowledge or standards.

3.4 Prototyping and technique selection

For the purpose of testing and improving the proposed traceability system, rapid prototyping as a research method is accepted to prove the concept of traceability in the construction industry. Prototype is the creation of low-fidelity objects enables designation with minimum investment in time and the cost of failure. Through making a simple and low-cost prototype, the traceability system is applied and tested in lab and field experiments to accelerate the iterative development.

Since the prototype is an integration of multiple techniques, a variety of advanced techniques are compared and selected, including wireless communication techniques, sensing techniques, etc.

3.4.1 Wireless communication techniques

Construction site is always crowd of building materials, such as concrete blocks, reinforcement bars and pipelines. These materials may have a series of considerable impacts on the information delivery by signals, such as reflection, transmission, absorption, diffraction and scatter. When a radio wave propagating in the atmosphere impinges on a dielectric material (concrete block, glass slab, etc.), part of it is reflected back and part is transmitted through the material. The proportion is determined by dielectric properties of the materials and the angle of incidence of the radio wave to the material.

As shown in Figure 3-3, for construction site, such a local and exposed environment, Wi-Fi, Near-Field Communication (NFC), Bluetooth, and RFID techniques are preferred because they are compatible with daily life electronic devices in which the cost and time for development is lower. In this research, BLE, as the new version of Bluetooth with less energy consumption, is used for wireless communication between sensors, terminals and the database cloud.

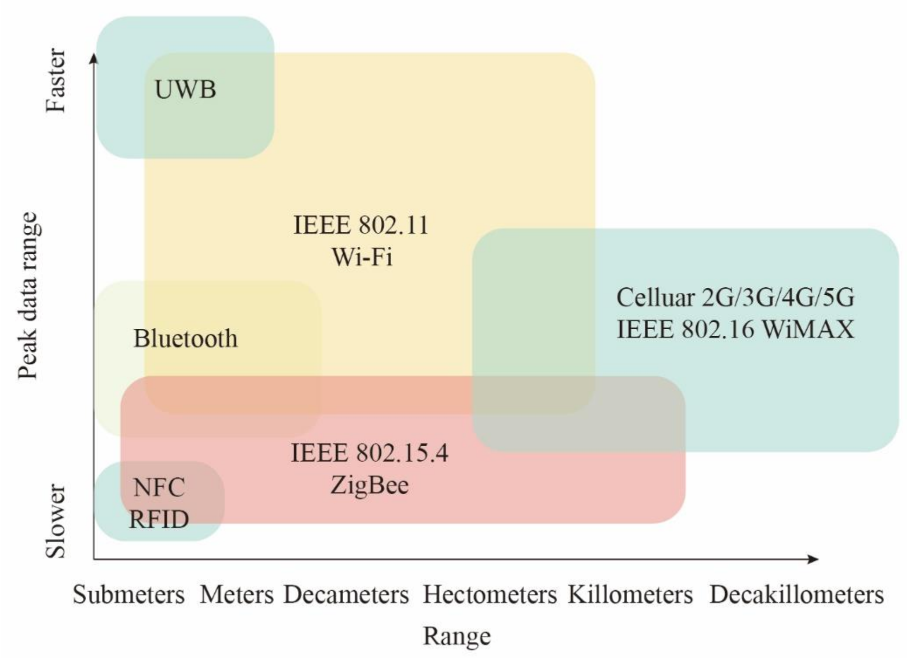

Figure 3-3 The comparison of several wireless communication techniques

3.4.2 Sensing techniques

Sensors are devices, modules or machines with the capability of detecting events or changes in their environments. With advances in micromachinery and easy-to-use microcontroller platforms, sensing techniques have expanded beyond the temperature, pressure, acceleration measurements and the sensitivity has been improved significantly. In addition, with the emergence of micro-electro-mechanical system (MEMS), a central unit (micro-processor) and several components (micro-sensors) are integrated by wet etching, dry etching or electro discharge machining so that the gadget is quite small in size but big in abilities. In this study, accelerometers, gyroscopes, e-compasses, temperature sensors are combined at present, and more sensors will be involved in future, such as pressure, touch, proximity, humidity sensors.

3.5 Discussion of the research methodology

To evaluate the trustworthiness of this study, validation (triangulation), complementarity, discrepancy (initiation), development, and expansion are the most important criteria for mixed-method research (Lee and Smith 2012, Greene, Caracelli, and Graham 1989). Validation refers to seeking convergence, corroboration, and correspondence of results from different methods studying the same phenomenon; complementarity is to seek elaboration, enhancement, illustration, and clarification of results from one method with results from another method, in terms that complementarity measures overlapping or different aspects of the same phenomenon; and discrepancy aims to discover paradox, contradiction, new perspectives of frameworks, and fresh insights that also reframes a research question by analyzing inconsistent results from different methods studying the same phenomenon; development refers to using results from one method to help develop or inform the other method; and expansion is to use different methods for different inquiry components in studying multiple phenomena.

In the literature study, the web and library sources are used to gather the relevant journals and production standards. Since web sources generally need more caution than printed materials, they are thereby double checked to verify the reliability.

The experiment ground truth is collected by vision-based methods using bullet cameras, and omnidirectional cameras, and thereby is quantitative and visible. This method is considered to be the most appropriate method to collect data at the construction sites because it can not only track the behaviors of an object, it also collects the context around the object. In addition, the visible data collection is irreversible that is treated as the ground truth for other data collections. There are however some risks related to the selected data collection methods. For instance, when recording an invisible construction task, such as concrete consolidation, the cameras will be seriously affected by the none-line-of-light effect, leading to risk of deficient data. At the same time, the workers under monitoring also may be reluctant to conduct their assignments since there is a risk that the employees may be feel they are not trusted by employers. These reasons may result in a loss of confidence and unreliable information.

3.6 Summary

This chapter introduces the methodology for data collection and analysis, and discuss its pros and cons in this research. The main findings are summarized as follows:

- Multiple methodological approaches are adopted to enhance the mixed-method research, including literature review, lab- and site-based experiments and mathematical models.
- To test the feasibility of the proposed traceability concept, wireless communications and sensing techniques are carefully selected according to the nature of the construction sites.
- As a reliable data collection, the visible records of construction activities by video cameras are considered as the ground truth in this research.

CHAPTER 4 IMU-BASED MOTION DATA COLLECTION OF CONSTRUCTION TOOLS

As described in Chapter 2, there exist two general approaches to construction data acquisition at the present: vision- and sensor-based methods. They are effective as they record the workplace behavior of workers directly; meanwhile they both raise issues about privacy, information security and employee-employer trust. This research therefore proposes a novel concept that using IMU to track tools instead of tracking workers, providing an alternative to construction progress monitoring. This chapter thus presents the new data collection in three parts: 1) the data to collect; 2) how to collect the data; 3) the pros and cons of this data collection.

The first Section 4.1 describes various construction tools from two perspectives: how to select right tools and how to use the tools right. The next Section 4.2 proposes an original concept that tracking the construction tools rather than tracking the construction workers for construction monitoring, followed by Section 4.3 discussing the pros and cons of the proposed approach. To address the error accumulation concerns, Section 4.4 analyzes the systematic and random errors by Allan variance techniques. Subsequently, sensor models for the accelerometer, gyroscope, and magnetometer are established in Section 4.5. The overall structure of this section is shown in Figure 4-1.

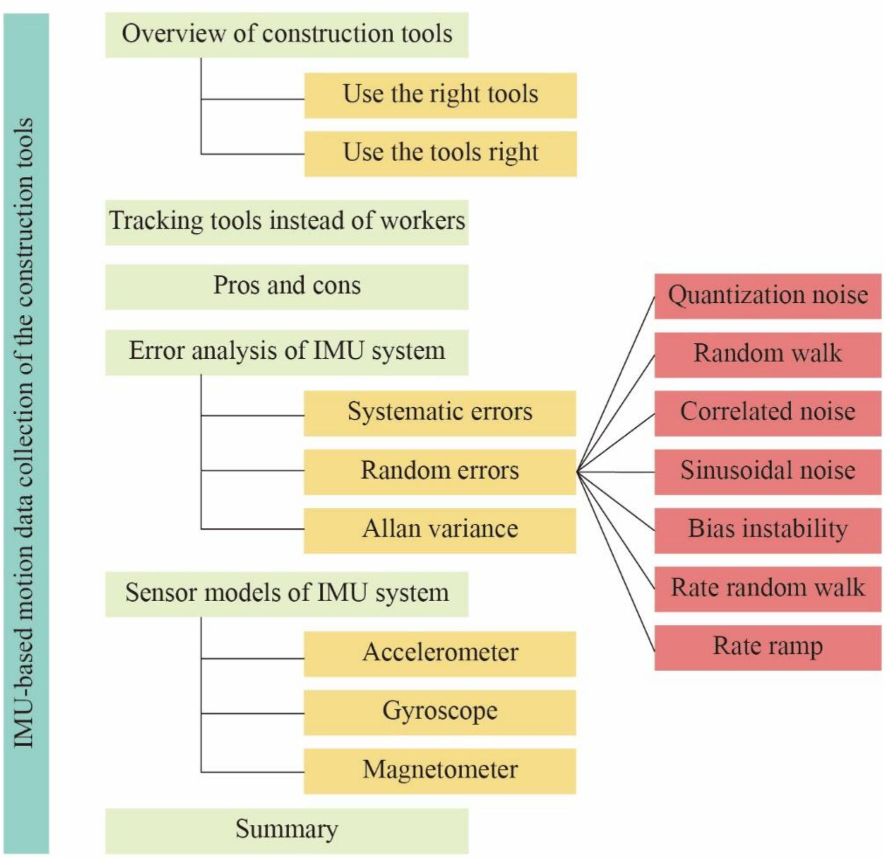

Figure 4-1 Structure of IMU-based data collection chapter

4.1 Overview of construction tools

It is believed that making and using complex tools is one of the intrinsic abilities (others include language, knowledge transfer, etc.) that set us human beings apart from other species in nature (Washburn 1960, Gibson, Gibson, and Ingold 1994). Construction is a typical labor-intensive industry in which a variety of construction assignments are accomplished manually, such as wood formwork, reinforcement bar placement, and pipeline installation. To improve the productivity as well as ensure safety, diverse tools have been developed and implemented at construction sites, and with the advances of construction tools, a large proportion of the construction tasks are performed more quickly and accurately but with fewer manpower.

The term tool generally represents the instruments that are used by hand, whilst the term equipment refers to a set of tools used for a single purpose. At the smaller scale where an individual construction worker is able to hold, there are some overlap between these terms: tools and light equipment. In this research, we focus on hand-control tools because they perform as the bridge between human actions and building materials or blocks where the kinematics of tools reflect the direct manipulation on building components.

Construction tools are classified as hand tools and power tools. Hand tools refer to non-powered tools, including a wide range of tools, such as hammers, screwdrivers, brushes, trowels, wrenches, knives, crimpers, clamps, and so on; power tools are powered by electricity, compressed air, gasoline, pressure from a liquid or an explosive, containing electric tools, pneumatic tools, liquid-fuel tools, powder-actuated tools and hydraulic tools. Construction power tools contain mixers, saws, cutters, drills, grinders, guns, breakers, and so on.

4.1.1 Use the right tools

The major problem that causing injuries is using a wrong tool for a specific job or a tool that has not been properly maintained. It is therefore important for workers to select a proper size, function, accessories, and platform. By the trade classification in the construction industry, the general tools for different technicians are summarized in Table 4-1 (Environment Transport and Works Bureau 2003). It can be seen that the general tools, such as hammers, spanners and trowels are widely used and multi-functional; meanwhile special tools, such as rebar tiers and concrete vibrators are only necessary for special trades. Since there exist a huge number of construction tools, it is important to pick the suitable tools for a particular job, otherwise there may be delays, or conduct the job with an inappropriate tool which may result in damages of the structures and injuries of the operator. The selection criteria contain the appropriateness for the job, quality, safety, weight, comfort, duration of use, available space for use, security, power and fuel requirements, the maintenance status, construction regulations and standards, and the potential to cause nuisance to surroundings, such as noise, dust, vibrations and so on.

For example, hammers have many types that each type has its own strengths and weakness: claw hammer is a daily-life tool driving nails and pulling out nails if required; cross-pein hammer is to hammer small pins and shape metal; brass hammer is used for safety in dusty environment as it does not create sparks; mallet/soft-face hammer is used in decoration works like driving nails without marring the surface of the wood; sledgehammer is for demolition with the heaviest head and the longest handle; ball-pein hammer refer to hardening and flattening metal works; geological hammer is used to break off rock samples; and jewellery hammer is specially for striking chisels.

Table 4-1 General tools for different construction trades

Job title	Job description	Tools
Scaffolder	To erect and dismantle bamboo, metal, and aluminum scaffolding required in construction, repair or decoration work	Scaffold spanners, tape measures, pipe cutters, rebar nips, scaffolding levels, podger hammers, scaffold keys, safety lanyards, etc.
Bar bender & steel fixer	To cut, bend and fix reinforcement steel bars	Bar bending tools and plates, rob benders, hand/automatic rebar tiers, etc.
Bricklayer	To lay bricks, concrete masonry units, and building blocks for construction and repair	Pointing/brick/finishing/edging trowels, brick bolsters, lump/claw/brick hammer, spirit/laser levels, clod chisels, brick jointer, brick tongs, rubber mallet, etc.
Carpenter	To erect and strike timber formwork for building and construction works	Standard/coping/tenon/rip/table/key-hole/circular/miter saws, hacksaws, screwdrivers, tape measures, clay hammers, wood mallets, levels, pry bars, combi/power drills, clamps, bradawls, oscillating tools, nail pullers/guns, sliding bevels, wood chisels, bench vices/grinders, pad sanders, etc.
Concreter	To mix, place, and compact concrete using vibrating machines and to carry out curing, levelling and smoothening of concrete	Shovels, digging spades, rubber gloves/boots, mixers, buckets, laser levels, floats, groove cutters and edgers, saws, plate compactors, internal vibrators, power hammers and drills, mixing paddles, etc.
Demolition worker	To demolish, dismantle, and remove buildings and structures	Sledge hammers, crowbars, pliers, nail pullers, snips, hammers, demo forks, wonder bars, power drills, etc.
Floor layer	To lay timber, PVC, and linoleum to floors, stair threads, skirtings, etc.	Rubber hammers, pull bars, tapping blocks, spacers, etc.
Paving block layer	To lay paving blocks on floor, compact the base layer with vibrating machines, and cut pave blocks to fit floor layout	Block mallets, gap wedges, alignment bars, rubber hammers, vaccum slabs, paving cutters, etc.

Job title	Job description	Tools
Leveller	To read and interpret drawings and set up job lines and levels	Spirit/optical/lase levels, tape measures, theodolites, nylon strings and lime powder, etc.
Welder	To carry out welding or cutting	Welding clamps, magnets, electrodes, angle grinders, metal brushes, welding helmets, shoes, gloves, masks, ear plugs, etc.
Plasterer	To apply coats of plaster to and to render walls and ceilings to produce finished surfaces, and screed floors, staircases and roofs	Pointing/window/corner/finishing trowels, hand-boards (hawks), tin snips, spirit levels, scrapers, artex texture brushes, plaster floats, taping knives, drywall/hack saws, claw hammers, mixing paddles, etc.
Plumber/ Pipelayer	To assemble, install, repair and maintain pipes, fittings, sanitary fixtures, cold, hot and flush water systems, and soil, waste and rain-water drainages systems To lay water mains, make pressurized joints by mechanical means, install pipes and fittings, and surround pipes with concrete	Pipe cutters, telescopic tube cutters, adjustable/radiator spanners, pipe wrenches, slip joint/long nosed pliers, pipe benders, hacksaws/jigsaws, pipe deburring tools, SDS/combi-drills, sabre saws, magnetic levels, stubby screwdrivers, angle grinders, etc.
Tiler	To cut, shape and set tiles on walls, ceilings and floors to specified levels and patterns	Tile cutters, sealant removers, grout rakes, drills, tile trowels, rubber grout floats, tile spacers, etc.
Electrician	To design, install, maintain and trouble shoot electrical wiring systems	Insulated/crimping/side cutting/long nosed pliers, cable cutters, screwdrivers, trimming knives, voltage detectors/multimeters/circuit testers, combi drills, wire strippers, spanners, etc.

4.1.2 Use the tools right

The other critical issue accounting for a large proportion of injuries in the construction industry is the improper use of hand and power tools, particularly, the cutting tools (knives, cutters, saws), digging tools (shovels), striking tools (hammers), surface tools (grinders and sanders), and boring tools (drills) are the leading sources of construction accident injuries by tools (Kendall Jones 2017). During the use of the construction tools, instructions for operation and standards for construction therefore should be followed all the time to achieve a safe, effective and efficient result. In addition, workers who use hand and power tools are exposed to the hazards of falling, flying, abrasive, and splashing objects, or to harmful dusts, fumes, mists, vapors, or gases must be provided with the appropriate personnel protective equipment. Basic rules for safety use contain:

- Examine each tool for damage before use
- Operate tools strictly according to the instructions and standards
- Wear the right personal protective equipment

For example, when use a hammer, one should: grip the hammer close to the end of its handle with dominant hand; place the nail at the right position and hold it near the bottom; watch the head of the nail all the time and swing the hammer loosely until the nail has sunk into the wood enough that it can stand on its own. It is suggested to use few, smooth, well-placed blows rather than pounding a nail with great force.

Similar to walking pattern in gait analysis, most of the construction tools performs a cyclic pattern when they are used at the construction sites, in terms that the use behavior of the construction tools is made up of a series of repetitive motions. According to the on-site observation and the construction standards, the corrective use of the following tools is likely to be spatial-temporally cyclic. As listed in Table 4-2, when a construction tool is placed at the right position, its periodic rotation, translation or their combination repeats at regular time intervals.

Table 4-2 Cyclic patterns in the use of general construction tools

Cyclic pattern	**Tools**
Stillness	Levels, automatic rebar tier, table/miter saws, Oscillating tools, nail guns, sliding bevels, bench vices, theodolites, pipe deburring tools, etc.
2D rotation around the end of handle	Hammers, Mallets, etc.
2D rotation around pivot point (pin)	Cutters, rebar nips, pliers, wire strippers, etc.
2D rotation around the head of handle	Spanners, scaffold keys, rob benders, pry bars (crow bars), nail pullers, shovels, etc.
2D rotation around the shaft	Hand rebar tiers, screwdrivers, mixing paddles,
Translation along a vector	Brick bolsters, clod chisels, brick jointers, tenon/rip/coping/drywall saws, hacksaws, tape measures, drills, concrete edgers, internal vibrator, knives, ground rake, etc.
Translation in a plane	Grinders, sanders, concrete float, plate compactors, vacuum slabs, metal brushes, etc.
Rotation and translation	Trowels, brick tongs, circular saws, etc.

To gain a deep insight into the use of the construction tool and the construction process, this research proposes a novel approach to record the kinematics of the construction tools by inertial measurement unit (IMU).

4.2 Using IMU to track tools instead of workers

Inertial measurement unit (IMU) is a device for measuring the inertial properties of objects. With the emergence and development of MEMS systems, the sensor has decreased in size, whereas the accuracy, robustness, and quick response have improved dramatically (Benoussaad et al. 2016, Seel, Raisch, and Schauer 2014).

Nowadays, an IMU is made of a tri-axis gyroscope, a tri-axis accelerometer, a tri-axis magnetometer, along with a thermometer, enabling the measurement of angular velocity, acceleration, the magnetic field, and temperature. MEMS gyroscope measures the angular rate through detecting the Coriolis force on the vibrating silicon rings embedded in the sensor; MEMS variable capacitive (VC) and piezoresistive (PR) accelerometer measures the acceleration by recording the changes of gap capacitor and resistance when the micro-machined proof mass moves; MEMS magnetic field sensor operates by detecting the effects of the Lorentz force on voltage or resonant frequency to measure the magnetic fields; and thermometer measures the temperature via detecting the actuating voltage generated by the effect of electron tunneling.

Figure 4-2 describes the schematic diagram for data collection, including direct measurements of acceleration, angular velocity, magnetic field, and temperature, and indirect measurements of velocity, orientation by integral calculation, angular acceleration by differentiating calculation, and displacement by dual integrals.

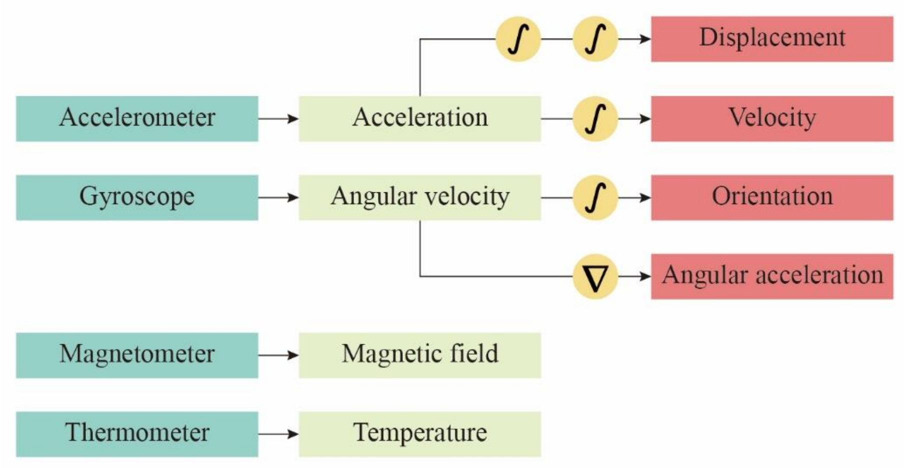

Figure 4-2 Block diagram of IMU for data collection

Since the construction hand tools are directly held or manipulated by hands, it is possible to evaluate the workloads according to the Newtonian mechanics. For example, force is equal to the mass times the acceleration (Newton's Second Law), in the same way, torques equals to the product of the rational inertia about the axis and the angular acceleration. The work (kinetic energy/translational energy) therefore is computed as the product of the force and displacement:

$$E_t = \int F \cdot ds = \frac{1}{2}mv^2 \tag{4.1}$$

where E_t represents the translational energy, F is the force, s is the displacement, m is the mass of the object, and v is the velocity.

The rotational work (angular kinetic energy/rotational energy) is assessed by the torque multiplying rotation:

$$E_r = \int \tau \cdot d\theta = \frac{1}{2} I \omega^2 \tag{4.2}$$

where E_r represents rotational energy, τ is the torque, θ is the rotational angle, I is the moment of inertial, and ω is the angular velocity.

And the total kinetic energy is the sum of translational and rotational kinetic energies:

$$E_k = E_t + E_r \tag{4.3}$$

where E_k represents the total kinetic energy.

4.3 Pros and cons of tracking tools

Compared with the vision-based data collection by surveillance cameras and the sensor-based data collection by wearable devices, using IMUs to track and trace the construction tools has a number of advantages.

- In the first place, the IMU-based process monitoring by the construction tools causes no privacy issues because no personal information of the participants has been collected.
- Another important advantage of this approach is non-intrusive that there is no need to wear any devices on human body and no excessive intrusion is generated into ones' daily productive activities.
- An additional advantage is that the measurement principle of the proposed system is simple that the size is small and portable. Also, the deployment is easy-handling, low-cost, energy-saving, and has a short start-up time.

Nonetheless, the IMU sensor system has a series of unavoidable sources of errors. That is the most considerable drawback because the integration and double integration embedded in the sensor leads to error accumulation over time (Alexiev and Nikolova 2013). Moreover, MEMS sensors are more sensitive to temperature changes than optical devices that the IMU-based data collection may fail in extreme environments like severe heat and cold weather.

4.4 Error analysis of the IMU-based system

Errors of the IMU-based data collection are the consequences of systematic errors and random noises. Systematic errors refer to improper installation, unreasonable design, and incorrect calibration. They are consistent or regular and their effects can be eliminated perfectly by reinstallation, redesign and recalibration; meanwhile the random noises are comprehensive to describe and are impossible to avoid because their sources are various and have no patterns.

4.4.1 Random error sources

The random noises in IMU are composed of constant bias, bias asymmetry and instability, angle random walk/velocity random walk, quantization noise, rate random walk, rate ramp, sinusoidal noise and Markov noise.

- Constant bias error is the average output of a fixed MEMS IMU over a period, which has no direct correlation with the sensor states. It is trivial to compensate for it by subtracting the bias from the output.

- Quantization noise (QN) is introduced by encoding an analogic signal into a digital signal, which is caused by the differences between the real amplitudes of the points sampled and the analog-digital converter resolution.
- Angle/velocity random walk (RW), also known as white noise, generally is the major noise of MEMS IMUs, resulting from the thermo-mechanical noise fluctuating, which is also named thermo-mechanical white noise. Such noise is a sequence of zero-mean uncorrelated random variables from the sensors are perturbed by a white noise sequence.
- Correlated noise (CN) is due to the mechanical shaking and decreases over time, which is also named Markov noise.
- Sinusoidal noise (SN) is caused by the cyclical factors in environments, which is characterized by a number of frequencies.
- Bias asymmetry and instability (BI) refers to the difference between the bias for positive and negative inputs and the variation over a finite sample of time, which is also known as flicker noise. The cause of BI may be the temperature drift, magnetism drift and so on.
- Rate random walk (RRW) is the errors type with unknown sources at the present time.
- Rate ramp (RR) is likely to be a deterministic error rather than a random noise, for long finite time spans.

4.4.2 Allan variance

Allan variance (AVAR) is a time domain technique designed for dividing and analyzing the random noises by characterizing the phase and frequency instability of precision devices (Oliver J. Woodman 2007), which is originally defined by:

$$\sigma_y^2(\tau_o) = \frac{1}{2\tau_o^2}\langle(x_{k+2} - 2x_{k+1} + x_k)^2\rangle \tag{4.4}$$

where $\sigma_y^2(\tau_o)$ represents AVAR as a function of the observation period τ_o and $\langle\cdot\rangle$ is the ensemble average. On expanding the ensemble average in equation (4.5), AVAR is thus computed by:

$$\sigma^2(\tau_o) = \frac{1}{2\tau_o^2(N-2)}\sum_{k=1}^{N-2}(x_{k+2} - 2x_{k+1} + x_k)^2 \tag{4.5}$$

where N is the total number of samples.

Since the sources of the random errors are independent, AVAR is considered as the sum of the various error components by:

$$\sigma_y^2(\tau_o) = \sigma_{QN}^2 + \sigma_{RW}^2 + \sigma_{CN}^2 + \sigma_{SN}^2 + \sigma_{BI}^2 + \sigma_{RRW}^2 + \sigma_{RR}^2 \tag{4.6}$$

where σ_{QN}^2 is the variance of quantization noise, σ_{RW}^2 is the variance of random walk/white noise, σ_{CN}^2 is the variance of correlated noise, σ_{SN}^2 is the variance of Sinusoidal noise, σ_{BI}^2 is the variance of bias instability, σ_{RRW}^2 is the variance of rate random walk, σ_{RR}^2 is the variance of rate ramp. Based on the power spectral density (PSD) of these random noises, their components in AVAR thus is hence distinguishable by the highest polynomial degree of the time interval (refer to Appendix A). For the purpose of characterizing the noises, Allan deviation (ADEV) is obtained through taking the square root of AVAR and different types of random process cause slopes with different gradients to appear on the ADEV on a log-log scale, as plotted in Figure 4-3.

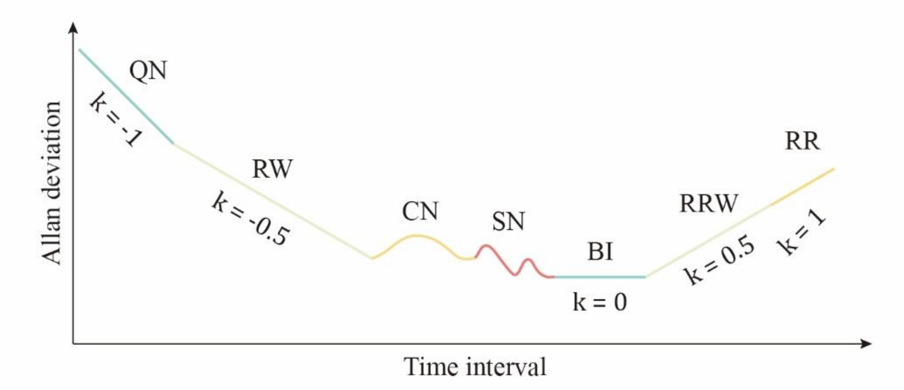

Figure 4-3 Schematic log-log plot of Allan deviation for noise deviation

4.5 Sensor models of IMU-based system

Once the sources of the IMU random errors are determined by AVAR, it is possible to establish a sensor model for IMU sensors and assess its effects on the performance of IMU-based data collection. The basic model for the gyroscope/accelerometer/magnetometer assumes that the direct output is made up of the true value of angular rate/acceleration/magnetic fields, a constant offset from systematic error, and a series of noises from random errors.

$$\hat{x} = x + c + \sum \varepsilon \tag{4.7}$$

where $\hat{x}$ represents the output of IMU sensor and the estimator of true value x, c is the constant offset/bias, ε is the IMU noise, such as random walk, sensor drift or the moving bias, and so on. Through AVAR and autocorrelation analysis, the relevant coefficients are determined and verified with the acceptable specifications.

The developed models for gyroscope, accelerometer, and magnetometer, taking bias instability, white noise, random walk and environmental drifts into consideration for simulation (MathWorks 2019), are introduced as below:

4.5.1 Model of accelerometer

The model of accelerometer inputs the ground-truth orientation and acceleration, and four drifts to simulate the accelerometer's output (see Figure 4-4). Although the accelerometer is designed for capturing the acceleration, in a way, it can gauge the orientation of a stationary item with relations to the Earth's surface. More specially, since the accelerometer is sensitive to both linear acceleration and the local gravitational field, the former measures the tri-axis motions while the latter develops the tilt sensing ability by computing the rotation equation between the gravitation and linear acceleration outputs if the initial gravity force of a stationary object is aligned with one of the sensor axes (Pedley 2013). That's the reason why orientation is also involved in the sensor model of accelerometer. Nevertheless, there is an exception to this rule. For example, in a free fall, outputs of the accelerometer are zero, ignoring the tilt entirely.

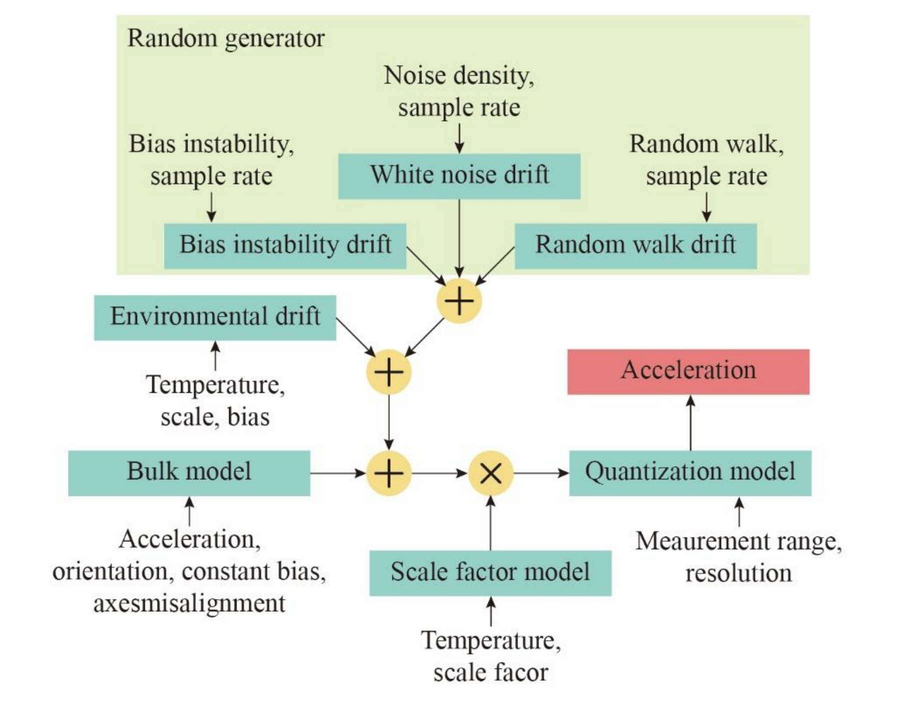

Figure 4-4 Sensor model of IMU accelerometer

4.5.2 Model of gyroscope

As shown in Figure 4-5, gyroscope's model is more complex that the simulation take ground-truth angular velocity, orientation, acceleration and a series parameter for drifts as the inputs and set the angular velocity as the outputs. In the simulation, acceleration has an adverse impact within the environmental drift since the gyroscope identifies an actual value until the object stabilizes when gauging the rate of rotation around a particular axis.

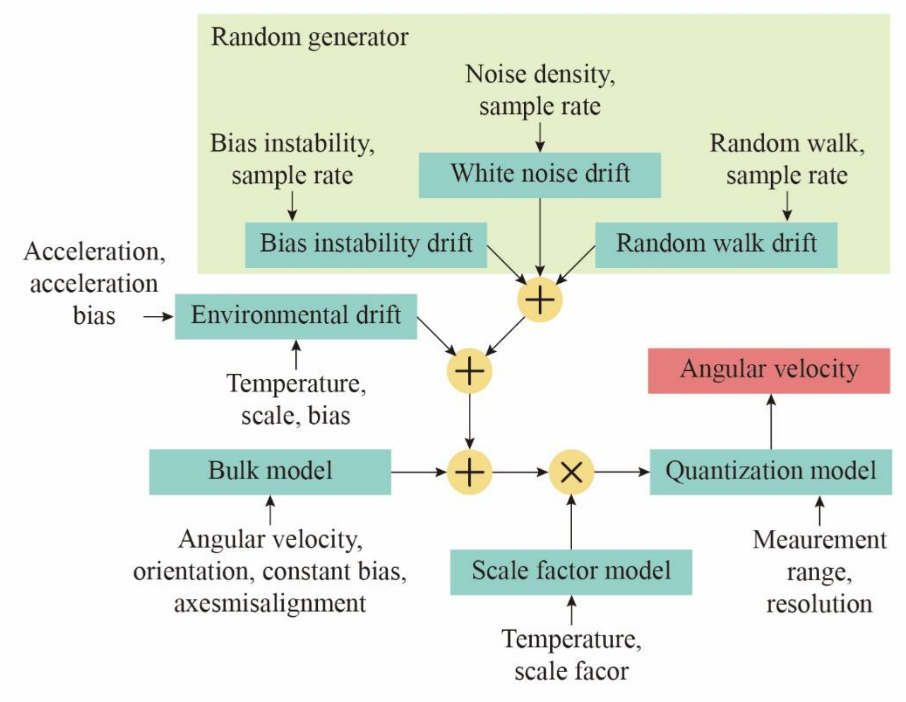

Figure 4-5 Sensor model of IMU gyroscope

4.5.3 Model of magnetometer

Magnetism varies from place to place because of the differences in Earth's magnetic field, due to differing nature of rocks and the interaction between charged particles from the sun and the magnetosphere of a planet. In the model of magnetometer described in ,Figure 4-6, the inputs of the model contain ground-truth magnetic field, orientation and parameters for drifts and the output is magnetic field. Since the magnetometer is composed of three orthogonally mounted fluxgates, if possible, the magnetometer should be used far from the magnetic materials so that the environmental effects on magnetic field are sufficiently small for accurate measurement.

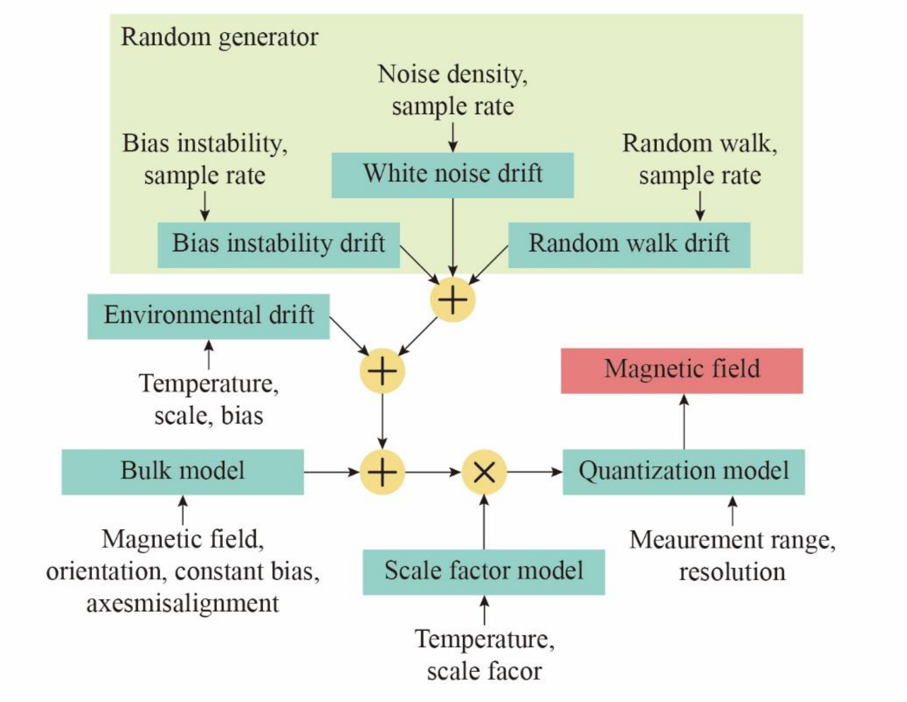

Figure 4-6 Sensor model of IMU magnetometer

4.6 Summary

This chapter mainly describes the IMU-based motion data collection of the construction tools, discusses the advantages and disadvantages of tracking tools rather than manpower, analyzes the errors and establishes the sensor models in the data collection. The main findings are summarized as follows:

- Various construction tools are generally used in almost all of the construction tasks. It is therefore an effective and efficient way to track the use of the construction tools instead of the behaviors of manpower for construction monitoring without intrusion and privacy concerns.
- The collected acceleration, angular velocity, magnetic field and temperature of the construction tools by IMU sensors provide a valuable insight into the kinematics and the workload of a construction process.

- Random errors should be carefully addressed in IMU-based system as they are likely to accumulate over time by integration and double integration in the data collection.

CHAPTER 5 TOOL KINEMATIC MODEL FOR CONSTRUCTION QUALITY ASSESSMENT

Once the data of the construction tools is collected by the proposed IMU-based approach in Chapter 4, this chapter thus conducts data processing and data fusion. Also, this chapter constructs a tool kinematic model and extract indicators for construction quality assessment in the end. In short, Chapter 5 is represented in four parts: 1) tool data processing; 2) tool data fusion; 3) tool kinematic model; 4) quality indicators extraction.

Section 5.1 firstly introduces the data processing techniques for IMU raw data, including converting between coordinate reference frames, integration and deviation, and gravity compensation. The next Section 5.2 presents the data fusion methods for orientation and position at both low-level and medium level, which use accelerometers to estimate pitch and roll angles, use magnetometers to measure jaw angle, and combine them with gyroscopes' measurements to generate orientations with a higher accuracy; use Kalman filter and Extended Kalman filter to fuse kinematic orientation and position data from different sources. In the Section 5.3, a tool kinematic model is built up based on the cyclic motion patterns during the use of the construction tools. This model is made up of cycle detection and periodic calibration, which are used to segment motions and extract quality variables for quality control and assurance in the Section 5.4. The overall structure of this section is shown in Figure 5-1.

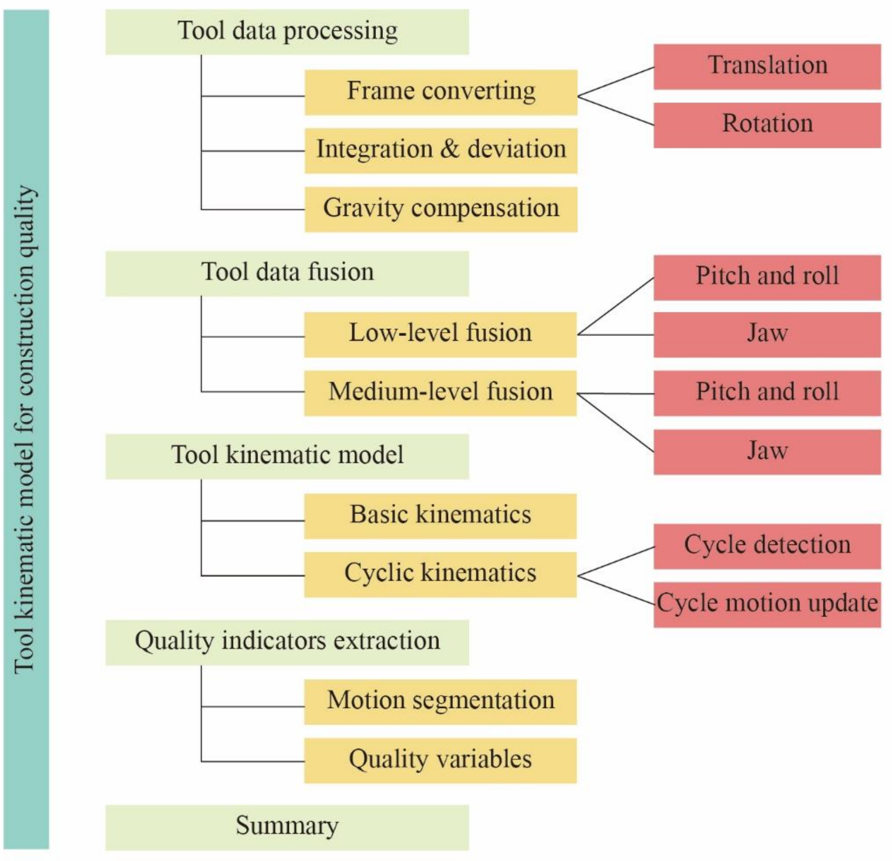

Figure 5-1 Structure of tool kinematic model chapter

5.1 Tool data processing

Since the IMU directly measures the acceleration, angular velocity, magnetic field and temperature of the sensor in its own frame, it is significant to take data processing techniques to obtain information of the tools rather than the sensor for further analysis. The data processing techniques consist of converting between coordinate systems, integration and deviation, and gravity compensation.

5.1.1 Converting between coordinate systems

There are five relevant coordinate frames in IMU-based systems, namely, an earth-fixed coordinate frame, a navigation coordinate frame, a local level coordinate frame, a strapdown inertial coordinate body frame, and a non-rotating inertial coordinate frame. They are introduced as below:

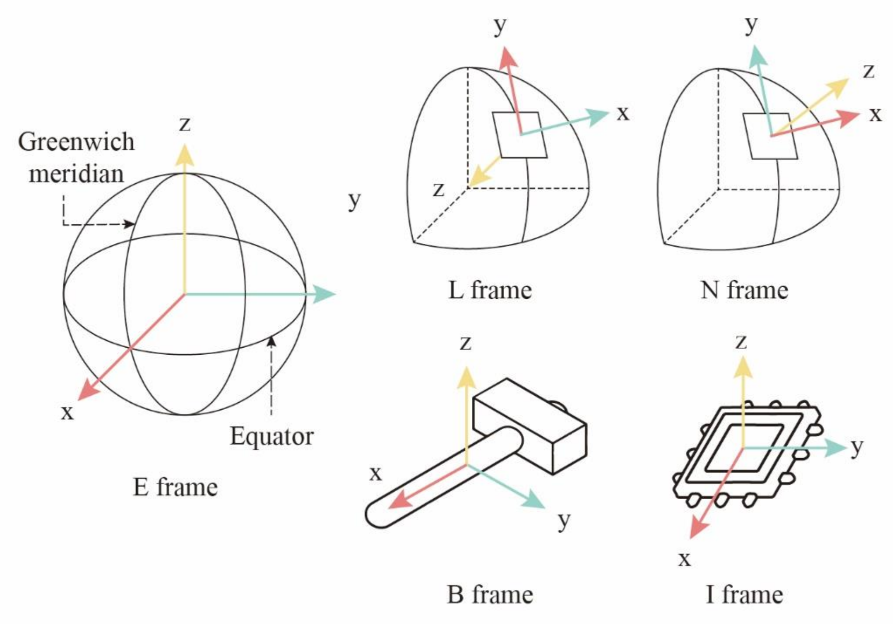

Figure 5-2 Coordinate frames of IMU-based system

- Earth-fixed coordinate frame (E frame) refers to the frame in which the center of mass of the earth is defined as the origin, the z-axis lies along the earth's polar axis pointing north, the x-axis is at the equator and along the plane of the Greenwich meridian, and the y-axis completes the right-hand coordinate system.
- Navigation coordinate frame (N frame) or east-north-up frame (ENU frame) serves at or near the surface of the earth, where the origin coincides with the center of the sensor, the x- and y-axes point east and north respectively, and the z-axis is orthogonal to these axes up into the sky.

- Local level coordinate frame (L frame) or north-east-down frame (NED frame) is similar to an N frame in that the axes are all parallel to those of the N frame, although the directions are different in that the x-axis points north, the y-axis points east, and the z-axis completes the right-hand coordinate system downward.
- Inertial coordinate body frame (B frame) is a right-hand coordinate system that is tied to the body and rotated along with it. The origin is located at the center of the object.
- Non-rotating inertial coordinate frame (I frame) represents a fixed right-hand coordinate frame on an IMU where the origin coincides with the center of the sensor and the axes coincide with the sensing orientations

The IMU-based system collects data in the I frame. For the purpose of tool motion analysis, these data have to be converted into B frame; for location estimation, these data have to be converted into N frame, integrating with GPS sensors; and for gravity compensation, those data in I frame and the Earth's physical model in E frame have to be both converted into L frame.

To convert between coordinate systems, two basic operations for solid-body transformation are involved: translation and rotation.

5.1.1.1 Translation

Translation is an operation that displaces points by a fixed distance along a given direction. In homogeneous coordinates, the translation matrix is written by:

$$\boldsymbol{Trans}(\Delta x, \Delta y, \Delta z) = \begin{bmatrix} 1 & 0 & 0 & \Delta x \\ 0 & 1 & 0 & \Delta y \\ 0 & 0 & 1 & \Delta z \\ 0 & 0 & 0 & 1 \end{bmatrix} \tag{5.1}$$

where $\Delta x, \Delta y, \Delta z$ represents the displacement in x-, y-, and z-axis respectively.

5.1.1.2 Rotation

Rotation refers to the operation that an angle is turned around an axis. Three rotation matrices corresponding to rotation about z, y, and x axes in homogeneous forms are:

$$\begin{gathered} \boldsymbol{Rot_x}(\phi) = \begin{bmatrix} 1 & 0 & 0 & 0 \\ 0 & \cos\phi & -\sin\phi & 0 \\ 0 & \sin\phi & \cos\phi & 0 \\ 0 & 0 & 0 & 1 \end{bmatrix} \\ \boldsymbol{Rot_y}(\theta) = \begin{bmatrix} \cos\theta & 0 & \sin\theta & 0 \\ 0 & 1 & 0 & 0 \\ -\sin\theta & 0 & \cos\theta & 0 \\ 0 & 0 & 0 & 1 \end{bmatrix} \\ \boldsymbol{Rot_z}(\psi) = \begin{bmatrix} \cos\psi & -\sin\psi & 0 & 0 \\ \sin\psi & \cos\psi & 0 & 0 \\ 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 1 \end{bmatrix} \end{gathered} \tag{5.2}$$

where ϕ, θ, ψ represents the roll, pitch, and yaw angles around x, y, and z axes.

5.1.2 Integration and deviation

As mentioned in the block diagram of IMU sensors for indirect measurements, velocity is an integral of acceleration over time, displacement is also an integral of velocity with respect to time. The integration schemes are represented by:

$$s(t) = s(0) + \int_0^t v\, dt$$
$$v(t) = v(0) + \int_0^t a\, dt \tag{5.3}$$

where s, v, a represent absolute displacement, velocity, and acceleration respectively. t refers to time.

Rotation is an integral of angular velocity over time, and angular acceleration is a derivative of angular velocity with respect to time. These indirect measurements are computed by:

$$r(t) = r(0) + \int_0^t \omega\, dt$$
$$\alpha(t) = \frac{d\omega}{dt} \tag{5.4}$$

where r, ω, α represents absolute rotation angle, angular velocity, and angular acceleration respectively.

Rather than providing a continuous absolute signal, the IMU-based system usually collects relative data at a fixed frequency. The above integral and derivative is therefore approximated by numerical presentations, such as the trapezoid rule, and Simpson's rule, and these formulas are summarized in Appendix B.

5.1.3 Gravity compensation

The G-force is also known as a specific force, which is not actually a force but a type of acceleration. This acceleration is a proper acceleration relative to a free-fall. Accelerometers on the surface of the earth measure the proper acceleration produced by the G-force exerted by the ground, which is a constant determined by the location of measurement. To compensate the G-force in IMU-based system, the basic idea is to obtain the accurate gravity at a specific position and then eliminate it from the measurement of acceleration.

5.1.3.1 Gravity model of Earth

The physical model of Earth is generally considered as an ellipsoid. Assume the normal radius and meridian radius are denoted as R_N, R_M, respectively. The geometry of Earth is calculated by:

$$R_N = \frac{R_E}{(1 - e_E^2 \sin^2 \varphi)^{\frac{1}{2}}}$$
$$R_M = \frac{R_E(1 - e_E^2)}{(1 - e_E^2\, sin^2\, \varphi)^{\frac{3}{2}}} \tag{5.5}$$

where R_E represents the Earth's equatorial radius/semi-major axis with a constant of 6,378.1370 km, e_E is the Earth's eccentricity with a constant of 0.08181919, and φ refers to the geodetic latitude of a specific location.

Given the latitude and longitude of a location, the gravity at a certain level is computed by:

$$g(h) = \frac{g_E(1 + 0.01512 \sin^2 \varphi + 0.045 \sin 2\varphi)}{\left(1 + \frac{h}{R_E}\right)^2} \tag{5.6}$$

where $g(h)$ represents gravity at the level of h, and g_E is the gravity constant with a value of 9.78032677 m/s^2.

5.1.3.2 G-force formula

Assume that a construction tools is controlled by extra force by a worker and gravity force by the Earth, the basic differential equation in I frame is:

$$\frac{d^2\boldsymbol{s}_I}{dt^2} = \boldsymbol{a} + \boldsymbol{g} \tag{5.7}$$

where $\boldsymbol{s_I}$ represents the ground-truth displacement in I frame, $\boldsymbol{a}, \boldsymbol{g}$ refer to the acceleration and gravity vectors, respectively. As Earth rotates eastward in prograde motion, the converting between I and E frame based on the Coriolis effect is:

$$\frac{d\boldsymbol{s}_I}{dt} = \frac{d\boldsymbol{s}_E}{dt} + \boldsymbol{\omega}_{IE} \times \boldsymbol{s}_E \tag{5.8}$$

where $\boldsymbol{s}_E$ represents the ground-truth displacement in E frame, and $\boldsymbol{\omega}_{IE}$ is the rotation vector, with magnitude ω_{IE}, of the rotating reference frame relative to the inertial frame. For Earth, the value is 7.2921159 rad/s. The differential of equation (5.8) is:

$$\frac{d^2\boldsymbol{s}_I}{dt^2} = \frac{d\boldsymbol{v}_E}{dt} + \boldsymbol{\omega}_{IE} \times \boldsymbol{v}_E + \boldsymbol{\omega}_{IE} \times (\boldsymbol{\omega}_{IE} \times \boldsymbol{v}_E) \tag{5.9}$$

Combine equation (5.7) and (5.9), the velocity in I frame is calculated by:

$$\frac{d\boldsymbol{v}_I}{dt} = \boldsymbol{a} - \boldsymbol{\omega}_{IE} \times \boldsymbol{v}_E + \boldsymbol{g}_p \tag{5.10}$$

where $\boldsymbol{g}_p = \boldsymbol{g} - \boldsymbol{\omega}_{IE} \times (\boldsymbol{\omega}_{IE} \times \boldsymbol{v}_E)$ represents the actual measured gravity on the Earth's surface, determined by the physical gravity model. Considering E frame as a transition coordinate frame, the velocity between N and I frame is clarified by:

$$\frac{d\boldsymbol{v}_I}{dt} = \frac{d\boldsymbol{v}_N}{dt} + (\boldsymbol{\omega}_{IE} \times \boldsymbol{\omega}_{EN}) \times \boldsymbol{v}_E \tag{5.11}$$

The relative acceleration of tool use in N frame is thus computed by:

$$\frac{d\boldsymbol{v}_I}{dt} = \boldsymbol{a} - (2\boldsymbol{\omega}_{IE} + \boldsymbol{\omega}_{EN}) \times \boldsymbol{v}_{\boldsymbol{N}} + \boldsymbol{g}_p \tag{5.12}$$

5.2 Tool data fusion

As discussed in the models of IMU sub-sensors, the collected acceleration, angular velocity, magnetic field, and temperature are correlated through orientation and position. It is a good idea for IMU sensors to fuse data for accuracy and quick response. The taxonomy based on levels of abstraction categorize the data fusion into low level fusion, medium level fusion, and high level fusion (Nakamura, Loureiro, and Frery 2007).

- Low level fusion refers to signal or measurement level fusion, providing more accurate data by integrating the raw data from multiple resources rather than individuals. The main integration approach of the accelerometer and magnetometer for orientation is at this level that the raw and orthogonal acceleration and magnetic field are combined.

- Medium level fusion represents the feature or attribute level fusion, which fuses the attributes and features of the objects (construction tools), such as the position integration with GPS and orientation integration within an IMU in this research.
- High level fusion takes symbols as input and combines them to provide an accurate global decision. High level fusion is out of the scope of this research, which has not been discussed here.

5.2.1 Low level data fusion

Low level data fusion in IMU conceptually refers to the combination of acceleration and magnetic field for orientation estimation where the pitch and roll matrices come from accelerometer and jaw matrix from magnetometer. Here, roll, pitch, and yaw matrices $\boldsymbol{R}_x, \boldsymbol{R}_y, \boldsymbol{R}_z$ referring to the rotations by angles ϕ in roll, θ in pitch and ψ in jaw about the x, y and z axes respectively, are:

$$\begin{gathered}\boldsymbol{R}_x(\phi) = \begin{bmatrix} 1 & 0 & 0 \\ 0 & \cos\phi & -\sin\phi \\ 0 & \sin\phi & \cos\phi \end{bmatrix} \\ \boldsymbol{R}_y(\theta) = \begin{bmatrix} \cos\theta & 0 & \sin\theta \\ 0 & 1 & 0 \\ -\sin\theta & 0 & \cos\theta \end{bmatrix} \\ \boldsymbol{R}_z(\psi) = \begin{bmatrix} \cos\psi & -\sin\psi & 0 \\ \sin\psi & \cos\psi & 0 \\ 0 & 0 & 1 \end{bmatrix}\end{gathered} \tag{5.13}$$

There are six possible ordering of these three rotation matrices, and they are equally valid in principle. In this research, the order x-y-z is adopted as the relative transformation from L frame (where the gravity force is aligned with the z) to I frame, and the corresponding transformation matrix is:

$$\boldsymbol{R}_{xyz}(\phi,\theta,\psi) = \boldsymbol{R}_x(\phi)\boldsymbol{R}_y(\theta)\boldsymbol{R}_z(\psi)$$
$$= \begin{bmatrix} \mathrm{c}\,\theta\,\mathrm{c}\,\psi & \mathrm{c}\,\theta\,\mathrm{s}\,\psi & -\mathrm{s}\,\theta \\ \mathrm{c}\,\psi\,\mathrm{s}\,\theta\,\mathrm{s}\,\phi - \mathrm{c}\,\phi\,\mathrm{s}\,\psi & \mathrm{c}\,\phi\,\mathrm{c}\,\psi + \mathrm{s}\,\theta\,\mathrm{s}\,\phi\,\mathrm{s}\,\psi & \mathrm{c}\,\theta\,\mathrm{s}\,\phi \\ \mathrm{c}\,\theta\,\mathrm{c}\,\psi\,\mathrm{s}\,\phi + \mathrm{s}\,\phi\,\mathrm{s}\,\psi & \mathrm{c}\,\phi\,\mathrm{s}\,\theta\,\mathrm{s}\,\psi - \mathrm{c}\,\psi\,\mathrm{s}\,\phi & \mathrm{c}\,\theta\,\mathrm{c}\,\phi \end{bmatrix} \quad (5.14)$$

5.2.1.1 Pitch and roll estimation

In the Earth's gravitational field, any axis with a value of g in the accelerometer output of a stationary item is obviously aligned with the Earth's downward gravity force. As a matter of fact, the tri-axis accelerometer mounted on the construction tool orients in the Earth's gravitational field, and undergoes linear acceleration measured in E frame (Pedley 2013). Thereby, based on the transformation matrix in equation (5.14), the equation between normalized acceleration readings and theoretic acceleration values generated by gravitational field is:

$$\frac{\boldsymbol{a}}{\|\boldsymbol{a}\|} = \frac{1}{\sqrt{a_x^2 + a_y^2 + a_z^2}} \begin{bmatrix} a_x \\ a_y \\ a_z \end{bmatrix} = \boldsymbol{R}_{xyz} \begin{bmatrix} 0 \\ 0 \\ 1 \end{bmatrix} = \begin{bmatrix} -\sin\theta \\ \cos\theta\sin\phi \\ \cos\theta\cos\phi \end{bmatrix} \quad (5.15)$$

where $\boldsymbol{a} = \left(a_x, a_y, a_z\right)^T$ represents the raw acceleration detected from the IMU accelerometer. Solve this equation and obtain the roll and pitch angles in x-y-z order by:

$$\phi = \tan^{-1}\frac{a_y}{a_z}$$
$$\theta = tan^{-1}\frac{-a_x}{\sqrt{a_y^2 + a_z^2}} \tag{5.16}$$

5.2.1.2 Jaw estimation

In the Earth's magnetic field, the components of down/up and north axes are parallel to the Earth's surface; meanwhile the component along with the east direction is empty, as shown in Figure 5-3..

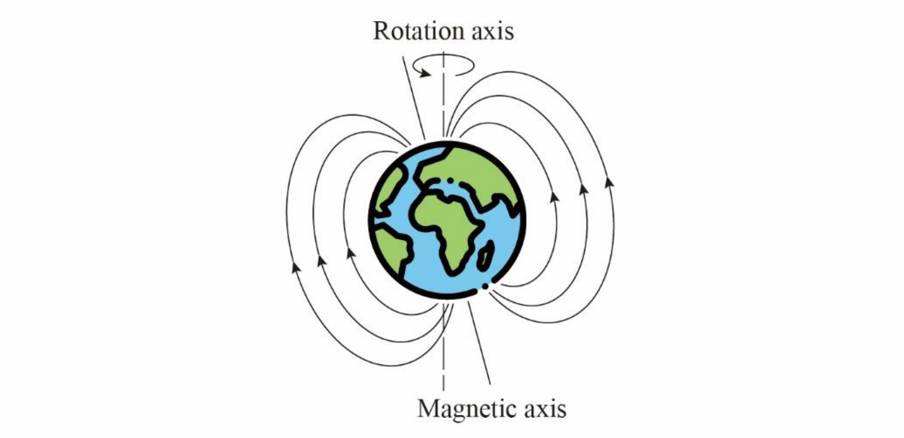

Figure 5-3 Magnetic field of Earth

The normalized magnetic field measurements therefore satisfy the following equation:

$$\frac{\boldsymbol{h}}{\|\boldsymbol{h}\|} = \frac{1}{\sqrt{h_x^2 + h_y^2 + h_z^2}}\begin{bmatrix} h_x \\ h_y \\ h_z \end{bmatrix} = \boldsymbol{R}_{xyz}\begin{bmatrix} h_N \\ 0 \\ h_D \end{bmatrix} \tag{5.17}$$

where $\boldsymbol{h} = (h_x, h_y, h_z)^T$ represents the magnetic field measured by the IMU magnetometer. h_N, h_D refer to the constant components of magnetic field relative to Magnetic North and Down. In the northern hemisphere, the magnetic field points downwards at the North Magnetic Pole and rotate upwards as the latitude decreases until it is horizontal at the magnetic equator, and vice versa in the southern hemisphere.

Solve the equation (5.17) and extract the jaw angle around z axis following x-y-z order by:

$$\psi' = \frac{h_x}{h_y} \tag{5.18}$$

where ψ' represents the computed jaw angle. However, the magnetic field north does not exactly point to the true geometrical north and there is a declination within the computed jaw angle. The ground-truth jaw angle is therefore computed via:

$$\psi = \psi' \pm \Delta\psi \tag{5.19}$$

where ψ represents the true jaw angle, and $\Delta\psi$ refers to the declination at a certain place. In Hung Hom, Hong Kong, the magnetic declination is around $2°59'$ relative to west.

5.2.2 Medium level data fusion

Medium level fusion refers to fusing the spatial-temporal features and attributes of the construction tools, containing orientations and positions from different sources within the IMU-based system and other integrated systems, such as GPS. Since these data sources are always noisy and the mathematical and simplified models for describing real phenomena are impossible to be perfectly accurate all the time, Kalman filter is adopted to take the uncertainties in measurements and models into account for the data fusion. The following hypothesis are satisfied in IMU-based system, Kalman filter is therefore globally optimal that the output is likely to be the ground truth based on the confidence on both measurements and models.

- The random noises in IMU measurements in exposed environment follow zero-mean uncorrelated Gaussian distributions.
- The translation and rotation motion of the construction tools is a Markov's chain that position and orientation at any time is only determined by the state attained at the previous time.
- The IMU-based measurement is time invariant and linear.

5.2.2.1 Standard Kalman filter

The basic concept of Kalman filter is to compute the most likely output by minimizing the quadratic weighted error between measurements and predicted states. The measurement process is modelled by:

$$\boldsymbol{z}_{\mathrm{t}} = \boldsymbol{H}\boldsymbol{x}_t + \boldsymbol{v}_t \tag{5.20}$$

where $\boldsymbol{H}$ represents the observation matrix, $\boldsymbol{x}, \boldsymbol{z}$ are the actual and observed state vector, and $\boldsymbol{v} \sim \mathcal{N}(\mu, \boldsymbol{R})$ refers to the observation noise drawn from a multivariate normal distribution with mean of zero $\mu = 0$ and a multivariable covariance $\boldsymbol{R}$. The prediction process identifies the true state at current time t is evolved from the state at the previous time $t-1$, and its linear discrete-time stationary model without a control loop is represented by:

$$\boldsymbol{x}_t = \boldsymbol{A}\boldsymbol{x}_{t-1} + \boldsymbol{B}\boldsymbol{u}_{t-1} + \boldsymbol{w}_{t-1} \tag{5.21}$$

where $\boldsymbol{\Phi}$ represents the state transition matrix, $\boldsymbol{B}$ is the control matrix of noises, and $\boldsymbol{w} \sim \mathcal{N}(\mu, \boldsymbol{Q})$ is the process noise following a multivariate Gaussian distribution with zero mean $\mu = 0$ and a multivariable covariance $\boldsymbol{Q}$.

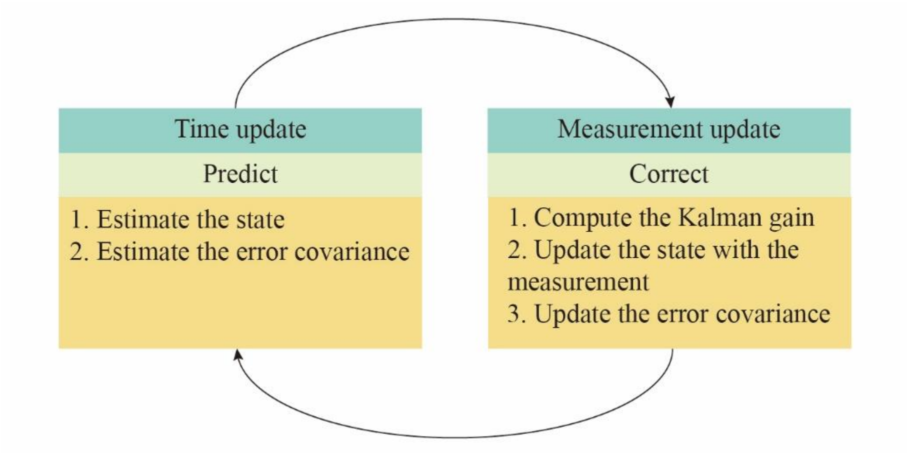

Figure 5-4 Discrete Kalman filter cycle

As shown in Figure 5-4, Kalman filter estimates a process and then obtains feedback from measurements to update the process estimation. As such, Kalman filter contains two groups: time update equations and measurement update equations. Time update process projects forward the current state and error variance estimates to update the prior estimates for the next time step, and the measurement update process is responsible for feedback that incorporates the measurements into the prior estimates to obtain improved posterior estimates.

In the time update process, the current state estimate is computed by:

$$\hat{\boldsymbol{x}}_{t|t-1} = \boldsymbol{A}\hat{\boldsymbol{x}}_{t-1|t-1} + \boldsymbol{B}\boldsymbol{u}_{t-1} \tag{5.22}$$

where $\hat{\boldsymbol{x}}$ represents an estimation on the system state, the subscript t refers to the instant time and $|$ is the Bayes' rule notation. The prediction error covariance is calculated by:

$$\boldsymbol{P}_{t|t-1} = \boldsymbol{A}\boldsymbol{P}_{t-1|t-1}\boldsymbol{A}^T + \boldsymbol{Q} \tag{5.23}$$

where $\boldsymbol{P}$ represents the prediction error covariance. In the measurement update process, the optimal Kalman gain is computed via:

$$\boldsymbol{K}_t = \boldsymbol{P}_{t|t-1}\boldsymbol{H}^T(\boldsymbol{H}\boldsymbol{P}_{t|t-1}\boldsymbol{H}^T + \boldsymbol{R})^{-1} \tag{5.24}$$

where $\boldsymbol{K}$ represents the Kalman gain. Subsequently, a posterior estimate by incorporating the measurement is computed by:

$$\hat{\boldsymbol{x}}_{t|t} = \hat{\boldsymbol{x}}_{t|t-1} + \boldsymbol{K}_t\left(\boldsymbol{z}_{\mathrm{t}} - \boldsymbol{H}\hat{\boldsymbol{x}}_{t|t-1}\right) \tag{5.25}$$

Finally, a posterior error covariance is estimated via:

$$\boldsymbol{P}_{t|t} = (\boldsymbol{I} - \boldsymbol{K}_t\boldsymbol{H})\boldsymbol{P}_{t|t-1} \tag{5.26}$$

where $\boldsymbol{I}$ represents the identity matrix.

5.2.2.2 Extended Kalman filter

Considering the uncertainties and non-linear stochastic processes embedded in the practices, the standard Kalman filter is improved to generate extended Kalman filter (EKF) (Philipe miranda de moura 2018). Thus, the prediction process is governed by non-linear stochastic different equation:

$$\boldsymbol{x}_t = f(\boldsymbol{x}_{t-1}, \boldsymbol{u}_{t-1}, \boldsymbol{w}_{t-1})4 \tag{5.27}$$

The measurement model is also modified as:

$$\boldsymbol{z}_{\mathrm{t}} = g(\boldsymbol{x}_t, \boldsymbol{v}_t) \tag{5.28}$$

where f represents the non-linear function that relates the states at sequential timestamps and g represents the measurement non-linear function relating the state to the measurement.

For the time update step, since the individual values of noises at each time step are unknown in practice, the current state estimate is simplified as:

$$\hat{\boldsymbol{x}}_{t|t-1} = f\left(\hat{\boldsymbol{x}}_{t-1|t-1}, \boldsymbol{u}_{t-1}, 0\right) \tag{5.29}$$

The prediction error covariance is computed by:

$$\boldsymbol{P}_{t|t-1} = \boldsymbol{A}_t \boldsymbol{P}_{t-1|t-1} \boldsymbol{A}_t^T + \boldsymbol{W}_t \boldsymbol{Q}_{t-1} \boldsymbol{W}_t^T \tag{5.30}$$

where $\boldsymbol{A}_t, \boldsymbol{W}_t$ represent the Jacobian matrices of partial derivatives of f with respect to x, w. Elements of these matrices are computed via:

$$\begin{gathered} A_{i,j} = \frac{\partial f_i}{\partial x_j}(\boldsymbol{x}_{t-1}, \boldsymbol{u}_{t-1}, 0) \\ W_{i,j} = \frac{\partial f_i}{\partial w_j}(\boldsymbol{x}_{t-1}, \boldsymbol{u}_{t-1}, 0) \end{gathered} \tag{5.31}$$

In the measurement update process, the optimal Kalman gain is similarly modified as:

$$\boldsymbol{K}_t = \boldsymbol{P}_{t|t-1} \boldsymbol{H}_t^T (\boldsymbol{H}_t \boldsymbol{P}_{t|t-1} \boldsymbol{H}_t^T + \boldsymbol{V}_t \boldsymbol{R}_t \boldsymbol{V}_t^T)^{-1} \tag{5.32}$$

where $\boldsymbol{H}_t, \boldsymbol{V}_t$ represents the Jacobian matrices of partial derivatives of g with respect to x, v, these are:

$$\begin{gathered} H_{i,j} = \frac{\partial g_i}{\partial x_j}(\boldsymbol{x}_t, 0) \\ V_{i,j} = \frac{\partial g_i}{\partial v_j}(\boldsymbol{x}_t, 0) \end{gathered} \tag{5.33}$$

The posterior state estimate is computed via:

$$\hat{\boldsymbol{x}}_{t|t} = \hat{\boldsymbol{x}}_{t|t-1} + \boldsymbol{K}_t \left(\boldsymbol{z}_{\mathrm{t}} - g\left(\hat{\boldsymbol{x}}_{t|t-1}, 0\right)\right) \tag{5.34}$$

The last equation of posterior error covariance remains the same as the standard Kalman filter by:

$$\boldsymbol{P}_{t|t} = (\boldsymbol{I} - \boldsymbol{K}_t\boldsymbol{H})\boldsymbol{P}_{t|t-1} \tag{5.35}$$

5.3 Tool kinematic model

5.3.1 Basic kinematic model

The state of any construction tool is defined by acceleration, velocity, position, angular acceleration, angular velocity, and orientation, which is also represented by:

$$\begin{aligned} \boldsymbol{x}_t &= (\boldsymbol{s}_t, \boldsymbol{v}_t, \boldsymbol{a}_t, \boldsymbol{r}_t, \boldsymbol{\omega}_t, \boldsymbol{\alpha}_t)^T \\ &= \left(s_x, s_y, s_z, v_x, v_y, v_z, a_x, a_y, a_z, r_x, r_y, r_z, \omega_x, \omega_y, \omega_z, \alpha_x, \alpha_y, \alpha_z\right)^T \end{aligned} \tag{5.36}$$

The transition and observation functions in an absolute reference frame are thus denoted by:

$$f(\boldsymbol{x}) = \begin{bmatrix} \boldsymbol{I} & T\boldsymbol{I} & 0.5T^2\boldsymbol{I} & \boldsymbol{0} & \boldsymbol{0} & \boldsymbol{0} \\ \boldsymbol{0} & \boldsymbol{I} & T\boldsymbol{I} & \boldsymbol{0} & \boldsymbol{0} & \boldsymbol{0} \\ \boldsymbol{0} & \boldsymbol{0} & \boldsymbol{I} & \boldsymbol{0} & \boldsymbol{0} & \boldsymbol{0} \\ \boldsymbol{0} & \boldsymbol{0} & \boldsymbol{0} & \boldsymbol{I} & T\boldsymbol{I} & 0.5T^2\boldsymbol{I} \\ \boldsymbol{0} & \boldsymbol{0} & \boldsymbol{0} & \boldsymbol{0} & \boldsymbol{I} & T\boldsymbol{I} \\ \boldsymbol{0} & \boldsymbol{0} & \boldsymbol{0} & \boldsymbol{0} & \boldsymbol{0} & \boldsymbol{I} \end{bmatrix} \boldsymbol{x} \tag{5.37}$$

$$g(\boldsymbol{x}) = \begin{bmatrix} \mathbf{0} & \mathbf{0} & \mathbf{0} & \mathbf{0} & \mathbf{0} & \mathbf{0} \\ \mathbf{0} & \mathbf{0} & \mathbf{0} & \mathbf{0} & \mathbf{0} & \mathbf{0} \\ \mathbf{0} & \mathbf{0} & \boldsymbol{I} & \mathbf{0} & \mathbf{0} & \mathbf{0} \\ \mathbf{0} & \mathbf{0} & \mathbf{0} & \mathbf{0} & \mathbf{0} & \mathbf{0} \\ \mathbf{0} & \mathbf{0} & \mathbf{0} & \mathbf{0} & \boldsymbol{I} & \mathbf{0} \\ \mathbf{0} & \mathbf{0} & \mathbf{0} & \mathbf{0} & \mathbf{0} & \mathbf{0} \end{bmatrix} \boldsymbol{x}$$

where $\boldsymbol{I}, \mathbf{0}$ represent the identity matrix and zero matrix with a 3×3 dimension.

In relative reference frames, the position, velocity and acceleration is related to the angular velocity and orientation that the transition function involves the converting matrix between I frame and N frame.

5.3.2 Cyclic tool kinematic model

Since the construction tools are always designed for specific activities, it is believed that the motions of the construction tools are highly specific for different types of motions and these mathematical spatiotemporal patterns bring an independent separation from common components (Tsai et al. 1994).

In gait analysis, cyclic walking pattern has become one of the significant characteristics of human behaviors. Also, the use of the construction tools performs a general cyclic pattern in motions (refers to Table 4-2). Here, the cycle motion is defined as the motion undertaken by a construction tool that follows a repeating path over time and the path is likely to 2D/3D rotation, translation, or their combines. Examples include turning a nut by a spanner, driving a nail by a hammer, and cutting wood by a coping saw.

The cyclic tool kinematic model proposed in this research is composed of two parts:

cycle detection and cyclic motion update.

5.3.2.1 Cycle detection

To detect cycles and identify events during the use of the construction tools, this research proposes a general batch-mode algorithm using acceleration, angular velocity and magnetic field as follows:

- Compute the magnitude of sensor data for each sample by:

$$x = \|\boldsymbol{x}\| = \sqrt{x_x^2 + x_y^2 + x_z^2} \tag{5.38}$$

where x represents the magnitude of the state data, and x_x, x_y, x_z refer to the direct measurement of acceleration, angular velocity or magnetic field along x, y, and z axes, respectively. Sometimes, a smooth filter, such as median filter and mean filter, is required to eliminate the fluctuations and isolated points causes by minor accidents.

- Compute the local variance and remove the constant bias by:

$$\sigma_i^2 = \frac{1}{2w+1}\sum_{j=i-w}^{i+w}\left(x_j - \bar{x}_i\right)^2 \tag{5.39}$$

where σ_i^2 represents the local variance of sample data at time step i. w defines the size of a moving window, and $\bar{x}_i$ is the average value of samples within the window. It is noticed that local variance is not the only feature for cycle detection, but it is more effective than mean, skewness, kurtosis, energies, max and min value in this study.

- Apply a threshold to recognize the events and segment the entire process.
- A cycle is detected if and only if, when the last phase of previous cycle ends and the beginning phase of the subsequent cycle starts.

5.3.2.2 Cyclic motion update

Cyclic motion update is a kind of virtual aiding proposed in the research, which is designed to enforce a constraint due to prior knowledge. It not only provides a periodic calibration to alleviate the noise accumulation over time, it also facilitates an empirical reference input to the control system for reliability. The basic concept is that the motions of the construction tools are supposed not to move outside a particular plane or line because the repetitive use of any construction tool is always in 1D line or 2D plane (refer to the cyclic pattern summarized in Table 4-2).

Referring to the zero velocity update (ZUPT) in inertial navigation system (INS), cyclic motion update is also a static calibration that relies on the fact that use of construction tools is stationary in the line or plane that is orthogonal to the working plane or line (Grejner-Brzezinska, Yi, and Toth 2001). The cyclic motion update events thereby are detected automatically by testing the acceleration, angular rate, and magnetic field components with a certain tolerance level as the following equation:

$$\left|x_i - x_i^0\right| \leq 3\sigma_{x_i}, \mathrm{i} \in \{x, y, z\} \tag{5.40}$$

where x represents the direct measurement from IMU sensors along the stationary orientation or in the stationary plane. x^0 refers to the empirical mean and σ_x is the tolerance estimated from empirical investigation.

During the construction process, the continuous signals are collected and monitored to identify the cyclic motion update events based on specific working patterns, and if the threshold for acceptance of the cyclic motion conditions exceeds a certain duration, the processing module switches automatically from monitoring to calibrating mode.

The tool kinematic model is established at the level of data, valuable indicators for quality assessment are more practical that they have visually physical meanings and are compatible with the current construction quality standards.

5.4 Construction quality indicators extraction

The segmentation and recognition of elementary actions from a construction process is a foundation in activity understanding and has a wide range of applications, such as quality assessment and safety and health management. Nonetheless, it is still an open challenge for segmentation in human activities due to high variability of appearance, shapes and possible occlusions. Fortunately, the segmentation in the use of the construction tools is simplified because of the clear motions and cyclic patterns.

5.4.1 Segmentation of motions

To distinguish different action segments from a sequence of human behaviors, researchers have developed two series of classifiers: sequence-based and feature-based methods. Sequence-based classifiers contain dynamic time warping (DTW), hidden Markov model (HMM), maximum-entropy Markov model (MEMM), and so on. Sequence-based approaches are specifically developed for time series analysis; whilst the extraction of high-level features from sequential motions bring comprehensive machine learning algorithms into the feature based methods, such as sparse coding, k-nearest neighbors (KNN), support vector machines (SVM), accumulated motion energy model, random forest (RF) and artificial neural network (ANN) (Huang et al. 1999, Shan and Akella 2014, Yan, Wang, and Xie 2008, Wang et al. 2012, Liu, Zhang, and Qi 2003, Müller and Röder 2006).

Compared with human skeleton, the classification algorithms of the construction tools are much simpler because there are less joints and chains in the tool motions. For example, a spanner is rigid without joint and a plier is made up of a pair of metal levels with a joint locating at the fulcrum.

In this research, the collected data are processed by fast Fourier transform (FFT), PSD, and autocorrelation functions to extract the characteristics in both time- and frequency-domain. And signal features like relative maxima, minima and local peaks are then obtained for segmentation classifiers. Since different construction tools have different working patterns and spatial-temporal characteristics, it is scientific to apply trials for the effective and efficient features and classifiers. The detail case is introduced in the following sections.

5.4.2 Process quality variables

Table 5-1 General quality indicators in the use of various construction tools

Quality indicators		**Relevant construction tool samples**
Absolute orientation	Levelness	Levels, table saws, etc.
	Verticality	Internal concrete vibrators, coping saws, etc.
Relative orientation	Parallelism	Brick tongs, concrete floats, grinders, etc.
	Perpendicularity	Drills, scaffold keys, etc.
	Rotation angle	Drills, spanners, wrenches, etc.
Absolute position		Almost all of the construction tools.
Positions	Depth/Height	Internal concrete vibrators, saws, etc.
	Width/Length	Brick blosters, metal brushes, grinders, etc.
	Effect area	Mixed paddles, pad sanders, taping knives, etc.
Velocity		Saws, vibrators, grinders, pad sanders, etc.
Time	Working time	Almost all of the power tools
	Accumulated time	Vibrators, etc.
Amount		Almost all of the power tools
Environmental variables	Temperature	Almost all of the tools with chips embedded
	Humidity	Almost all of the tools with chips embedded
	Illumination	Optical construction measurement tools
Other specific variables		Specific tools for specific tasks

In a sufficient long motion sample with multiple repetitions of atomic actions, the movement of certain tools show acceleration and deceleration with respect to position or rotation alternately. To quantitative the construction process, it is crucial to convert these data changes into process quality variables. According to construction standards, safety and health regulations, there are a number of construction process variables for quality management. Here, the indicators relative to the use motion of the construction tools are summarized in Table 5-1.

To extract those quality indicators, Figure 5-5 illustrates the workflow based on the motion data generated from IMU-based tracking system. It can be seen that real-time quality indicators describe the construction process and ensure the quality without complex computation; meanwhile the time-delayed quality indicators show the level of completion of the construction process that integrated with time and prior knowledge, providing an overview of construction quality. Here, levelness and verticality represent the absolute orientations pointing or are orthogonal to upward/downward; parallelism and perpendicularity refer to the relative orientations between building components and construction tools; and rotation angle is an integral of angular velocity from the beginning phase to the end action segment. Most of the orientation indicators are relative to the measurement tools, which have significant impacts on the performance of measurement. Position data are mainly used for effect areas, depth or length estimation which describes the places where the jobs have done and also reveals the blank places that the jobs should be done. In addition, the combination of time and atomic action data are able to show the amount of the tool cyclic working patterns as an objective measurement of labor inputs for piece-rate pay and the average or accumulated working time for time wage. Besides, environmental variables are also necessary as the temperature, humidity, and illumination have significant impacts on the measurements by electric chips.

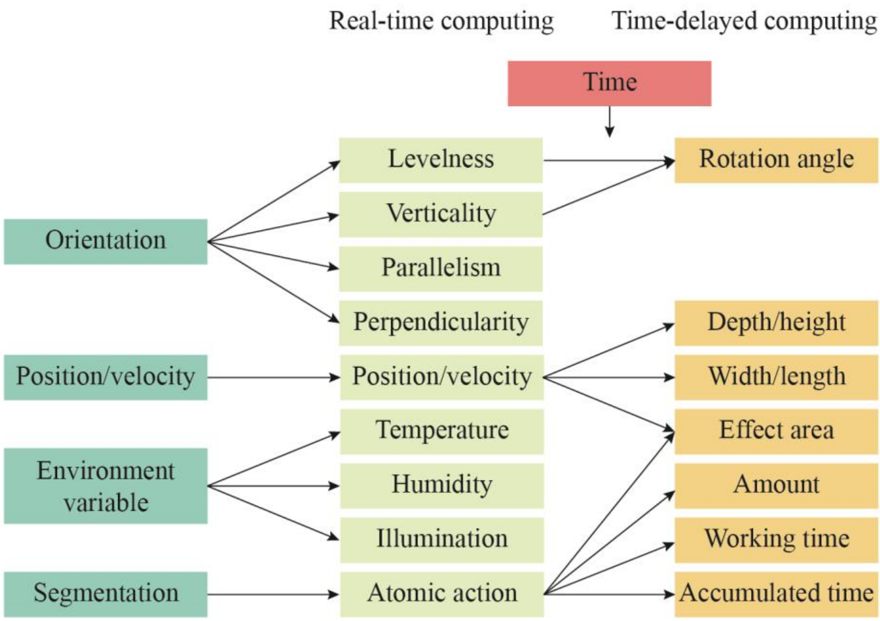

Figure 5-5 Schematic diagram of quality indicators extraction

5.5 Summary

This chapter mainly illustrates the data processing algorithms for the raw tool data, introduces the data fusion techniques at low and medium levels, establishes the crucial tool kinematic model by cyclic use patterns, and extracts the quality variables from the model finally. The main findings are summarized as follows:

- The use of the construction tools performs an obviously cyclic pattern due to the repetitive nature of the construction tasks. Spatial-temporal kinematic models enable an accurate description of such cyclic patterns in a mathematical representation.

- During the use of any construction tools, the repetitive use patterns are likely to be observed along a specific direction/around a specific axis/within a specific plane. The calibration based on such kinematic characteristics provides a feasible method to address the IMU error accumulation issue.
- IMU-based system for tracking tools provides a wealth of data. By data fusion at different levels from multiple sources, the accuracy and quality of data can be significantly improved and enhanced.

CHAPTER 6 TRACEABILITY CHAIN MODEL FOR CONSTRUCTION QUALITY MANAGEMENT

To bridge the gap between construction quality-relative process and the final building products' quality, this chapter therefore establish a traceability chain model that describes the causes and effects of construction defects based on probabilistic and graph theories. This chapter also represents the mechanism of tracking forward and backward within a traceability chain. Above all, Chapter 6 is structured in three parts: 1) construction traceability chain; 2) trace forward; 3) trace backward.

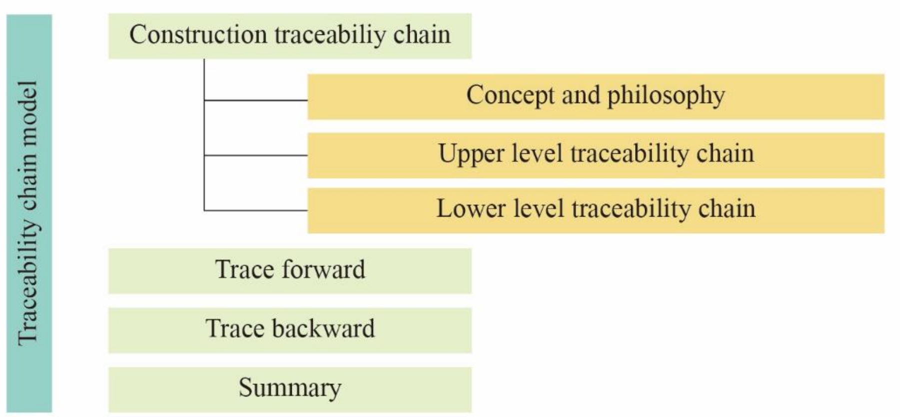

Figure 6-1 Structure of the traceability chain chapter

Section 6.1 introduces the basics of the traceability chain in the construction industry, including its concept and philosophy, the way to construct the upper and lower traceability chain. The following section 6.2 and 6.3 present the methods to trace forward and trace backward respectively.

6.1 Construction traceability chain

The tasks in construction projects are always carried out in a comprehensive way that four kinds of task interdependences are involved, including sequential interdependence, reciprocal interdependence, and pooled interdependence. Thus, the defects in the previous construction task is likely delivered to the subsequent or other relevant tasks, sometimes lead to reworks and even hazards (Yang et al. 2017).

Draw upon from the experiences and development in the food and drug industries (refer to literature review), traceability chain is proposed in this research to model the transformation of construction defects over construction trades.

6.1.1 Construction traceability and philosophy

The terminology, traceability, etymologically comes from the French "contre-rolle", which literally means "counter roll". The concept has been applied in various domains, such as food traceability, drug traceability and manufacturing traceability (refer to the section of literature review). Although traceability is now a pervasive term, its definitions and interpretations required further development in the construction industry, the definition of which is modified as *the ability to trace the history, location and motion/behavior of a building component or its relevant process for quality management.*

To achieve the construction traceability, this research proposes a probabilistic model based on Bayesian network (BN) theory as the construction process is commonly a combination of sequential activities/tasks, which is reasonable to use a directed acyclic graph (DAG) for description. This model allows to combine certain and uncertain knowledge and exploit both data at the present and knowledge from the history. This chain model is presented by $G(V, E)$, where V is a set of the graph vertices and E is a set of the graph edges that link those vertices. In the model, each node is relative to a marginal or conditional probability distribution table (CPT) whose entities are conditional probabilities of a child node given parent nodes, and each edge shows the child-parent relationships between those nodes.

There are two approaches to construct a BN. One aims to learn the structure of a BN directly from the collected data by machine learning techniques, while the other approach is that experts define local graph patterns according to known relationships along with determined CPT and then a complete BN is constructed by combining them together. Since a construction project is always composed of a sequence of tasks, and a task is always accomplished by a group of workers cooperating, the traceability chain thus is constructed by a series of nodes representing tasks or men in chronological order following the second approach.

6.1.2 Upper level traceability chain

Construction process is area-restricted that the building components are fixed whilst the workers shift to complete building tasks step by step. Given the location and time data of a worker, it is possible to measure the labour inputs and assign responsibility to individuals in a quantitative way. Assume that manpower has to conduct their jobs close to their locations that a person can only manipulate objects within one's reach, and based on this assumption, a specific task can be mapped to a specific worker over time, therefore, the comparison between actual task accomplishments at the construction stage and predefined tasks assignment at the design stage enables the identification of discrepancies between as-built and as-planned procedures.

Consider each task by an individual or a group as a node, place these tasks in chronological or logical order, and link each node to all its following nodes because the quality performance of any construction task has an impact on every task conducted afterwards. A simple upper level traceability chain therefore describing the responsibility delivery across five tasks is plotted in Figure 6-2. For example, to build a concrete beam/column/slab/wall, the general building process consists of formwork establishment, rebar placement, HVAC or electrical installation, concrete pouring and consolidation, and formwork removal. These five tasks all have apparent effects on the quality performance of the final concrete product. In addition, the quality of the former tasks also has impacts on the latter tasks, such as the improper construction of wood formwork is likely to cause issues in the installation and removal of rebars and other house accessories.

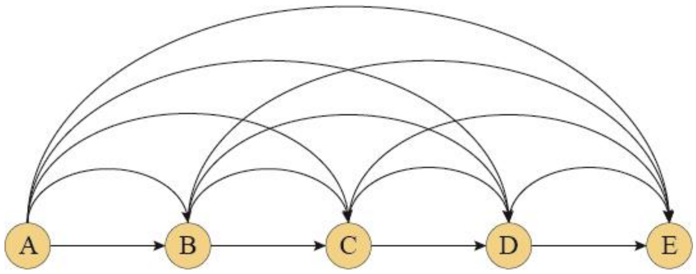

Figure 6-2 Sample plot of a task-level traceability chain

6.1.3 Lower level traceability chain

Within a single task, there are a number of variables that reveal the quality of the process, which is also considered as indicators to assure the quality performance at an early stage. Consider each variable as a node, and each causal relationship is represented as a directed link between nodes. Thus, a fault diagnosis network, also is named lower level traceability chain is generated. The construction of such models is always determined by intuition that the models may be incomplete and the causal relationships may be incorrect. At present, to automate the construction process, novel methods that learn the structure from the data are proposed and tested. However, the performance of these methods is seriously affected by the richness (amount and category) of the data, and the prior knowledge of the network before. For a single construction task, it is suggested to apply traditional ways to construct the traceability chain at the beginning and use data-driven approaches for establishment if adequate data of these variables are collected.

There are three possible connections by which the variables can generate impacts in a directed graph: diverging, serial and converging connections. As shown in Figure 6-3, a diverging connection is an appropriate model whenever it is believed that variable A is relevant for both B and C, and that B and C are conditionally independent given A. In other words, if the state of A is known, the belief about the possible states of B is not affected by the knowledge of C, and vice versa. If the state of A is unknown, then the knowledge of C provides information about the possible states of B, and vice versa. Serial connection refers to the sequential reasoning, typically apply to task-level traceability chain. A serial connection is an appropriate model whenever it is believed that variable A is relevant for B, that B is relevant for C, and that A and C are conditionally independent given C. If the state of B is known, the knowledge of A does not change the belief about the possible states of C, and vice versa. If the state of B is unknown, the knowledge of A then generate impacts on the possible states of C, and vice versa. A converging connection illustrates a more complicated reasoning relation whenever it is believed that B and C are both relevant for A, and B is relevant for C given known A, but B and C are conditionally independent given unknown A, that means if the state of A is known, B provides information about the possible states of C, and vice versa; meanwhile B and C are irrelevant variables if the state of A is unknown.

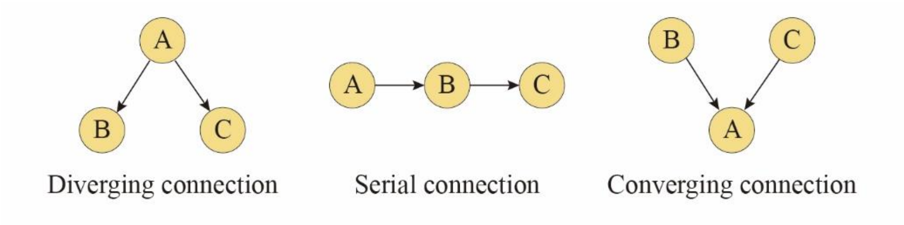

Figure 6-3 Possible connections in a variable-level traceability chain

Take typical concrete consolidation process as an example, temperature, humidity, aggregate gradation and water-cement ratio are critical factors contributing to the concrete viscosity, which are built by converging connections; concrete viscosity is relevant for almost all of the defects in concrete consolidation, such as honeycombs, segregation, etc. These are modeled by diverging connections; considering the concrete viscosity as an unknown transfer variable, the environmental and material specification variables are relevant for the performance of concrete consolidation which are described by serial connections.

6.2 Trace forward

Once the traceability chain was established based on the collected data, it is reasonable to infer the quality issue with the tool data. Here, tracing forward refers to pursuing the downstream direction along the structure of the Bayesian network. Given information I, the probability of a proposition at each node that the construction quality meets the construction standards and the user requirements, i.e.,

$$0 \leq P(X = x|I) \leq 1 \tag{6.1}$$

For a discrete random variable is an uncertainty quality that can take a discrete number of mutually exclusive and exhaustive values with probability.

$$\sum_x P(X = x|I) = 1 \tag{6.2}$$

Based on the multiplication law of probability and chain rule, the joint distribution of the network is the set of probabilities:

$$P(X_1, \dots X_n|I) = P(X_1|I) \times P(X_2|X_1, I) \times \dots \times P(X\_n|X_1, \dots X_{n-1}, I) \tag{6.3}$$

for all possible values x_i of variable or task X_i.

The probability of a variable or task can be obtained by marginalization as the sum over all of its relevant joint distribution:

$$P(X = x|I\ ) = \sum_y P(X = x, Y = y|I) \tag{6.4}$$

For any pair of propositions about the quality of variables or tasks in the traceability network, the degree of belief that A is true, given that one assume that B is true, is equal to the degree of belief that A and B are both true given background information I, divided by the degree of belief that B is true, given background information I, provided that $P(B|I) > 0$.

$$P(A|B, I) = \frac{P(A, B|I)}{P(B|I)} = \frac{P(B|A, I) \times P(A|I)}{P(B|I)} \tag{6.5}$$

Equation (6.5) is named Bayes' theorem, which is important due to the fact that it is the basic rule for updating degrees of belief in the traceability chain on receiving new tool data as the evidence for evaluation and management.

Specifically, $P(A|B,I)$ represents the probability of A, conditional on B, meanwhile $P(B|A,I)$ is the likelihood of A, conditional on B. The confusion between the likelihood and probability of the same hypothesis and evidence is called fallacy of the transposed conditional from the fact that if A has occurred, then B occurred with a high probability, it is erroneously concluded that if B has occurred, then A occurs with a high probability as well.

For more than two propositions, the updating process can be carried out in various ways, given that the multiplication law is commutative, it is notable that the paths following different temporal orders can be selected for convenience.

6.3 Trace backward

Tracing backward aims to investigate the root causes in the upstream direction along the traceability chain, enabling the identification of relevant construction procedures and the division of personal responsibilities.

The process of ensuring the construction quality in conformity with the construction standards and user requirements can be modelled as a sequence of steps in time domain. At time t_0, it is planned to seek evidence B for hypothesis A that B is related to A due to prior knowledge.

$$P_0(A|B,I) = \frac{P_0(B|A,I) \times P_0(A|I)}{P_0(B|A,I) \times P_0(A|I) + P_0(B|\bar{A},I) \times P_0(\bar{A}|I)} \tag{6.6}$$

where $P_0(A|I)$ and $P_0(\bar{A}|I)$ represent prior or initial probabilities of hypothesis A, and $P_0(A|B,I)$ is the probability of hypothesis A, conditional on evidence B, $P_0(B|A,I)$ and $P_0(B|\bar{A},I)$ refer to the likelihood of A and its complementary set, given B. At time t_1, it is found that B is true, satisfies the demands, or obeys the rules with a tolerance. Thus, the knowledge of B has been learnt and become a part of the background information, the overall belief in A at this time is equal to the belief in A, conditional on determined B, written as

$$P_1(A|I) = P_0(A|B,I) \tag{6.7}$$

It can be concluded that this situation is the same as when there is information at time t_0 that a proposition B that had not been thought before time t_1. To assess the relevance of B for A and the effect of this relevance on the degrees of belief, thoughts of likelihood and prior knowledge on the probability are necessary.

Since the conditional probability of node A given B is related to the converse conditional probability of B given A due to the Bayes' theorem, it is possible to reverse all edges and construct a new directed acyclic graph. But the simple reversing graph may not be an equivalent Bayesian network. Notably, supplementary edges are added to represent all of the original independence relationships as well.

6.4 Summary

This chapter introduces the construction of the traceability chain and its traceable use according to the specific knowledge and work experiences. The main findings are summarized as follows:

- Since the construction tasks are sequential dependent over time, it is reasonable to use a directed graph model to describe and visualize the relations between construction activities.
- Similar to diagnose network, Bayesian network is an effective and efficient way to model the traceability along the construction process, providing a scientific and quantitative method to trace forward and backward.

CHAPTER 7 PROTOTYPE OF SMART CONSTRUCTION TOOL GADGET

To validate the proposed concepts and methods, this chapter then builds an early prototype with low-cost and energy-saving sensors and processors. Above all, Chapter 7 is represented in three parts: 1) system framework; 2) instruments and devices; 3) data visualization.

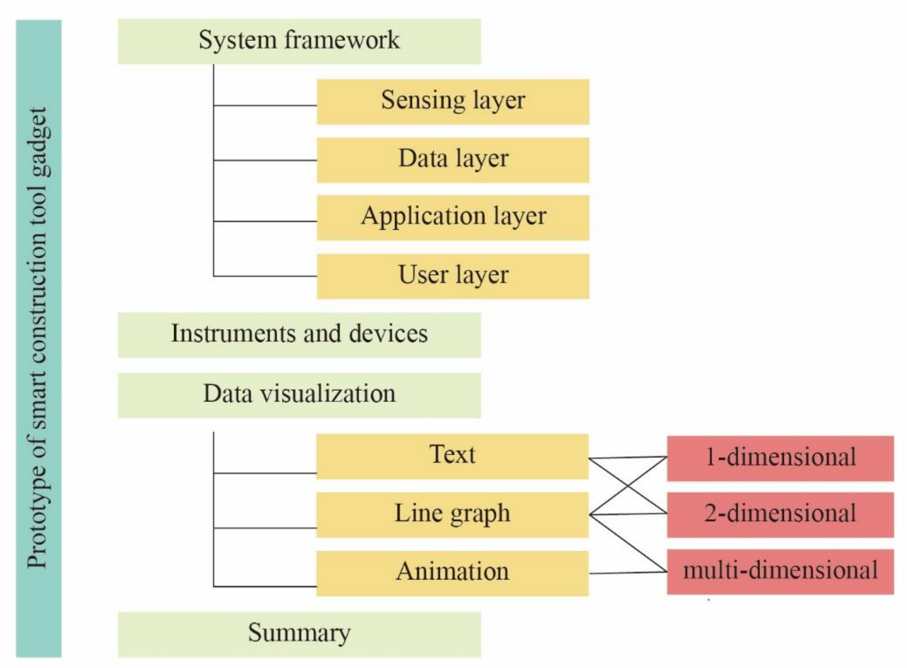

Figure 7-1 Structure of the prototype chapter

Section 7.1 roughly introduces the entire system framework of the rapid prototype for data collection, processing and storage at the beginning. The following Section 7.2 describes the relevant sensors and their specifications, which are selected and developed with respects to robustness, accuracy, precision, weights, etc. The last Section 7.3 represents the implementation of data visualization, specifically for concealed projects which are invisible for inspectors in a timely manner. The overall structure of this section is shown in Figure 7-1.

7.1 System framework

To monitor the behaviors of the construction tools for construction quality management, this research proposes a general system, which is simple, advanced, integrated, and intelligent. In this proposed system, there are four crucial layers as shown in Figure 7-2. Sensing layer is composed of multiple sensors and actuators, which are used to sense the changes of construction components and environment; data layer contains several databases for common and specific construction tasks, a data processor and a platform for data collection, processing, analyzing, sharing, and AI algorithms to improve the automation and intelligence of the system, such as the enhancement of the data compression and the optimization of data-driven expert system; application layer represents the various applications of the proposed system that provides a helpful assistant in the construction management domain with respect to multiple domains; and user layer refers to the potential end users of this system, including government, owners, the public and individual workers.

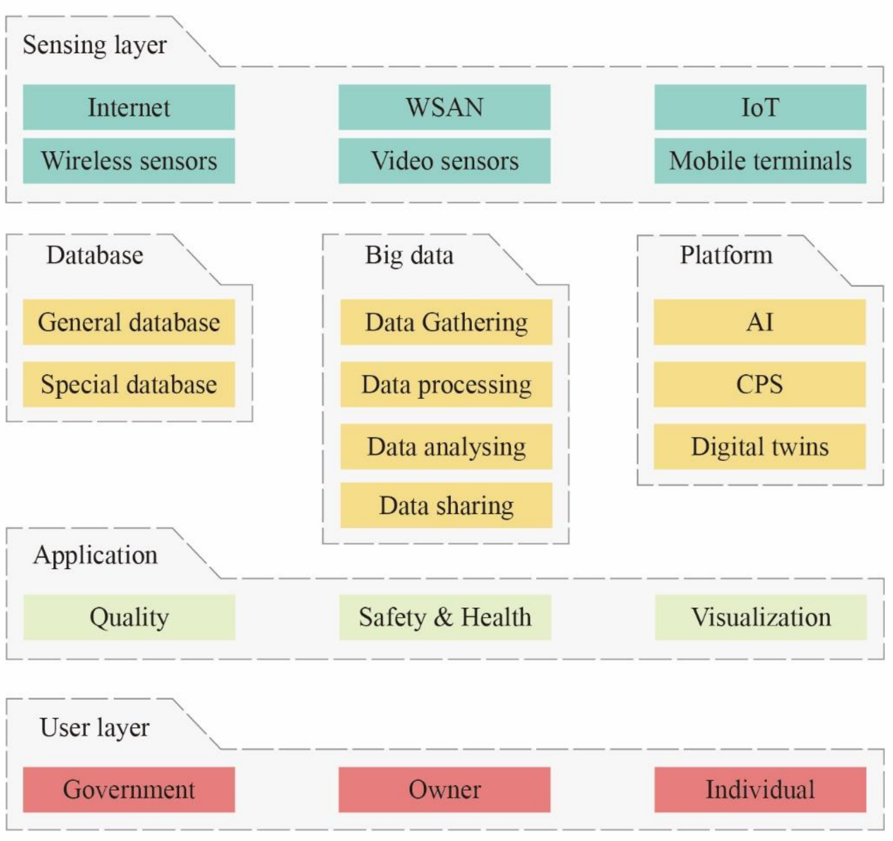

Figure 7-2 The system framework in this research

To deploy the system, sensors have appended on tolerant body of hand tools or embedded in the electrical board of power tools to collect dynamic signals; facilitator hubs, such as mobile phones, laptops or portable devices, are carried for convenience to gather signals from the remote sensors and send these signals to the cloud database station and remote processors for further analysis; and visualized terminals and platforms are installed and established for human-machine interactions, including construction process tracking, quality visualization and real-time monitoring. Figure 7-3 describes the potential deployments on power tools, hand tools, personal protective equipment, common equipment, heavy equipment and surveillance cameras, where the wearable sensors are communicated by BLE and the cameras are connected by wireless networks. The organized network is scalable and extensible that more sensors or actuators can be added and connected.

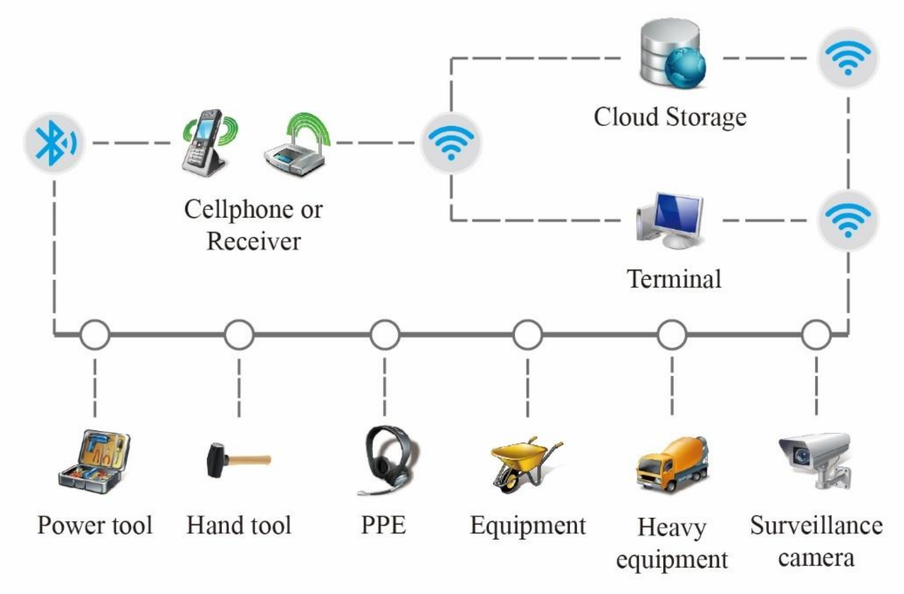

Figure 7-3 The comparison of several wireless communication techniques

7.2 Instruments and devices

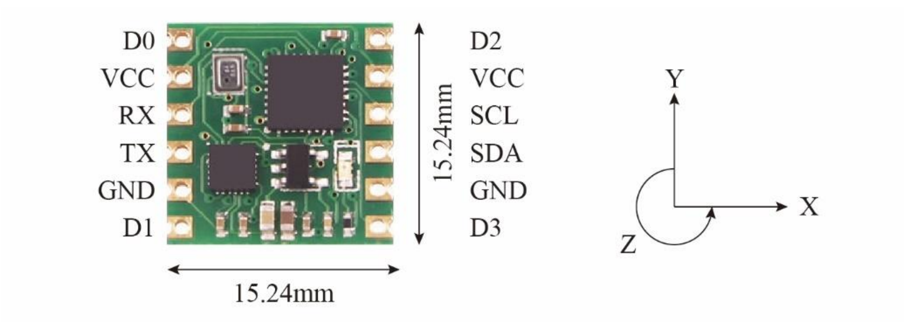

Figure 7-4 The JY901 chip

The electric chip used in the rapid prototype is JY901, which is produced in Shenzhen, China. As shown in Figure 7-4, this chip is composed of a MEMS tri-accelerometer, a tri-gyroscope, a tri-magnetometer, a thermometer and a barometer, which measures the acceleration, angular velocity, magnetic field, temperature and barometric pressure. The pin description is listed in Table 7-1.

Table 7-1 Pin description of chip JY901

Pin category	**Pin name**	**Details**
Serial	RX, TX,	used to receive and transmit TTL serial data.
Input/output	D0, D1, D2, D3	Used as digital, analog, and PWM input or output pins.
Power	GND, VCC	VCC: 3.3 ~ 5 V, power supply used to power microcontroller and other components on the board. GND: ground pins.
TWI	SCL, SDA	Used as I2C or IIC pins for two wire serial communication (TWI) SCL: serial clock SDA: serial data

Particularly, the Kalman filter and Attitude and Heading Reference System (AHRS) are embed in the sensor to decrease the measurement errors and increase the measurement accuracy. The specifications of JY901 is listed in Table 7-2.

This research suggests the users to create a screw closure holding the sensor and batter inside, which is easily reclosable and cost-effective. By this means, the sensor is fixed at the end of the handle and the rotation of z axis indicates the dynamic motions of the construction activities. With respect to the combination tools, such as combination wrenches and pliers, the sensors are suggested to attached on the middle surface or joint of the handles that the rotation around z axis describes the crucial motions of the construction activities. Also, the sensors can be immediately placed on the PPE gloves by Velcro, which is an easy hook-and-loop solution for fastening.

Table 7-2 The specifications of chip JY901

Item	**Specifications**
Operating voltage	3.3 V
Voltage limits	3.3 ~ 5 V
Operating current	25 mA
Dark current	0.1 mA
Current limits	0.1 ~ 40 mA
Measurement range	Acceleration: -16 ~ 16 g Angular velocity: -2000 ~ 2000 degree
Measurement precision	Angle: 0.05 degree (static), 0.1 degree (dynamic) Magnetic field: 1 mg Barometric height: 0.5 m
Baud rate	2400 ~ 38400 bps
Output frequency	0.1 ~ 200 Hz

The protype has been iteratively developed and improved for three times. In the first iteration, BLE module is added to realize the wireless communication; in the second iteration, the chip board is revised and reintegrated to reduce the size in order to be more portable; and in the latest iteration, the GPS module is added to provide the latitude and longitude data for automated acceleration and magnetic field adjustment, but the antenna is a must for the accuracy of GPS module. This prototype is therefore still under development for a wireless version.

7.3 Data visualization

Multivariate and multiview data are collected in this research, the data type of IMU sensors is composed of 1-dimensional measurements, 2-dimensional locations and multi-dimensional kinematic measurements (Richter 2009). 1-dimensional data type refers to the linear data collected from a thermometer and this information is organized in a linear way; 2-dimensional data represent the geographical location tracks coming from the GPS or INS module where data are projected on a plane; multi-dimensional data type mainly represents 3-dimentional positions and postures, generated by the integral of 3-dimentional acceleration and angular velocity. These data illustrate the translation and rotation and their combination as 6-dimensional data describe the complete rigid-body dynamics of the objective tools under the action of external forced by users.

To visualize these sensor data for management, certain principles are adopted to facilitate the understanding and design a generous interface of good quality. For example, the temperature is visualized with a color scale that blue is mapped to cool temperatures and red represents hot temperatures. With such perception properties in common, the data visualization in this research is designed at three levels: text level, line-graph level and 3d-graph level. Text level represents the form of digital characters that single sensor data are displayed on the screen directly, which is achieved by PyQt 5 directly; line-graph level refers to the form of scatterplots, line and multiple line graph that sensor data are expressed by points and lines over time, this dynamic plot is created by PyQtGraph; and 3d-graph level is the form of animation that a virtual rigid body is used to show the position and posture of the objective tool. This research adopt Pygame and Blender to visualize the construction tools in virtual reality with a fixed perspective projection and a flexible view, respectively.

7.4 Summary

This chapter mainly represents the crucial components that construct the prototype of the smart construction tool gadget, including the system framework, the used instruments and devices, and the data visualization methods. The main findings are summarized as follows:

- The construction project is composed of visible part and invisible part. For the visible part, it is effective and efficient to apply surveillance cameras to monitor the construction activities meanwhile for the concealed projects, it is wise to utilize wireless sensors to track the motion of tools instead of workers.
- Prototype as an early model of the smart construction tools is a reliable test of the concept proposed in this research for a non-intrusive construction progress management.
- To enhance the automated construction management, the sensor data are represented in different kinds of visualizations where an interaction between real world and computer virtual environment is possible, by which an ordinary user can easily understand.

CHAPTER 8 REBAR CONNECTION EXPERIMENT

As mentioned in Section 1.1, the rebar connection issues of the metro platform have caused serious anxiety in the public, for they clearly relate to worrying the safety at the maintenance and operation stage. But there may be one nimble way to try to address the issues and outwit the public anxiety and that is with a question that the proposed concept ensures the quality of the rebar connection – that it can capture the associated construction processes and evaluate the strength by analyzing the process of turning the rebar couplers.

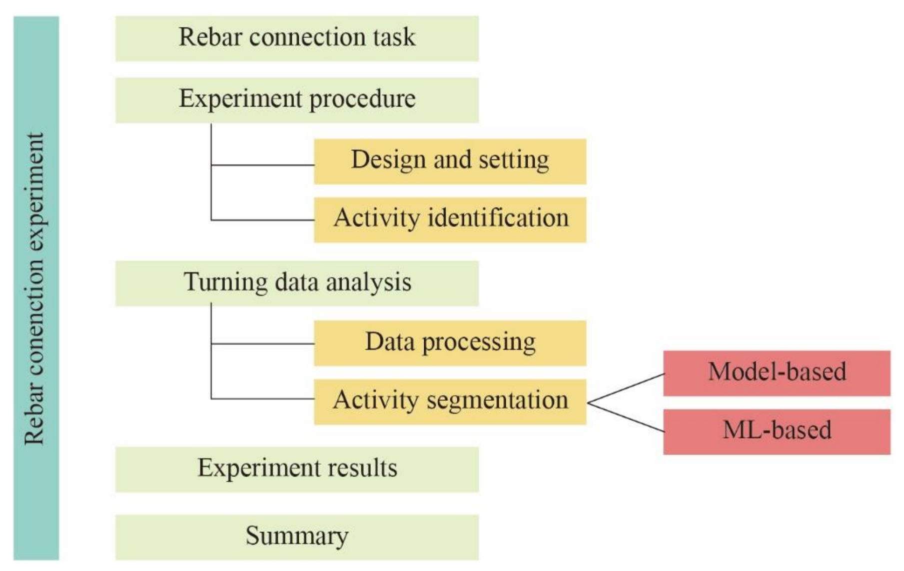

Figure 8-1 Structure of rebar connection experiment chapter

This chapter therefore presents the experiment of the rebar connection via applying the prototype in Chapter 6 to validate the new concept and enhance the performance in a real, working world rather than a theoretical one. The experiment is described in four parts: 1) rebar connection task; 2) experiment procedure; 3) turning data analysis; and 4) experiment results.

Section 8.1 introduces the background and significance of rebar connection tasks in common construction structures and it is reasonable to take it as a typical case for testing the proposed prototype and methods. The next Section 8.2 explains the detail experimental procedure and identifies the four activity phases for detection. The experiment data are then analyzed and segmented in Section 8.3 using model-based and machine learning techniques respectively. The last Section 8.4 presents the experiment results and compares them with record videos and participant reports to prove the feasibility of the developed prototype and proposed methods. The overall structure of this section is shown in Figure 8-1.

8.1 Rebar connection task

Mechanical rebar connection / splicing refers to joining certain lengths of two reinforcement steel together. Such system saves the materials and simplifies the processes that is more efficient and effective than traditional welding and overlapping rebar connections. This connection consists of two parts: one is female steel coupler, and the other is male threaded rebar coupler. According to construction standards, the characteristics of the connection are demanded to be stronger or at least equal to that of an uninterrupted reinforcement rebar so that the full tensile strength can be transferred with variable loads.

Generally, the couplers are installed by torque wrench that enable the fasten of a nut or a bolt with a appreciate torque. In the case of Hung Hom station expansion project, simple visual check is the only method used to ensure the position of the rebar couplers for safety, allowing a fast and easy construction process without special tools, power sources or adequate training of the personnel. However, the subcontractor trims the steel bars deliberately to make it look like they had been screwed properly into the couplers. Ultrasonic detection reveals that there is a gap of around 10 mm inside the couplers which may result in leakage, crack or other safety issues in the underground platform.

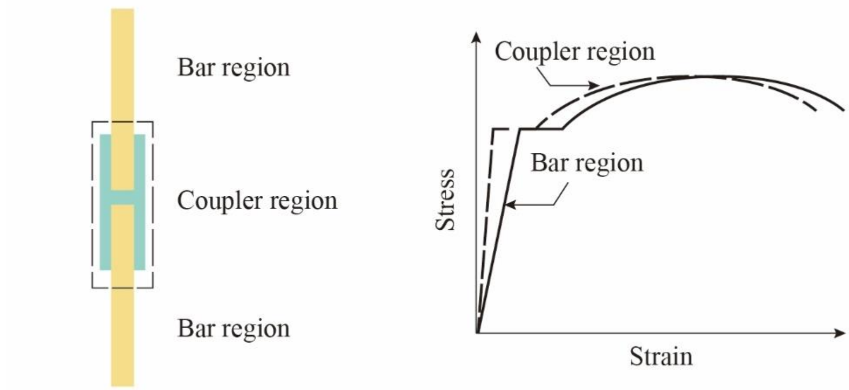

Figure 8-2 Stress-Strain model of rebar connection

Standards governing rebar splicing, such as International Building Code (IBC), America Concrete Institute (ACI) codes, China National Standards, and Hong Kong Construction Standards, set the embedded length of threaded rebars in the quality control program (Tazarv and Saiidi 2016). This length not only generates impacts on the performance of transferring both tensile and compressive forces but also expand the prefabricated concrete structures in moderate and high seismic zones.

As Figure 8-2 illustrates, although the soft initial stress-strain behavior is attributed to the threaded anchoring mechanism, the larger rigid length within the coupler increases the overall stiffness. The adjoining length of rebars and their couple is therefore an important indicator for the quality of rebar connection task.

8.2 Experiment procedure

To test the proposed concept, a study with a descriptive design is presented, in which the rebar connection task is performed to track the behaviors of the wrench by the prototype, analyze the segmentation of the connecting stages by the tool kinematic model, and assess the labor inputs and quality performance by the traceability chain.

8.2.1 Design and setting

A total of 10 workers between 22 and 30 years old are recruited to conduct the experimental rebar connection tasks in the Smart Construction Lab at The Hong Kong Polytechnic University, Hung Hom, Hong Kong SAR.

Prior to the task, the experiment is explained to the participants in details and trials without data collection are performed to check the understanding and practice.

In Figure 8-3, the prototype is positioned on the handle at the front of the adjustable wrench, allowing the detection of all kinematic factors in exposed environment. The entire experiment is performed under the supervision of an inspector and a video camera and the video data is used to validate the proposed method in the following sections.

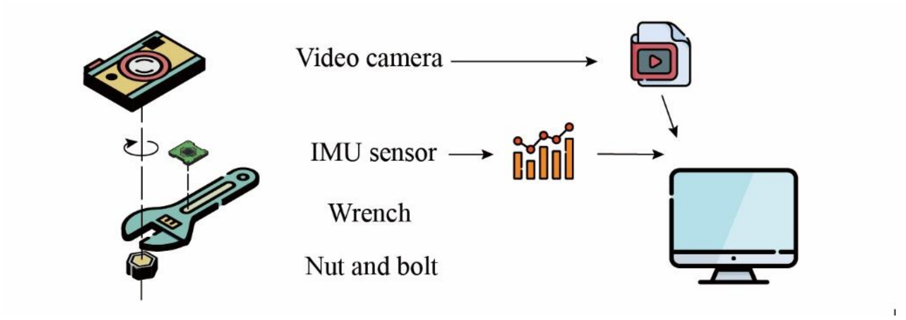

Figure 8-3 Set up for the rebar connection experiment

8.2.2 Activity identification

Normally, the rebar connection task is performed by a single worker when installing prefabricated building components, placing rebars prior to pouring fresh concrete, or connecting new entities with existing building structures. Such task may occur anywhere and anytime, and it consists of four phases: 1) jaw-fitting phase; 2) turning phase; 3) jaw-leaving phase; 4) returning phase. As shown in Figure 8-4, the jaw-fitting phase begins when the worker opens the jaw enough for the female or male coupler to fit in. It is common that the opened jaw is a bit larger than the size of the coupler; the turning phase refers to applying torque over the wrench that the wrench is held and turned in a clockwise direction or counter-clockwise direction to tighten or loosen; the jaw-leaving phase describes the process that the wrench is removed from the coupler in a limited workplace; and the returning phase is the procedure that the wrench is reset to the original position for the next cycle. These four activities are repeated until the coupler and the rebar are tightly connected that no more torque could be added or loose enough to remove the coupler directly.

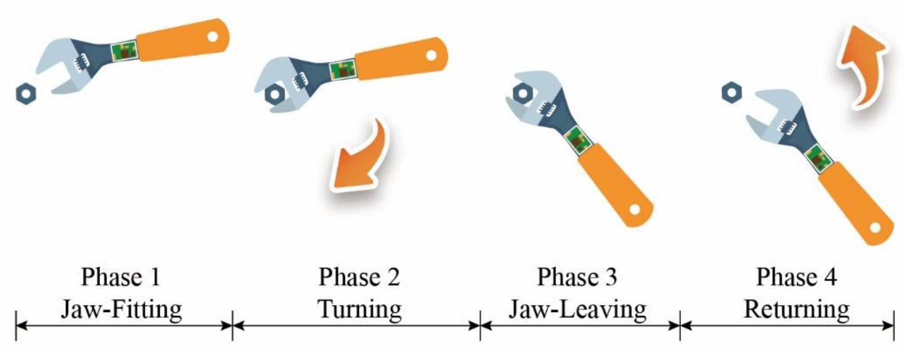

Figure 8-4 Activities performed in rebar connection task

8.3 Turning data analysis

Applying the data processing techniques in Chapter 5, the collected turning data is filtered and fused at the preprocessing stage, following by segmentation for further analysis.

8.3.1 Data preprocessing

Considering the sampling rate of 100 Hz, more than 50,000 samples are collected across 5 tries. Figure 8-5 shows a sample of collected raw acceleration data from the experiment. As the main activity of turning wrenches is rotating motions, the x, y components of accelerations fluctuate around zero whilst the z component fluctuates near to the constant one due to z axis pointing at the ground where it parallels to the gravity.

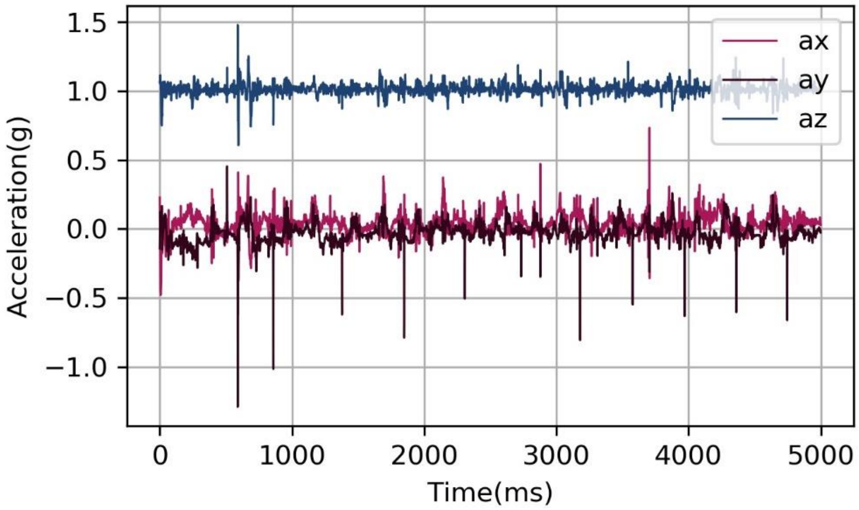

Figure 8-5 Samples of collected raw acceleration

It can be proved by Figure 8-6 that the crucial motion of rebar connection task is applying torquer on wrench to forcing it to turn around z axis. The amplitudes of z component of the raw angular velocity are extremely large than that of x and y axes. In addition, the repetitive plot also identifies the repetitive patterns during the use of the wrench.

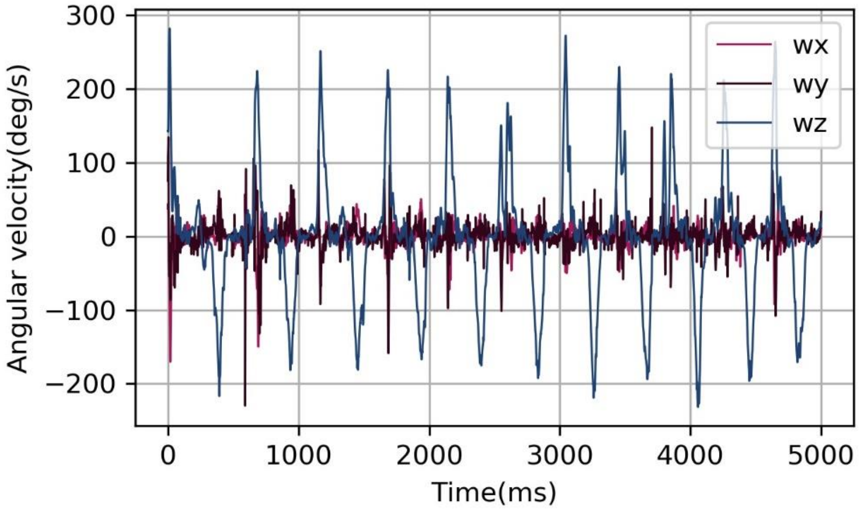

Figure 8-6 Samples of collected raw angular velocity

Compared with the raw data of angular velocity, as shown in Figure 8-7, the raw magnetic fields perform a clearer repetitive pattern as the rectangular wave repeats over time. The component of x axis remains relatively constant while the y and z components increase/decrease dramatically and stays constant temporally.

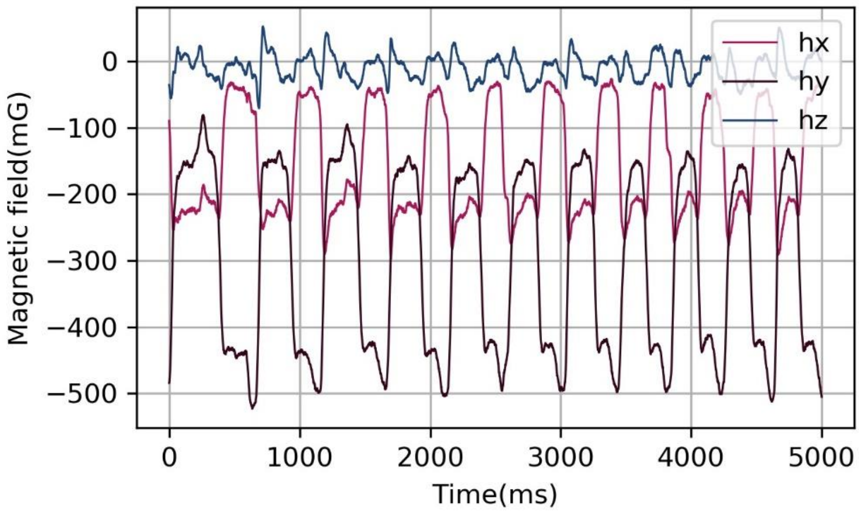

Figure 8-7 Samples of collected raw magnetic field

To address the systematic and random noises within the signals, AVAR is employed to determine the main source of noises and the noises are then modelled to penetrate within the signals.

8.3.2 Activity segmentation

With respect to the real-time applications, model-based algorithms due to the cyclic working patterns are adopted to recognize the cycles and count the numbers; meanwhile for the off-line applications, for example, the daily reports and productivity measurement, RNN-based algorithms using data features are employed to segment the motion stages and obtain the quality variables.

8.3.2.1 Model-based cycle detection

Referring to the tool kinematic model proposed in Section 5.3, the magnitudes of raw data, containing accelerations, angular velocities and magnetic fields, are plotted in Figure 8-8.

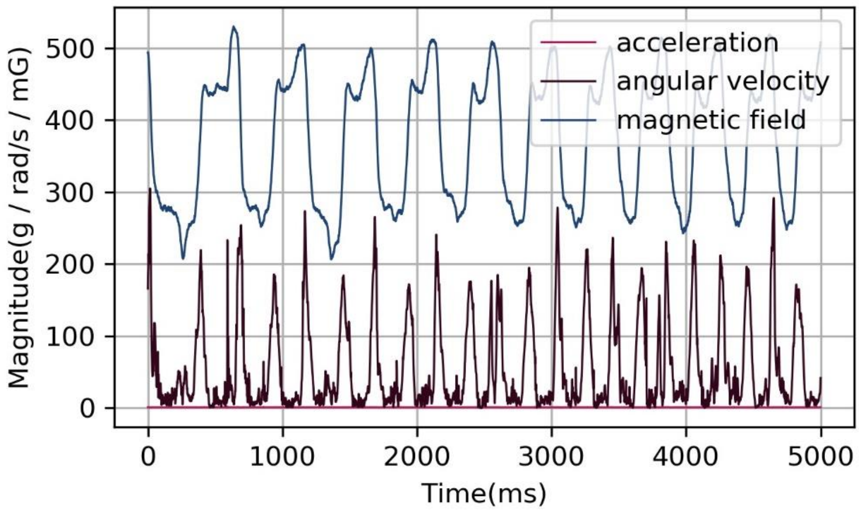

Figure 8-8 Samples of magnitudes of acceleration, angular velocity and magnetic field

Since the crucial motion of a wrench is rotating around the target nut or bolt, the motion of rotation is plotted by integration of angular velocity, suggesting the wrench is forced to turn clockwise to tighten between the rebars and steel couplers. Moreover, the rotation around z axis appears to be much larger than that around x and y axes, indicating that the main operation on the wrench is to apply torque to turning around z axis.

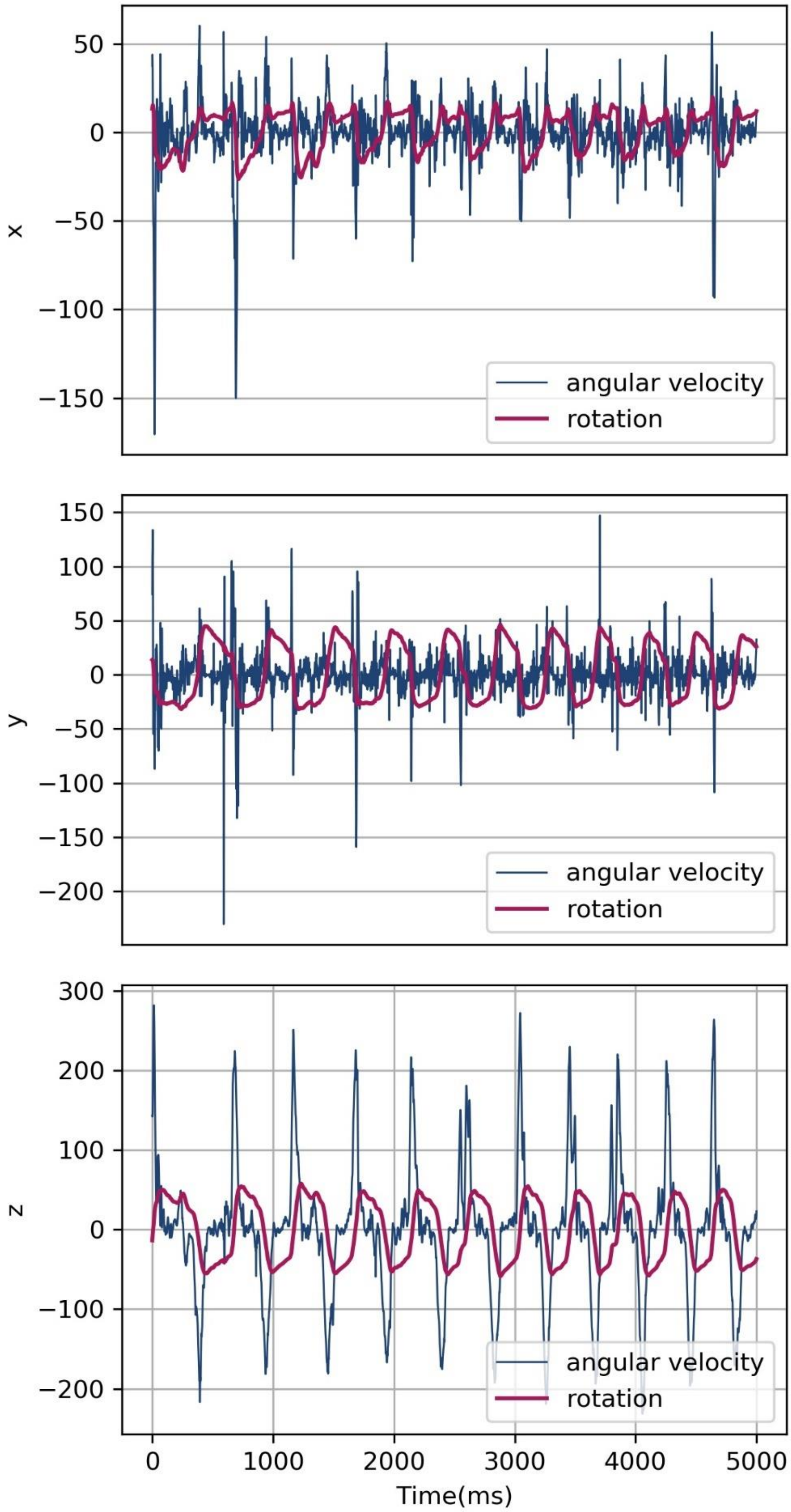

Figure 8-9 Samples of rotations by integration of angular velocity

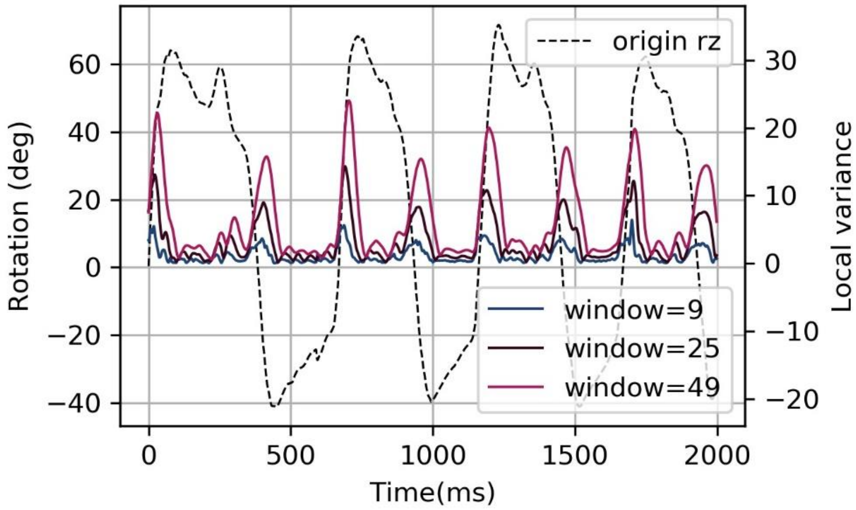

Figure 8-10 Comparison of local variance with different window sizes for rotation

To segment the cyclic motions, the local variance is computed with different sizes of moving windows at first. As shown in Figure 8-10, the line of local variance achieves local highest peaks when the rotation angle changes dramatically. The larger window size is, the higher peaks of the local variance waves reach. Meanwhile the offset between the catastrophe point of the raw rotation and the maximum point of the local variance decreases over the window size; that is to say, when the origin data begin to increase, the local variance changes subsequently with a delay, the delay increases with the enlargement of the moving window size, contributing to the reduction of sensitivity, and vice versa. A careful balance has to be maintained between sensitivity and visibility for the choose of parameters. In this experiment of rebar connection, 49 as an odd window size is adopted.

The motion cycles – turning the wrench around z axis therefore are detected by applying a threshold immediately. Figure 8-11 indicates the cycles detected by the model-based segmentation algorithms, which is simple and flexible for multiple kinds of construction tasks. It can be seen that a cycle is composed of two adjacent local peaks. One represents the process that a worker is applying torque (turning phase); the other one refers to resetting the wrench to its beginning place (returning phase). The gentle curves following these peaks are phases that the worker adjust the wrench to the target (jaw-fitting phase) or remove it from the target (jaw-leaving phase). Since the quick adjustment of a wrench requires some specific skills and working experiences, the subjects in this experiment sometimes cannot grasp the nut or bolt at the first time. That's the reason why there also exist tiny peaks at the gentle phases. Once the cyclic motions are detected and the phases are segmented, the productivity can be measured quantitively by counting turning cycles, and the final rotation of wrench is calculated as the product of the amount of cycles and the average rotation of each cycle.

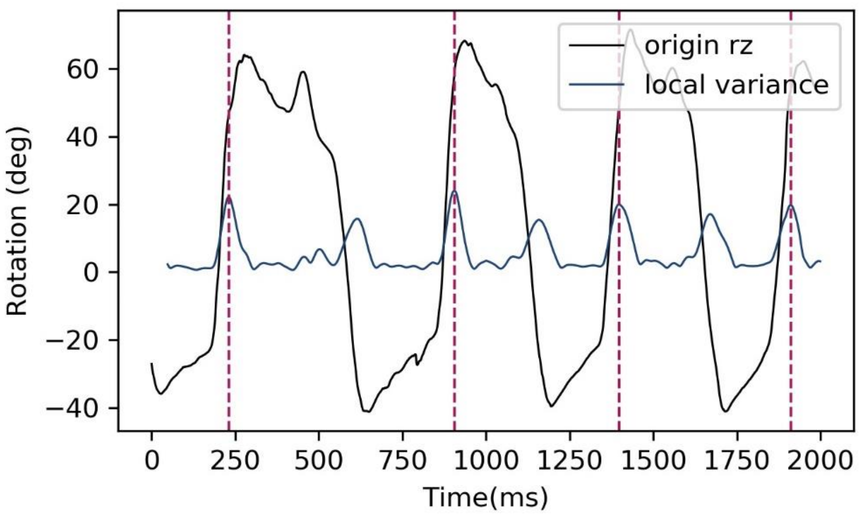

Figure 8-11 Samples of cycles detected by model-based segmentation from rotation

8.3.2.2 ML-based cycle detection

Compared with the model-based cycle detection algorithms, the machine learning (ML) techniques are simple to apply but comprehensive to understand. ML-based cycle detection has been widely used in waveform segmentation, such as human electrocardiogram (ECG) signals and electroencephalography (EEG) signals. Similarly, the construction task can be modelled as a sequence of motions as a sequence of kinematic data collected by IMU sensors on the construction tools.

In this research, the authors build up an open-source dataset, aiming to provide a reference for measurements that useful for segmenting the use phases, assessing the overall quality of the construction tasks and the presence of abnormalities.

The ML-based cycle detection consists of two steps: feature selection and classification. The raw data are sampled in fixed-width sliding window of 1.28 sec and 50% overlap, that each record contains 128 samples from IMU sensors. For each window, the following features are obtained by calculating variables from the acceleration, angular velocity and magnetic field in both time and frequency domain.

Table 8-1 Features of IMU data for machine learning

Signals	Time-domain feature	Frequency-domain feature
ax, ay, az, wx, wy, wz, hx, hy, hz, rx, ry, rz	Mean	Frequency components
	Standard deviation	Fundamental frequency (2nd)
	Mean absolute deviation	Spectral centroid
	Maximum/ minimum	Spectral flux
	Signal energy	Spectral density
	Interquartile range	Spectral roll-off
	Entropy	
	Autocorrelation (lag=1)	
	Zero cross rate	
	Maximum amplitude	
xy, xz, yz (a, w, h, r)	Correlation coefficient	
xyz (a, w, h, r)	Magnitude	

Prior to feature extraction, the raw data in time domain has to be transformed into frequency domain, which describes the distribution of data components within different frequencies. As Figure 8-12 illustrates, the components of acceleration are distributed evenly overall the frequencies, and no frequencies dominates where the repetitive pattern is not clear or its frequency is not stable.

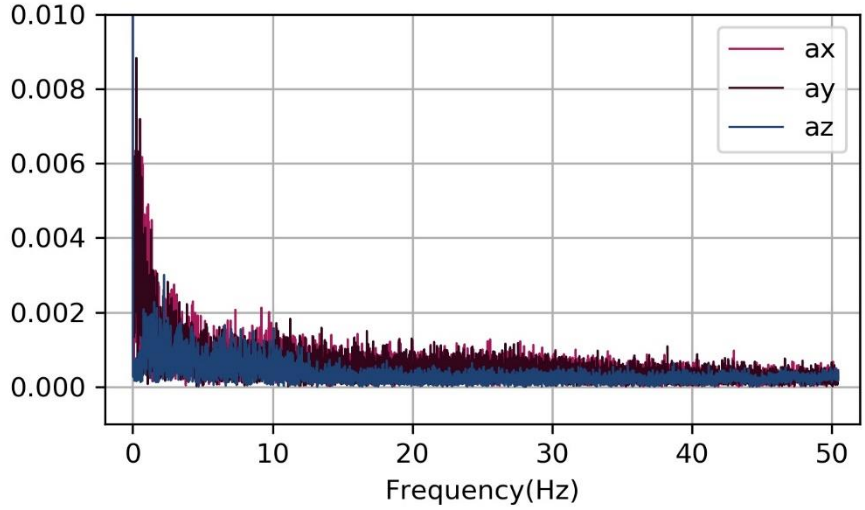

Figure 8-12 Frequency components of collected raw acceleration

With respect to raw angular velocity, it can be seen from the Figure 8-13 that the main components are located within lower frequencies. Particularly, the angular velocity around z axis, which locates from 0 to 2 Hz, represents the crucial motions during the rebar connection task.

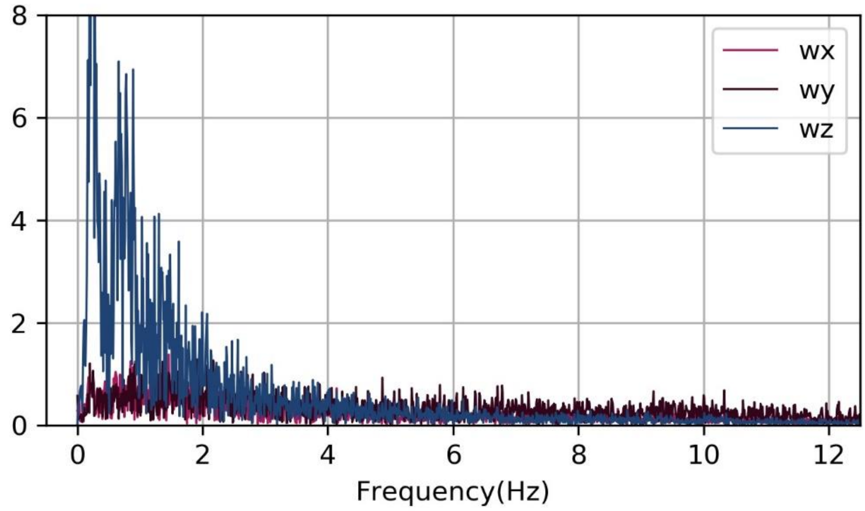

Figure 8-13 Frequency components of collected raw angular velocity

Similar to the raw magnetic field in time domain, Figure 8-14 also reveals that the lower components dominate along with the y and z axes in frequency domain, particularly the component of 0.25 Hz, possibly suggesting the frequency of the crucial repetitive motion cycles.

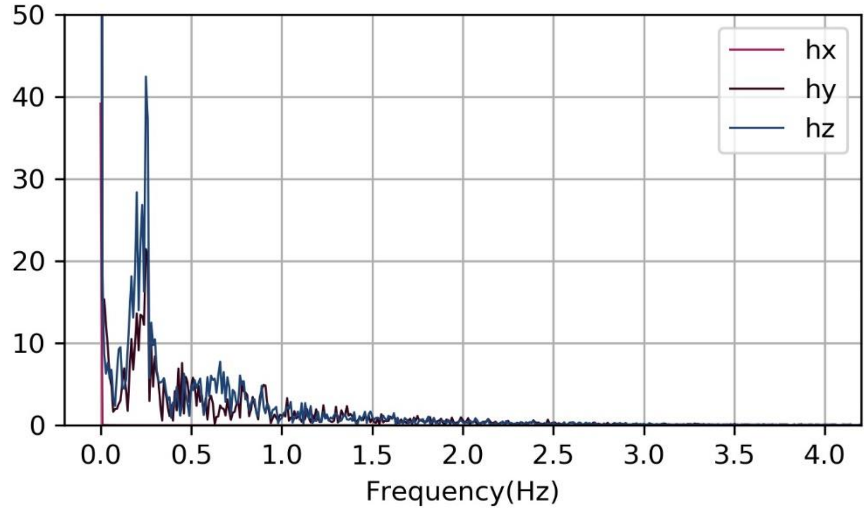

Figure 8-14 Frequency components of collected raw magnetic field

The simplest ML model selected in this research is support vector machine (SVM). State-of-the-art ML models, such as long short-term memory model (LSTM) and prohet time series forecasting model, are examined in further research, which is out of the scope of this study.

8.4 Experiment results

With respect to the amount of turning motions, the model-based activity segmentation is capable of achieving 100% accuracy in the laboratory environment due to suitable parameters and regular activities in conformity with the construction conventions and standards. However, under the circumstance that the project is carried out in exposed environment, two assumptions must be fulfilled before the implementation of model-based activity recognition. One assumption is to ensure the workers carry out their tasks according to the normal practice; the other is to adjust the model parameters carefully, containing the size of the moving window and the threshold for filtering.

On the other side, the classification results of the ML-based model are depicted by a confusion matrix, which is listed in

Table 8-2. Given the accuracy, precision, and recall, more than a half of samples can be identified correctly. The matrix shows that the classification precision of picking/putting phase performs better than others, meanwhile the recall of picking/putting phase and jaw-leaving phase are both better. Rather, for turning phase and returning phase, although the precision is more than a half, the recall is far from acceptance. This exposes some false detection mostly in the dynamic and short-duration activities possibly due to the rolling windows size since larger window size captures more time and frequency information but fuzzies the boundaries between adjacent motions, and vice versa. In addition, the number of short-duration phases is less than that of long-duration activities, the corresponding coefficients are insufficiently finetuned.

Table 8-2 Confusion matrix of SVM for rebar connection task

Activity	PP	JF	TN	JL	RT	Recall
Picking/putting (PP) phase	73	0	0	2	0	97.33%
Jaw-fitting (JF) phase	11	139	4	26	2	76.37%
Turning (TN) phase	1	44	23	59	3	17.69%
Jaw-leaving (JL) phase	8	24	9	191	3	81.28%
Returning (RT) phase	1	32	1	46	19	12.09%
Precision	77.66%	58.16%	62.16%	58.95%	57.89%	61.29%

Figure 8-15 describes the activity segmentation of the experiment after synchronization with recorded videos. Within a repetitive cycle, the JF, TN, JL, and RT activities are carried out one by one to enforce the nut or bolt tighten. Commonly, although applying torque is the crucial and productive activity for rebar connection task, its time lasts for only a small portion across the construction stages. Therefore, collecting the rotation angle around z axis of sensor can reveal the performance of the connection tasks, including total turning angle, total turning time, and productivity, which are used to trace backward the construction process with reliable proofs, particularly the embedded length of the threaded rebars.

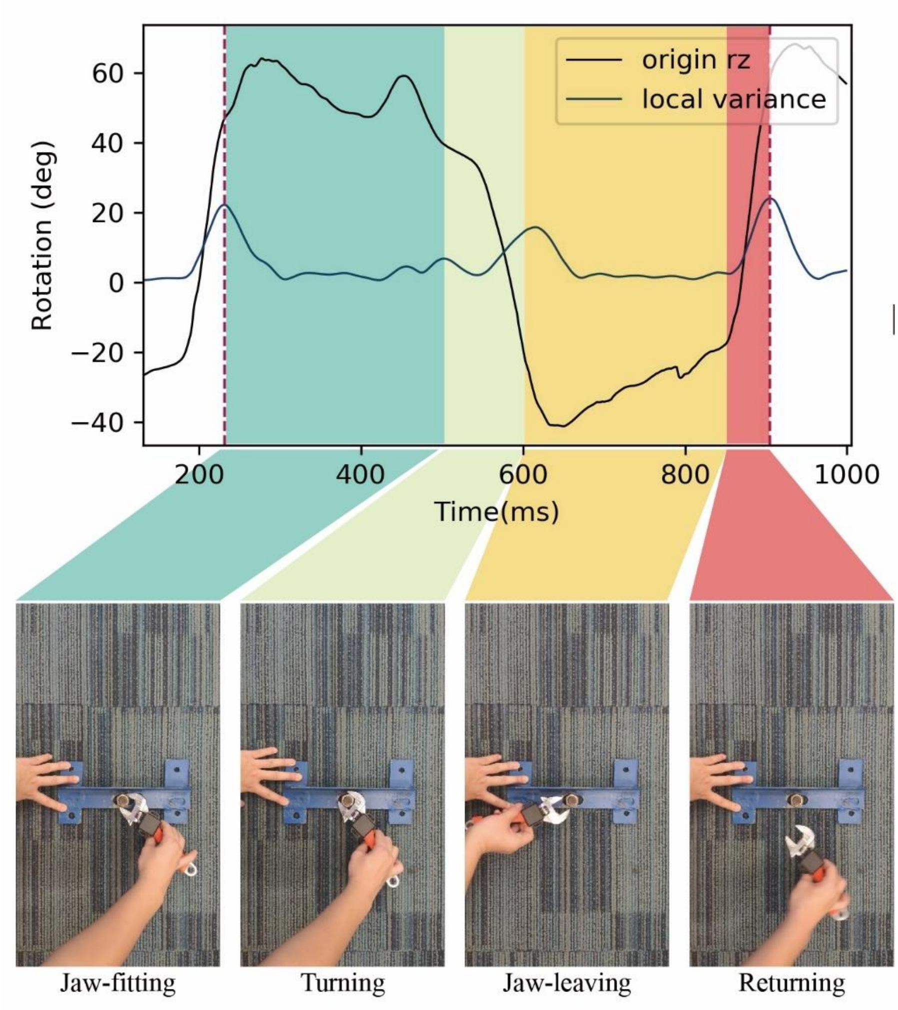

Figure 8-15 Activity detection using proposed prototype and models

Considering the entire rotation angle equals to the product of rotation amount and rotation angle, it is believed to draw a conclusion for quality evaluation based on the collected data from IMU sensors according to the traceability chain of rebar connection tasks as shown in Figure 8-16. The variable N refers to the amount of repetitive turning activities which is detected by activity segmentation model and the variable R representing the rotation angle of each turning activity is identified by the integration of angular velocity in turning phase. The variable of total rotation angle is thus obtained by the product of variable N and R, which can be mapped to embedded length by multiplying the screw pitch of the nut/bolt or thread, providing the crucial assessment for connection quality.

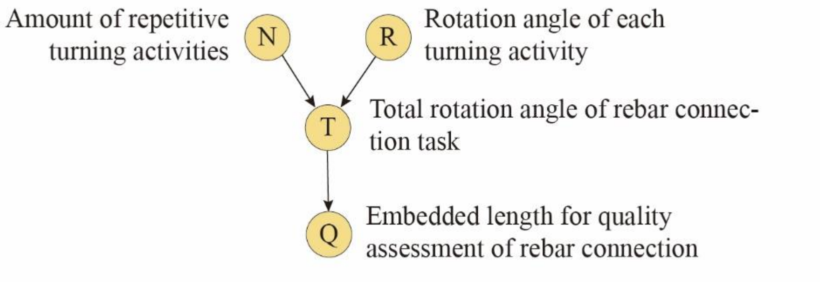

Figure 8-16 Rebar connection traceability chain

In the experiment, each time and each subject is required to force the wrench rotate around the nut or bolt for 120 degree, and the wrench revolves the nut or bolt for 21 or 22 loops, in terms that the wrench has to be turned by 7 circles to tighten the nut and bolt. Here, the amount of rotation loops is recognized correctly by the activity segmentation proposed in this research, and for each repetitive rotation, the average rotation angle is 106.67 degree with a standard deviation of 6.50 degree. As the histogram in Figure 8-17 describes, most of the rotation angles cannot reach 120 degree as suggested, and the total rotation angles for each test are 2146.38, 2112.03, 2253.56, 2186.57, 2278.06 degree. The discrepancies between suggestion, recorded videos and the collected data by proposed methods are the possible results of personal work experiences, skills and their subjective consciousness towards the rebar connection tasks. In conclusion, the direct measurement using IMU sensor with an accuracy of 88.81% provides a reliable and quantitative reference for decision making process, particularly for concealed projects that are invisible.

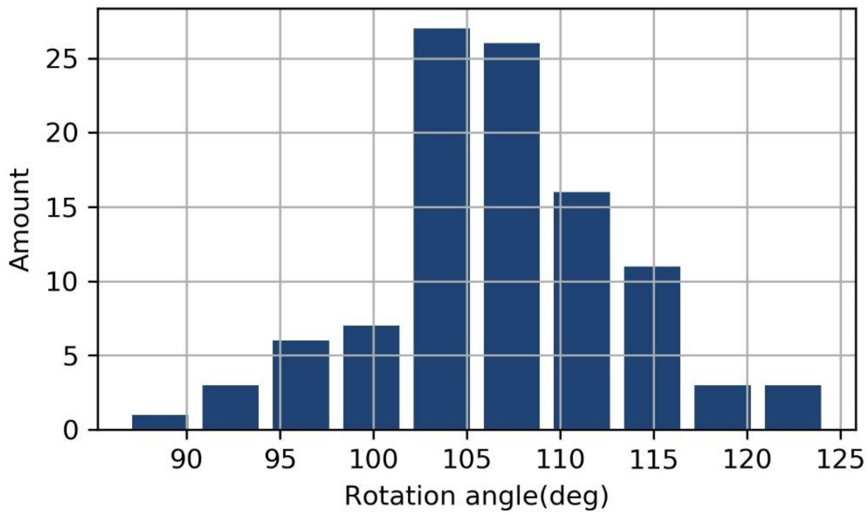

Figure 8-17 Histogram of rotation angle for rebar connection experiment

8.5 Summary

This chapter chiefly shows the feasibility of applying the prototype developed and the model proposed in previous sections by a rebar connection experiment. The results prove the effectiveness and efficiency of the smart construction tool gadget using a solo IMU sensor attached on an adjustable wrench. The primary findings are summaries as follows:

- Rebar connection plays an important role in the construction of concrete structures. To ensure the strength of the connection, the rigid length must be governed to be conformity with standards.
- Since the nuts, bolts and threads at construction sites are always joined by turning crews, rigid length is thus determined by the rotation process of a wrench; that is to say, monitoring the use of a wrench enables the management of the rebar connection tasks.
- Model-based approach to detect repetitive motions is simple and effective but

requires predefined parameters determined by work experiences, meanwhile ML-based cycle detection is flexible and robust under different personal circumstances but fails for dynamic and short-duration activities due to the sample size.

- Compared with the record videos and oral reports of the participants, the result draw using the smart construction tool gadget is likely to be rigorous because of possible signals delays and discrepancies caused by personal work experiences, skills and their subjective consciousness.

CHAPTER 9 CONCRETE CONSOLIDATION EXPERIMENT

Apart from visible construction processes in a project, there are also a number of invisible processes that cannot be inspected and monitored directly or covered by other building components, such as concrete consolidation and cast-in-place concrete components (piles, beams, walls, slabs, and columns). The only way to control and manage the quality of these construction process and products is to track the entire construction process with novel methods that are not affected by none-line-of-light effects.

This chapter thus test the developed prototype and proposed methods in a typical concealed project – concrete consolidation experiment with a concrete internal vibrator. The experiment is introduced in four parts: 1) concrete consolidation task; 2) experiment procedure; 3) moving data analysis; and 4) experiment results.

Section 9.1 briefly represents the importance and the mechanism of the concrete consolidation, but it is hardly to monitor with the current ways due to its invisible property. The following Section 8.2 introduces the design and setting of the experiment procedures and the activity identification of the concrete consolidation by a model-based approach using the repetitive features in the use of the vibrator. The collected data are then processed and analyzed in Section 9.3, following by the

Section 9.4 describing the results with physical meanings. The last Section 9.5 establishes the traceability chain to combine the dependent and independent variables from manual efforts and environmental effects for the evaluation of the concrete quality. The overall structure of this section is shown in Figure 9-1.

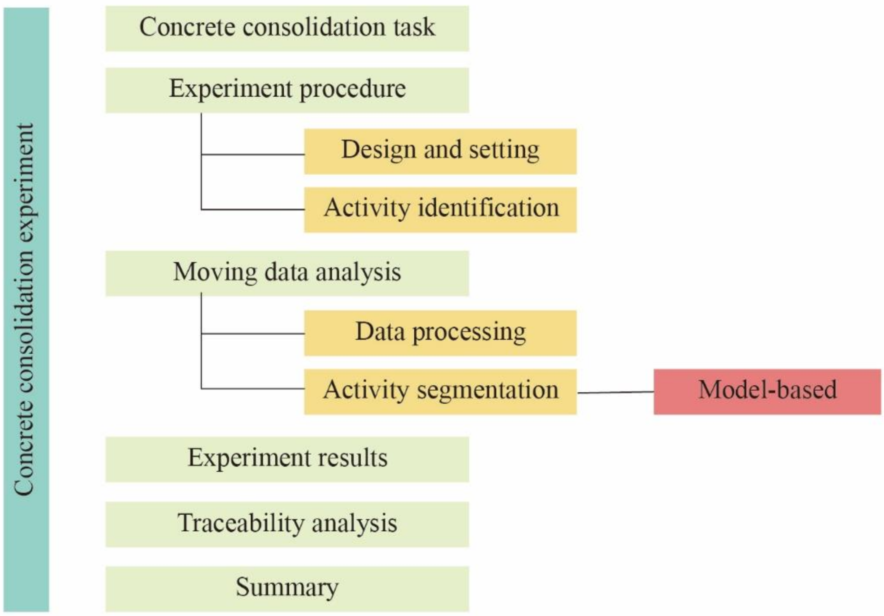

Figure 9-1 Structure of rebar connection experiment chapter

9.1 Concrete consolidation task

The consolidation of concrete plays an important role in the short- and long-term performance of concrete building components with respect to the mechanical, aesthetic and functional aspects. To ensure the consolidated quality of a concrete construction, it is common and economical to utilize internal/immersion, surface, external vibrators, and rebar shakers. An internal vibrator as the most common used power tool aims to eliminate an excessive amount of entrapped air and facilitate the concrete consolidation process. However, the vibration process is invisible due to the fresh concrete is not transparency that the level of concrete consolidation is immeasurable if it is pouring into the formworks.

Improper concrete consolidation may cause a series of concrete defects, such as over-vibration and insufficient vibration, which leads to the reduction of the long-term compressive and tensile strength and durability (Eghtesadi and Nokken 2017). For example, well-proportioned concrete has adequate consistency that is not readily susceptible to segregation because of over-vibration. But if the mixture containing excess mortar, it is prone to serious segregation that some size groups of aggregates separate from cement mortar in terms that the denser aggregates settle to the bottom while the lighter cement paste tends to move upwards. The upper layer is therefore weaker than the lower that possibly make failures of the concrete structure during the operation because of the potential plane of weakness. In short, the segregated concrete performs weak in strength and inhomogeneous in quality, resulting in plastic shrinkage cracks on the surface and difficulties at the concrete compaction. By the contrary, concrete with insufficient vibration or without vibration reduce the actual strength and durability dramatically as the trapped air and voids cannot prevent the rebars from environmental damages and steel corrosion. In addition, as the fresh concrete carbonates over time, the pH drops along the front deeper, the passive oxide layer that formed around the steel dissolves, and the rebar corrosion proceed, all facilitating the further reduction of strength and durability. It can be learnt that the concrete vibration underscore strength and durability of the fresh concrete, without which, the reinforcement concrete can hardly be used.

Therefore, the core indicator to evaluate the concrete quality is the area of effect (AoE) of the internal vibrator. When an immersion/internal concrete vibrator is inserted into the fresh or soft concrete, a compression wave is formed around the body of the poker body, which is broadcast within the concrete to transmit the force and energy. Thus, the concrete particles are forced to flow like a liquid where the internal friction decreases. The aggregates are reconstructed to sink, and the trapped air rises, resulting in the consolidation of the concrete. However, the shear forces weaken over distance and time and are affected by the intrinsic specifications of the concrete vibrator. When the shear force is less than the internal friction, the concrete is not allowed to flow, which is called a Bingham plastic effect. As Figure 9-2 illustrates, the AoE of an internal concrete vibrator is a cylinder where the fresh concrete within the cylinder is vibrated. It is thus obvious to conclude that the tracking the position of the vibrator is the effective and efficient way to monitor the quality of concrete consolidation.

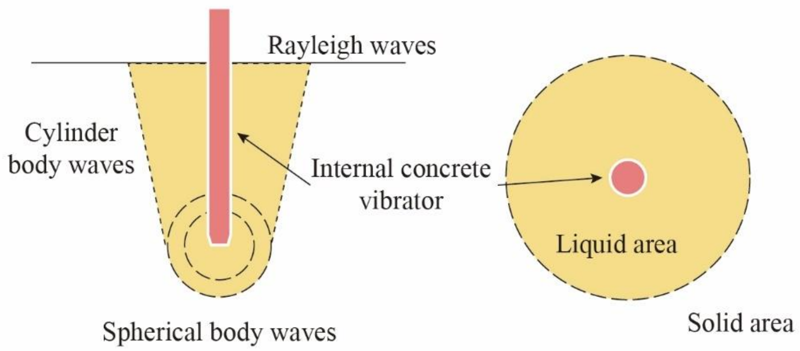

Figure 9-2 AoE of an internal concrete vibrator

In this research, the radius of the work region is affected by the attenuation of the compression waves (Dessoff 1937), the recommend formula of which can be written as follows:

$$v_r = v_0 \sqrt{\frac{r_i}{r} e^{-\frac{\Omega}{r - r_i}}} \tag{9.1}$$

where v_r is the radial velocity at radius r, v_0 refers to the velocity of the vibrations of the vibrator surface, r_i represents the radius of the poker body, and Ω is the coefficient of damping, of which the consistency for concrete ranges from flowing to plastic, which is determined to have a value of between 0.04 and 0.08, respectively .

9.2 Experiment procedure

Similar to the rebar connection task experiment, concrete consolidation experiment is also conducted by the smart construction tool gadget in the laboratory. The difference is that the process of concrete consolidation is invisible, and the processing data is positions instead of postures.

9.2.1 Design and setting

There are 10 participants in this experiment, and each of them is asked to simulate the use of an internal concrete vibrator in virtual fresh concrete. The developed prototype is installed inside the tube body (vibrator head) of the internal concrete vibrator. The IMU sensor integrated with BLE module is settled in the head cap filled with protective and cushioning materials. The head cap is then connected to the vibrator by mechanical threads which is simple and easy handling for charging. Notably, this connection is feasible for wireless IMU sensor that the signals can transmit through metal materials. Rather, for IMU integrated with GPS module, it is suggested to embed the sensor in the board of the vibrator which is accessible by wires and antennas.

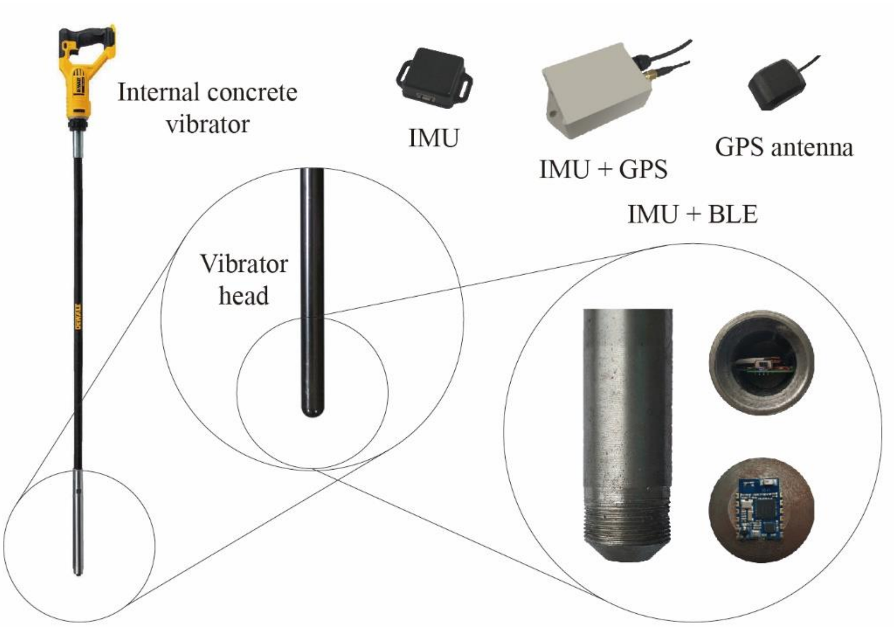

Figure 9-3 Deployment of the IMU sensor in concrete consolidation experiment

9.2.2 Activity identification

The concrete consolidation task is commonly divided into four steps, the acceleration, velocity, and displacement exhibit periodic changes. These four steps consist of putting down phase (D phase), vibration phase (B phase), pulling up phase (U phase), and moving phase (T phase). As Table 9-1 lists, these four phases have totally different characteristics according to the position of the vibrators.

Table 9-1 Confusion matrix of SVM for rebar connection task

Activity	Key characteristics
D phase	Putting the vibrator down
B phase	Vibrating the concrete at the bottom
U phase	Pulling the vibrator up
T phase	Moving the vibrator to another place

In addition, not only the positions are critical features used for activity identification, the other dynamic motion features, such as the velocity and acceleration, can also be used for activity recognition. For example, when a vibrator jams quickly into the wet concrete under a steady state, the displacement reaches the appropriate depth, and the velocity increases from zero and decreases to zero at different speeds owing to medium changes. After a short sinking time, the vibrator rises into the open air, where the displacement returns to the initial value, and then repeats the increase-decrease cycle again. Each time the concrete vibrator sinks into the wet concrete, it will promote the concrete particles to settle into a solid mass as well as encourage trapped air pockets and voids to rise out of the wet concrete. Therefore, the associated progress variable for concrete consolidation contains various indicators, containing position, vibration time, velocity, acceleration, etc.

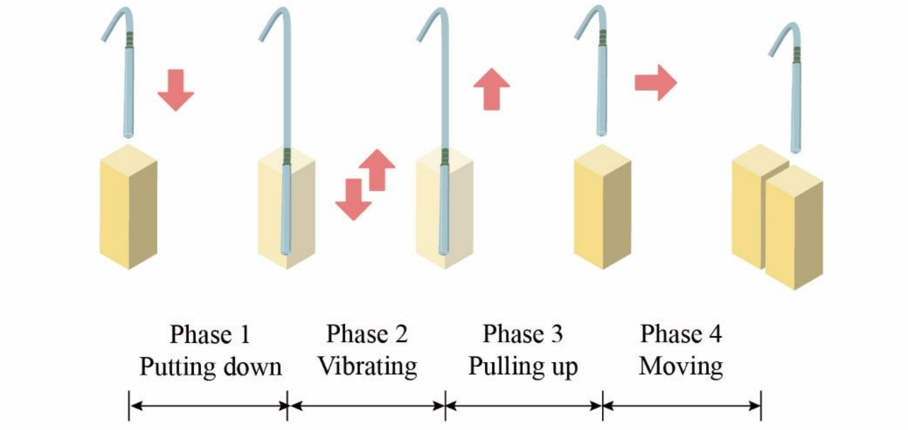

Figure 9-4 Activities performed in concrete consolidation task

9.3 Moving data analysis

In the concrete consolidation experiment, this section focuses on the moving data analysis. Rotation is the direct integral of the raw angular velocity for rebar connection task. Rather, position is calculated as the quadratic integral of the raw acceleration, which is more comprehensive and error-prone due to the cumulated random noises. Such noises are delivered from acceleration to velocity, passed to final position, and become larger and larger over time.

9.3.1 Data processing

The raw data collected with sampling frequency of 100 Hz is shown in Figure 9-5. It can be seen that the acceleration along z axis fluctuates around 1 due to gravity, which can be eliminated by gravity compensation in Section 5.1.3. While the raw acceleration along x and y axes appears to change around 0. An interesting finding is that the x-axis acceleration decreases meanwhile the y-axis acceleration increases at the same time. Such situation may be the result of right-handed effect that when participants cannot hold the vibrator strictly vertical, they are prone to move the vibrator back to original position and posture along different orientations.

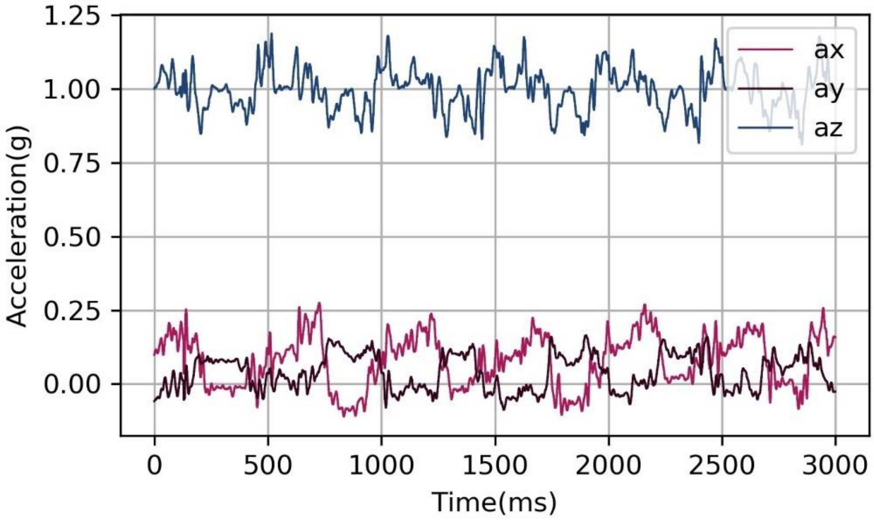

Figure 9-5 Samples of collected raw acceleration

The above discussion can be proved by the plot of the raw angular velocity in Figure 9-6. Since the vibrator is required to keep straightly across the experiment, the tri-axis angular velocity should be constant at zero. But this figure reveals that for each movement, it is impossible for subjects to behave strictly following the ideal regulations. Therefore the signals seem to perform a cyclic patter from the systematic view but random from the personal view.

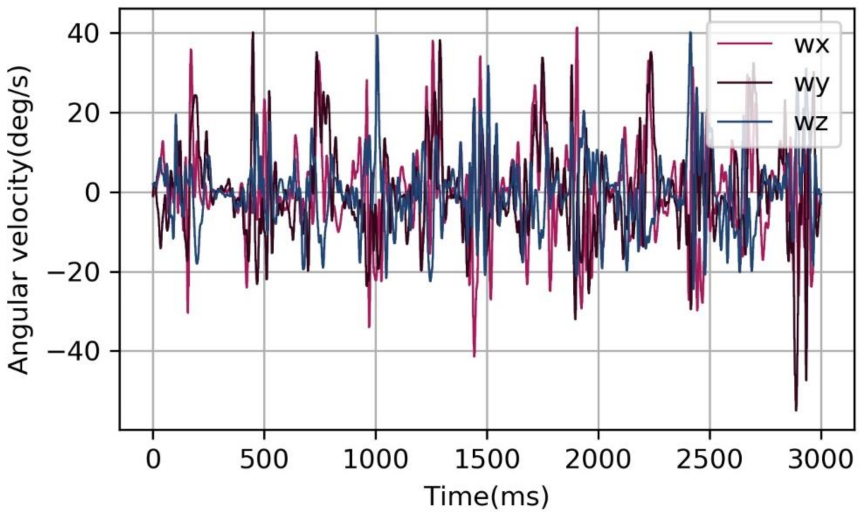

Figure 9-6 Samples of collected raw angular velocity

For the raw magnetic field, Figure 9-7 shows the clear repetitive patterns in all of the axes. It can be concluded that for each time of inserting the vibrator, the tri-magnetic field increases and decreases dramatically, following by a stable state, and repeats the increase and decrease process again.

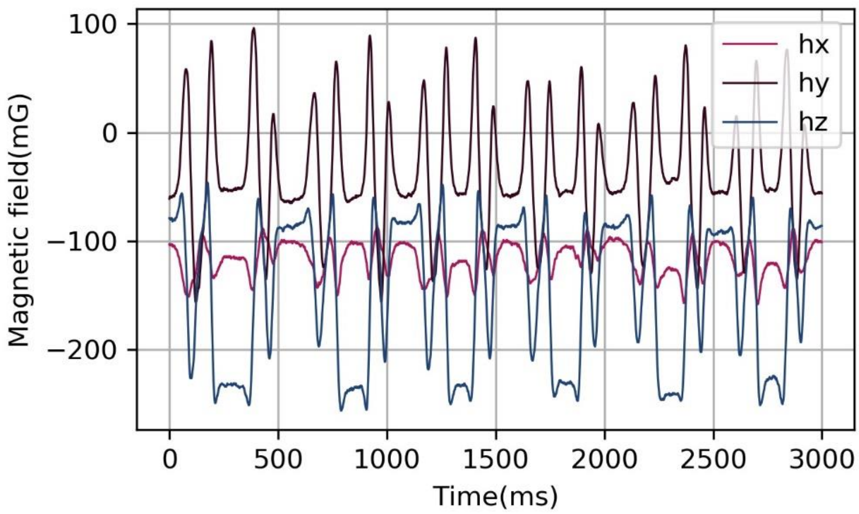

Figure 9-7 Samples of collected raw magnetic field

9.3.2 Activity segmentation

As identified in the previous sections, the vibration cycle is composed of four phases and their characteristics are listed as follows:

- D phase - The immersion vibrator sinks into the soft concrete. At this stage, the vibrator begins with an acceleration larger than gravity, and ends with an acceleration smaller than gravity, leading to a static beginning state and a static ending state. Simultaneously, the magnetic field signals suggest similar patterns.
- B phase - The vibrator is immersed in concrete, which should remain stable for a certain time.
- U phase - The vibrator rises from the concrete, which is almost the same as the down phase but should be slower to avoid voids and hidden holes.
- T phase - The vibrator remains in the air for another movement. The acceleration, angular velocity and magnetic field are commonly determined based on the working path patterns, such as a zigzag or spiral.

Commonly, the less random noises the raw data contain, the clearer information they provide. To improve the performance of activity segmentation, the raw data are transformed into frequency domain to determine the features. Figure 9-8 describes the distribution of acceleration components from 0 to 30 Hz, where most of them locate within 5 Hz. It is obvious that the acceleration along z axis occupies the largest proportion with respect to the strength, indicating the crucial motion of the vibrator is to move upwards and downwards, whereas most components of the acceleration along x and y axes are low-frequency components since the vibrator is moved horizontally after the completion of consolidation at a certain place.

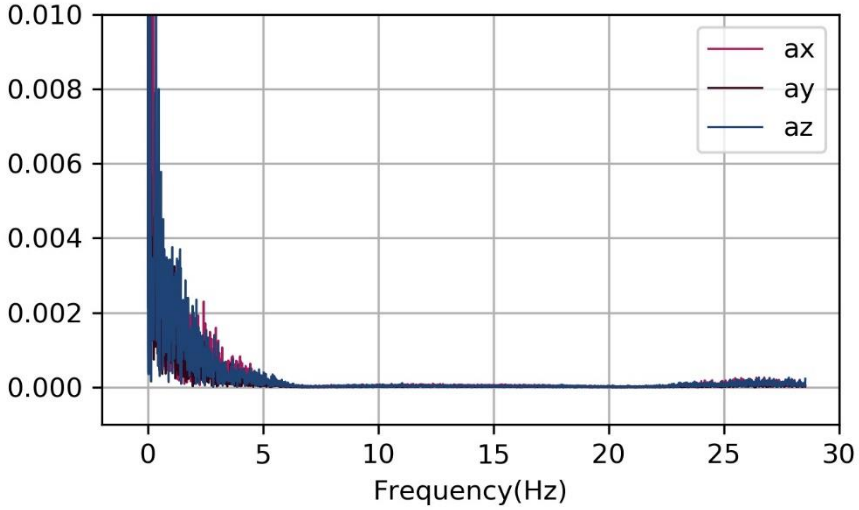

Figure 9-8 Frequency components of collected raw acceleration

For the angular velocity, there exist two main frequency components in Figure 9-9. The lower frequency components are similar to that of the acceleration, resulting from the movement of vibrator from one place to another, meanwhile the higher frequency components refer to the random noises.

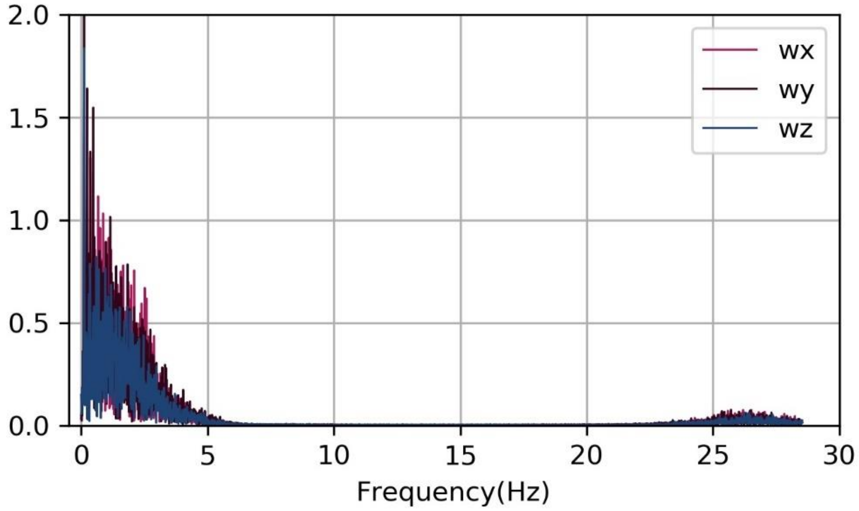

Figure 9-9 Frequency components of collected raw angular velocity

The magnetic field performs best with respect to the distribution of the frequency components. As shown in Figure 9-10, there are almost no random noises embedded in the raw magnetic field data due to no high frequency components. Among the low frequency components along z axis, the fundamental frequency is 0.12 Hz, 0.48 Hz, and 0.61 Hz.

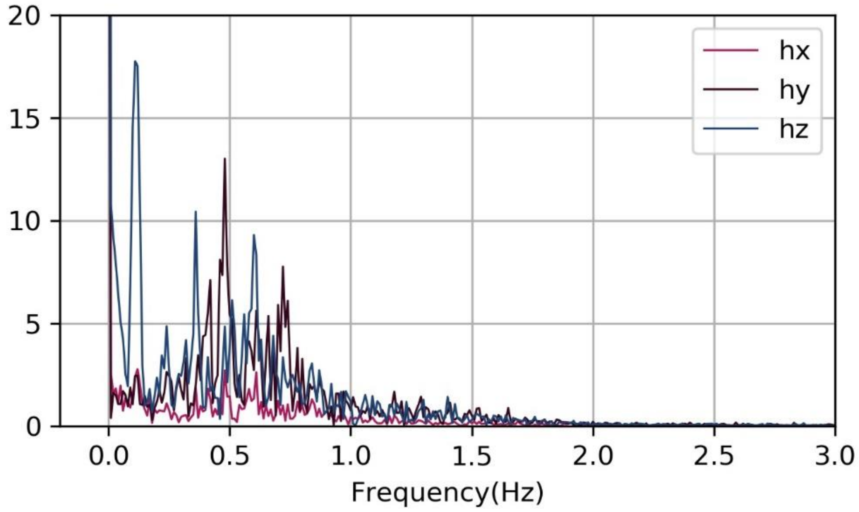

Figure 9-10 Frequency components of collected raw magnetic field

9.4 Experiment results

The simplest task for concrete consolidation experiment is to count the number of vibrations. However, since the direct characteristic of the concrete consolidation experiments is the position of vibrator, which is quadratic integral of the raw collected acceleration, the direct segmentation using the location tracks is error-prone due to the cumulated random noises over time. Therefore, this study tests the proposed methods on acceleration and magnetic field. Figure 9-11 illustrates the counting results relying on the acceleration data. From the systematic view, although the acceleration data are likely to segment the activities, the hidden repetitive pattern is not obvious because of a number of peaks from random noises.

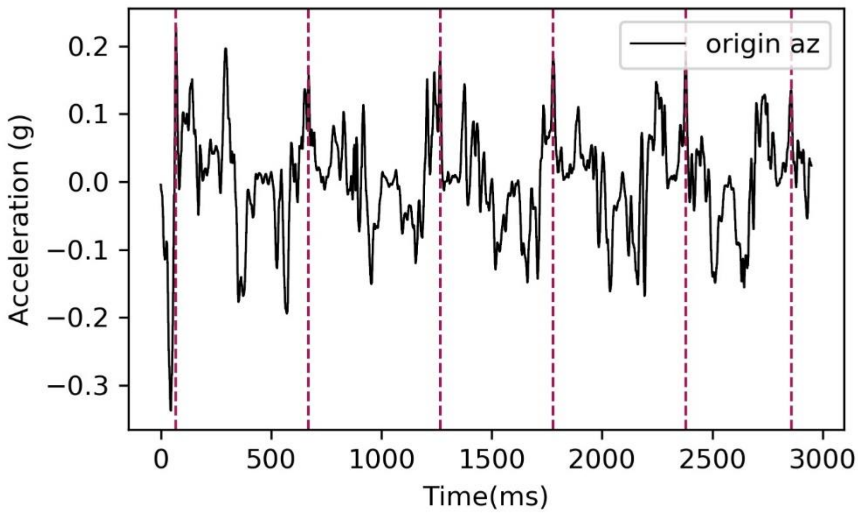

Figure 9-11 Counting the number of vibrations by magnetic field

Compared with acceleration data, magnetic field data is simple and clear so that the repetitive pattern can be easily identified in Figure 9-12. It is therefore to conclude that the accuracy of counting by segmentation on magnetic field data is more effective and efficient than the others.

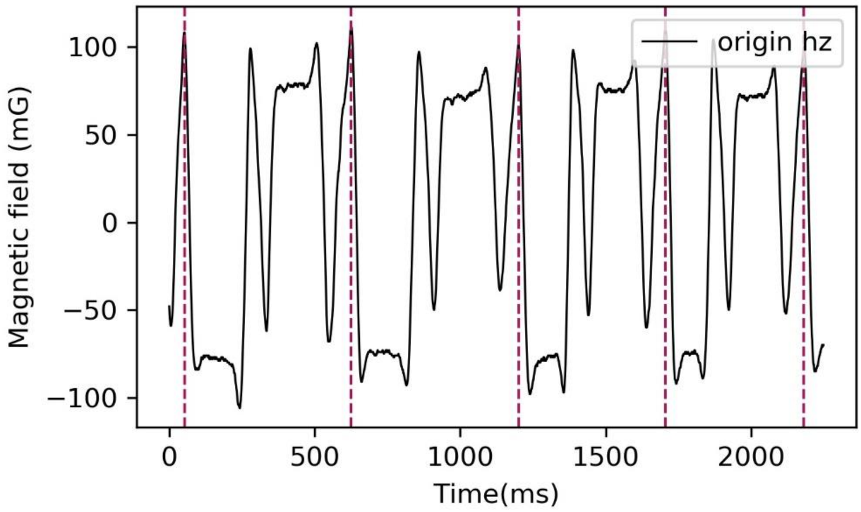

Figure 9-12 Counting the number of vibrations by magnetic field

Once each of the repetitive cycle is segmented, the four phases for the use of the internal concrete vibrator can be recognized based on their dynamic features of motions. As Figure 9-13 describes, at the D phase, the magnetic field along the gravity direction increases and decreases dramatically to insert into the fresh concrete; at the B phases, it keeps constant for a while until no more air can escape from the concrete; at the U phase, the signal follows its path at D phase, but in opposite direction; and at the T phase, the vibrator moves to another place and its magnetic field remains constant as well.

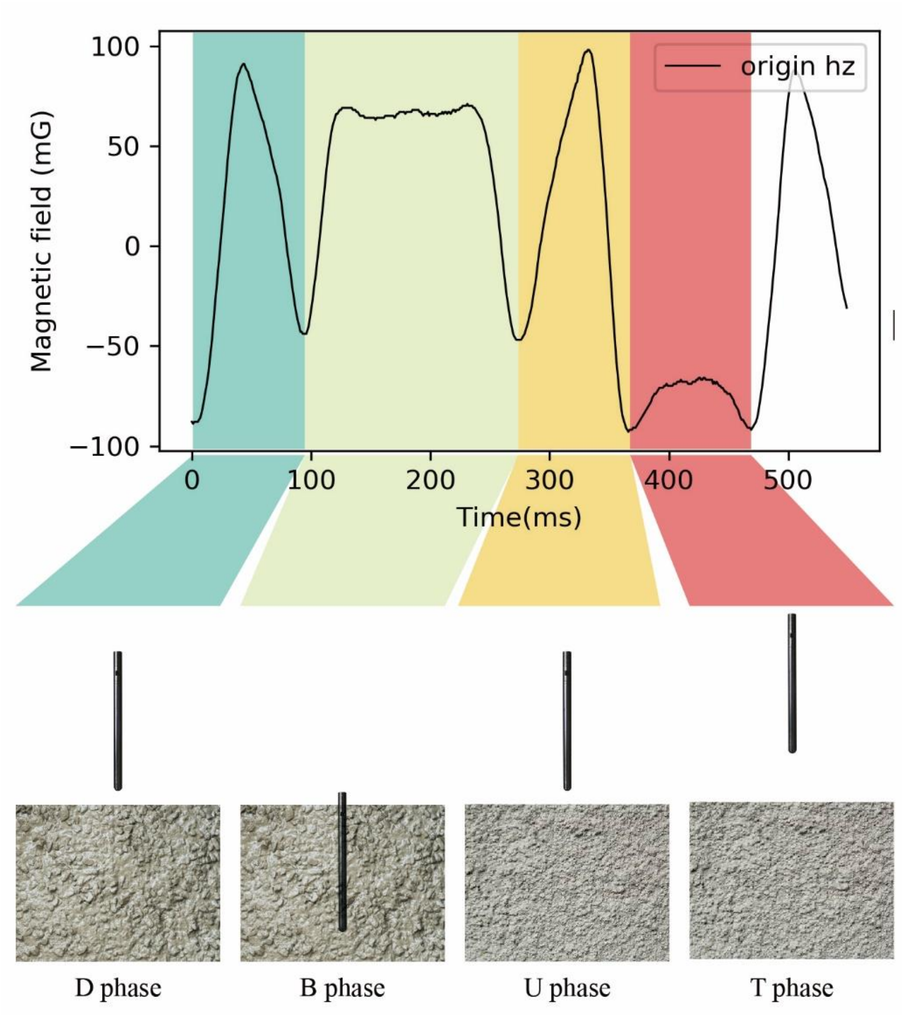

Figure 9-13 Activity segmentation using proposed prototype and models

Besides, the rotation of the vibrator is also a critical variable as it has direct impact on the placement quality of steel rebars according to the construction standards, particular for the cast-in-site concrete structure and reinforced concrete block structures. Assume the local coordinate system of an internal concrete vibrator is shown in Figure 9-14, and the acceptable rotation angles around x and y axes are 15 degrees, ensuring that the vibrators do not vibrate the rebars or formwork when putting or pulling.

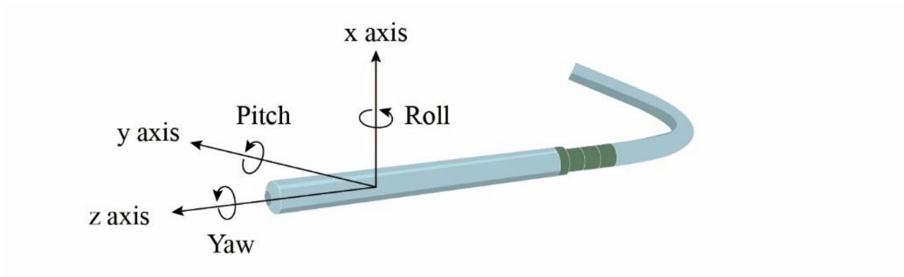

Figure 9-14 Local coordinate system of an internal concrete vibrator

Figure 9-15 shows samples of rotation angles calculated as the integral of the raw angular velocity. It can be seen that the rotations around x and y axes are in conformity with the assumption. Notably, the rotation around z axis, yaw motion is caused by rotating the body of vibrator by hands, which has few impacts on the performance of the concrete consolidation.

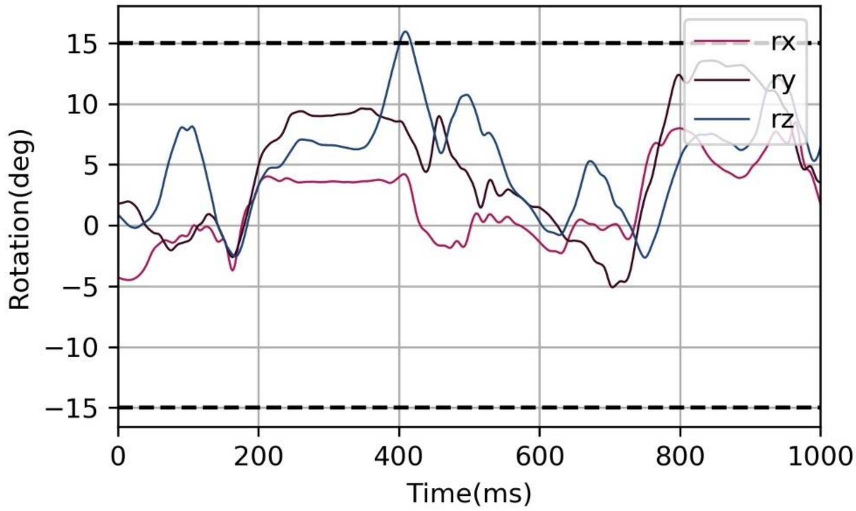

Figure 9-15 Samples of calculated rotation angles

Thus, based on the on-site experience, an under-vibration or low temperature during the pouring of concrete contributes significantly to a honeycomb surface, particularly when the temperature of the concrete is less than 5° during the pouring procedure in winter, whereas an over-vibration is accountable for a serious segregation. An assessment of the vibration at a specific location is clearly affected by the vibration duration, number of vibrations, and the vibration effect. It is well known that a long vibration duration leads to an over-vibration, whereas a short vibration duration results in an under-vibration. With respect to the vibration effect, the key factors are the number of vibrations, vibration action region, viscosity of the concrete and the vibrator specifications, whereas high-viscosity concrete with a flowable property increases the effects of the vibration and low-viscosity has an adverse impact. To model these dependencies, a traceability chain model is established in Figure 9-16. The node S represents the specifications of the vibrator, contains running time, maximum vibrations per minute (VPM), length and diameter. V refers to the viscosity of the fresh concrete, known as the resistance to deformation at a given rate. N, R, and D nodes are number of vibrations, vibration rotation angle, and vibration depth respectively, generated by the developed prototype and the proposed models. These nodes determine the efforts of the operator during a vibration at a certain place, which is named node E, from which it can be concluded that the construction subprocess is over-vibration, insufficient vibration or proper vibration. Node E, S and V are account for the node A, describing the area of effect per vibration. Combining them and vibration position of node P, and environmental variable of node T (such as temperature and humidity), the vibration quality of node Q can be evaluated in a quantitative way. Based on these probabilities, it can be used to infer the quality risks of some certain concrete defects, such as honeycomb surface and segregation. For example, if the detected data of the vibrator reveals the vibration time is less than expected, the vibration effect is prone to be insufficient, and the risk of honeycomb surface of the concrete increases subsequently. On the contrary, if the data shows that the number of vibrations exceeds the expectation, the fresh concrete is therefore over-vibrated that may lead to segregation and the reduction in strength.

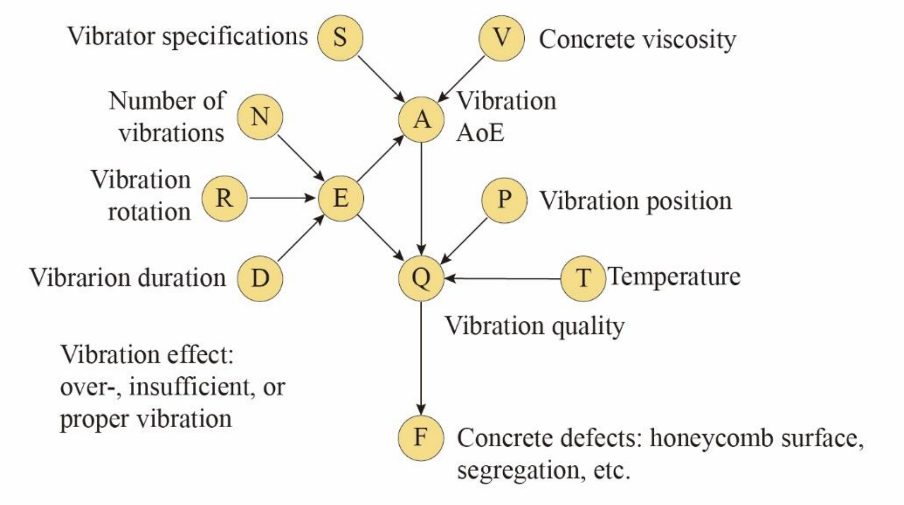

Figure 9-16 Concrete vibration traceability chain

In this experiment, the vibration cycle is segmented by the magnetic field data around z axis. Figure 9-17 illustrates the histogram of the vibration time for the concrete consolidation experiment, the mean value and standard deviation of which are 1015.70 ms and 81.18 ms. The reason for the small deviation is that the subjects conduct the experiment with a stopwatch to ensure that the vibration time locates between the acceptable minimum and maximum durations around 10 s.

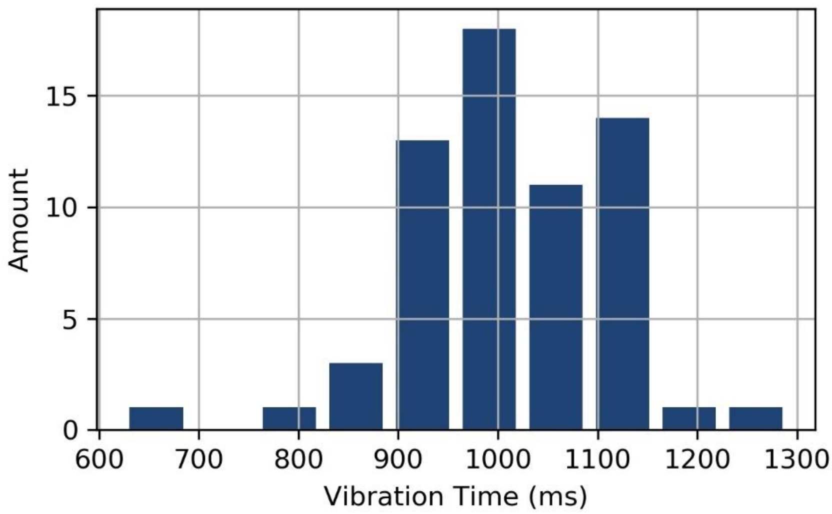

Figure 9-17 Histogram of vibration time for the concrete consolidation experiment

Based on the vibration cycles, the rotation angles in each cycle are plotted in Figure 9-18. It can be seen from the subfigures that all of the vibration samples satisfy the assumed regulations that all of the angles around x and y axes are less than 15 degree. Therefore, the node probabilities collected from the vibrators are generated and the trace forwards and backwards are available.

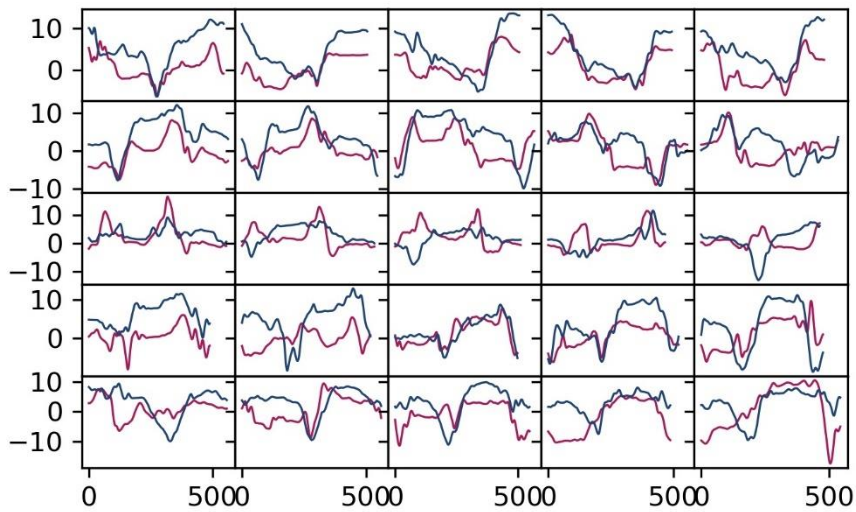

Figure 9-18 Sample of rotation around x and y axes in vibration cycles

In addition, the depth of vibration is calculated by the integral of the raw acceleration in each cycle. As Figure 9-19 illustrates, although the required vibration depth in this simulated experiment is 1.5 m, most of the participants tend to move the vibrator for a longer distance with a mean of 1.36 m and a standard deviation of 0.17 m.

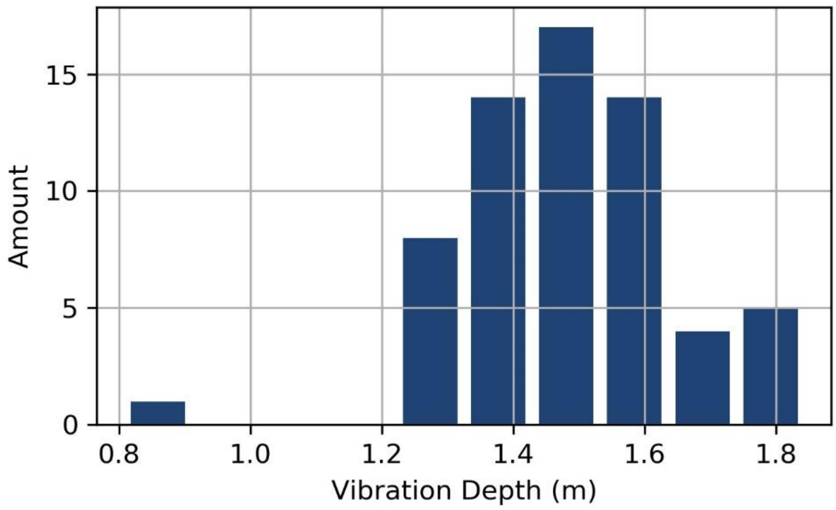

Figure 9-19 Histogram of vibration depth for the concrete consolidation experiment

9.5 Traceability analysis

Aiming to infer the quality issue according to the tool data, a trace forward refers to pursuing the downstream direction along the structure of the Bayesian network. Based on the Bayesian network theory, the inference expresses the joint distribution of the entire network which can be calculated based on the chain rule. Therefore, the conditional probability distributions are then denoted by tabular probability distributions as a simple representation.

Since the prior probabilities of some nodes in the traceability chain are unknown according to the current knowledge, this section thus begins with some assumptions that provides the basic information for the traceability analysis.

- Node V: the concrete viscosity is categorized into high, medium or low levels. Assume their probabilities equals and the marginal probability of node V can be represented by Table 9-2.

Table 9-2 Marginal probability of the concrete viscosity

Concrete viscosity	High	Medium	Low
P(V)	0.33	0.34	0.33

- Node S: the vibrator specifications are commonly fixed in a construction project. It is assumed to be normal and suitable for the concrete consolidation here to simplify the inference. The node S is therefore considered to be totally right with a probability of 1.
- Node N: the number of vibrations is detected exactly by the developed prototype and the proposed method. According to the result, all of the concrete at the required places is vibrated, and the probability of node N is determined to be 1 as well.
- Node D: the duration of vibrations is also captured by the smart construction tool gadget. Assume the acceptable vibration time varies from 0.8 to 1.2 m, the tabular probability of the vibration time is summarized in Table 9-3.

Table 9-3 Tabular probability of the vibration duration

Vibration duration	Long	Medium	Short
P(D)	0.02	0.96	0.02

- Node R: the rotation angles are also collected to ensure the verticality during the vibration and assume the states of vibration include acceptable rotation and unacceptable rotation. In the experiment, all of the vibrations are in conformity with the current regulations and the probability of node R is thus described in .

Table 9-4 Tabular probability of the vibration rotation

Vibration rotation	Acceptable	Unacceptable
P(R)	1.00	0.00

- Node P: the vibration position refers to the coverage rate of the vibration process. Since no participants have missed certain vibration points, the probability of node P is therefore considered to be 1.
- Node T: as the temperature in the experimental environment is suitable for the fresh concrete. The effect of temperature on the fresh concrete is reasonable to be ignored for simplification.

The above nodes, generated from collected data, work experiences and prior knowledge, are independent variables. But the following nodes are dependent nodes that conditional probabilities are provided based on prior knowledge of the construction quality management.

- Node E: the vibration effect mainly refers to the manual efforts on the performance of the concrete consolidation, which is composed of three states: over-vibration, insufficient vibration and proper vibration. This probability is determined by the number of vibrations, the vibration rotation and vibration time. Considering all the vibration rotations and the number of vibrations meet the requirements, and the tabular probability distribution is thus simplified and assumed in Table 9-5.

Table 9-5 Tabular probability of the vibration effect

P(E|D)	Vibration effect		
Vibration duration	Over-vibration	Proper vibration	Insufficient vibration
Long	0.7	0.2	0.1
Medium	0.1	0.8	0.1
Short	0.0	0.2	0.8

- Node A: the vibration area of effect represents the action region of each vibration, which is determined by the concrete viscosity, the vibrator specifications and the vibration effect. Considering all the vibration rotations meet the requirements of regulations, the tabular probability of the area of effect is listed in Node Q: represents the vibration quality from a systematic view that combines vibration positions, their vibration AoEs, vibration effects, and environmental variables, such as temperature and humidity. For this node, it is suggested to apply weighted average to calculating the systematic quality of the concrete consolidation. Notably, the node Q has a continuous 2D distribution due to the 2D input - vibration positions.
- Node F: refers various concrete defects that the stake holder concerns so the conditional probability is provided by experts and skilled workers, such as

honeycomb surface, segregation, exposed bars, etc.

- Table 9-6.
- Node Q: represents the vibration quality from a systematic view that combines vibration positions, their vibration AoEs, vibration effects, and environmental variables, such as temperature and humidity. For this node, it is suggested to apply weighted average to calculating the systematic quality of the concrete consolidation. Notably, the node Q has a continuous 2D distribution due to the 2D input - vibration positions.
- Node F: refers various concrete defects that the stake holder concerns so the conditional probability is provided by experts and skilled workers, such as honeycomb surface, segregation, exposed bars, etc.

Table 9-6 Tabular probability of the vibration AoE

P(A|E, V)		Vibration AoE	
Vibration effect	Concrete viscosity	Proper vibration	Improper vibration
	High	0.1	0.9
Over-vibration	Medium	0.2	0.8
	Low	0.4	0.5
	High	0.6	0.4
Proper vibration	Medium	1.0	0.0
	Low	0.6	0.4
	High	0.4	0.6
Insufficient vibration	Medium	0.2	0.8
	Low	0.0	1.0

Given the conditional probabilities, the joint distribution of all attributes can be calculated by the chain rule, which can be written as follows:

$$P(X_1, \cdots X_n) = \prod_{i=1}^{n} P\left(X_i | Par(X_i)\right) \quad (9.2)$$

where $Par(\cdot)$ is the parent of node X_i. The Lauritzen-Spiegelhalter, Shenoy-Shafer and Hugin algorithms can be used to conduct a belief propagation, providing a time-saving and storage-saving solution to exactly identify the conditional quality issues (Lepar and Shenoy 2013). Thus, the distribution of the vibration effect is showed in Table 9-7, and that of the vibration AoE is listed in Table 9-8.

Table 9-7 Probability distribution of the vibration effect

Vibration effect	Over-vibration	Proper vibration	Insufficient vibration
P(E)	0.11	0.776	0.114

Table 9-8 Probability distribution of the vibration AoE

Vibration AoE	Proper vibration	Improper vibration
P(A)	0.619566	0.376804

9.6 Summary

This chapter reshows the feasibility of applying the developed prototype and the proposed models in this research by a more complex and comprehensive experiment – concrete consolidation experiment. The results prove the effectiveness and efficiency of the smart construction tool gadget for a concealed project – concrete consolidation tasks with an internal concrete vibrator. The main findings are listed as follows:

- Concrete consolidation as a concealed project in the construction industry determines the quality performance of the final concrete products. The only way to monitor such invisible projects is to control and track the associated construction tasks.
- The number, time, depth, position and posture of the vibrator all have impacts on the performance of the concrete consolidation. It is reasonable to apply kinematic models to analyze the use of the vibrator by its repetitive features.
- As the manual efforts on the vibrators are evaluated in a quantitative and scientific way, subjective variables and objective variables (such as environmental and material variables) can be combined together in the traceability chain for tracking and tracing.

CHAPTER 10 DISCUSSIONS

The aim of this study is to present a concept idea of traceability to monitor and manage the construction process without privacy issues and intrusions. It is proposed to track the construction hand and power tools instead of tracking worker by an IMU sensor integrated with a BLE module, enabling the trace forwards and backwards of the associated construction process for quality assessment and root cause identification. The focus of this chapter is the prototype, smart construction tool gadget, developed by the authors in Chapter 4, 7, and the data process and analysis methods, proposed by the authors, in Chapter 5 and 6. This chapter therefore discusses three topics: 1) validity of the results; 2) generalization of the prototype and methods; 3) limitations of this study.

10.1 Validity of the results

The prototype – smart construction tool gadget has been developed for manual construction tasks with hand or power tools, and the model has been proposed based on solid work experiences and construction knowledge. Two experiments are carried out to test them for improvement. The first experiment is rebar connection task using an adjustable wrench, which is common, typical and significant in the construction industry. The second experiment is concrete consolidation task using an internal concrete vibrator, which is invisible and distributed at the construction sites. In total, more than 20 participants have engaged in the lab experiment although they are not working as construction labor in daily life. To ensure the simulation close to the reality in practical projects, all of the participants are required to be trained and tested prior to the tasks so that their productivity and accuracy can achieve the appropriate levels.

Considering the potential errors generated from the developed system, the authors also have installed surveillance cameras to compare the IMU collected data with recorded videos and manual reports. The results show the high accuracy and reliability of the smart construction tool gadget with respect to the acceleration, angular velocity, magnetic field and temperature. For other indirect variables, such as displacement, velocity and rotation, these data are produced by numerical mathematical equations with an acceptable error. For example, the error term of the Trapezoid rule for integration is related to the 3th power of the sample interval, which is less than 10^{-6} and is considered to be acceptable for motion analysis.

Since there is limited research associated to traceability concept or applications in the construction industry, the proposed traceability chain model is built up based on the mature traceability models in other industries, containing food and drug industries. Even if the proposed model has not been completely and exactly verified, this traceability model and analysis model is still to the greatest extent based on literature within the construction field. The validity of the data model and traceability chain therefore depends on the validity of the literature used and a number of practical experiments. On one hand, many of the frameworks in literatures have been tested and proved to be effective and efficient in practice; on the other hand, two experiments of rebar connection task and concrete consolidation have been investigated and studies to highlight the feasibility of applying new concepts in the conventional construction industry without a huge change in normal activities. They both increase the validity of the data model and traceability chain, which in turn increase the validity of the developed prototype as well.

10.2 Generalization of the prototype and models

As discussed before, no published studies associated with the traceability concept in the area of construction has been found by the authors. It is therefore believed that the prototype developed, and the models proposed in this research can make a great contribution to the construction informatics within the construction industry.

For the smart construction tool gadget, since it is designed to be portable and easy-handling, the sensor is capable of installing on the body of tools, crewing to the handle of tools, and embedded in the board of power tools. If the model-based data model is adopted, the use of the tools must contain repetitive rotation or movement patterns as the patter is the foundation of activity segmentation in model-based kinematic models. Moreover, if the ML-based approach is implemented, it can be widely used for any kinds of construction tools after training or finetuning the artificial intelligence.

With respect to the traceability chain, the establishment of the Bayesian network, particularly, the structure and the conditional probability, is heavily relied on the prior knowledge and work experience. For example, researchers have shown the relation between the rigid length and the mechanical strength of steel coupler. It is obvious to build up a traceability chain that contains the node of rigid length, and the node of the connection quality as well as links them with an arrow to describe their cause-effect relation. With the advances in data-driven methods to construct the complex network, it is also possible to work out the structure and conditional probabilities of traceability chain without prior knowledge, but with adequate collected motion data of the associated tools in the future.

In addition, since the rebar connection and concrete consolidation are quite common at the construction sites, the implementation of the developed prototype and the proposed methods can expand to most of the other construction activities, even certain invisible activities that current approaches cannot monitor, such as formwork by a hammer, rebar cut by a cutter or bender, rebar placement by a tie wire twister, etc.

10.3 Limitations of this research

Although this research develops a novel framework to monitor the construction quality performance and addresses the privacy and intrusion issues in the conventional data collection at sites, there are still certain limitations that may prevent the implementation and application of the prototype and models. These limitations are summarized as follows:

- For the construction tasks without tools, such as carrying heavy entities and manual inspections, although the smart construction tool gadget can be installed on the personal protective equipment, the data model based on repetitive features can not be applied immediately as the human body is not rigid without deformations.
- Though the experiments in this study are typical and valuable to show the feasibility of smart construction tool gadget, more complex scenarios are not investigated and tested. For example, one of the most comprehensive construction tasks is formwork. When carpenters are forming for concrete structures, they carry and use various construction tools, containing hammers, nail guns, etc. To monitor the entire construction progress of formwork, all associated tools must be tracked and recorded at the same time, and data from multiple sources must be fused for traceability. The authors at the present time cannot construct the traceability chain and evaluate the quality performance without a strong knowledge background. Such limitations expose the risks of applying the prototype and models to more complex construction tasks.
- Despite of the repetitive rotation and displacement, there are also other kinds of repetitive patterns. However, this research only focuses on rigid with repetitive patterns, the shape of which does not change across the construction stages. The construction activities that have no repetitive motions are not tested and examined in this research. For example, using concrete forming plastic chairs to place rebars may cost larger than expectation as the sensors are disposable.

10.4 Summary

In this research, the results of the two experiments have clearly shown the effectiveness and efficiency of the smart construction tool gadget. The accuracy of the collection motions by IMU sensor and BLE module compared with recorded videos is more than 80 % and the proposed data model is capable of monitoring and tracing the entire construction process with a structured network for the rebar connection task and the concrete consolidation task.

Although the developed prototype and models are applied and tested in practical experiments, it is still the authors' belief that the prototype and models still require to be improved in the long run, and they should be adjusted to each construction activity for different construction defects.

CHAPTER 11 CONCLUSIONS

To conclude, this chapter 1) summarizes the answers to the research questions at the beginning of this research; 2) presents the theoretical contributions and the practical implications to the construction industry; and 3) suggests the following research in the future.

11.1 Answers to the research questions

The purpose of this research is to improve the construction quality by introducing and increasing its traceability. To fulfill this purpose, the three-folded research questions are answered in the thesis:

- How to collect the construction activities/processes data through the advanced techniques without privacy and intrusion issues?
- A novel data collection using IMU and BLE techniques to track the construction hand tools and power tools for construction monitoring is proposed in this research. This tool-based data collection not only collects the kinematic motions of the tools, containing acceleration and angular velocity, it also records the dynamic changes of environment, including the magnetic field and temperature. Such data collection provides a non-intrusive alternative to the traditional construction tracking systems, such as wearable devices and surveillance cameras. In addition, the proposed data collection enables the

construction continuous monitoring of certain concealed projects.

- How to analyze certain construction activities and evaluate their quality to determine whether they are conformity with the construction regulations relying on the collected data?
- A tool kinematic model and several sensor models are proposed in this research to deal with the collected tool data. Here the tool kinematic model is composed of data processing, data fusion, data segmentation and feature extraction. The data processing module converts the direct measurements of IMU into the rigid movement of the construction tools; the data fusion module combines the data from different sources and integrates the data at adjacent times to improve the accuracy; the data segmentation module utilizes the cyclic patterns during the use of the tools to recognize the construction activities at different phases; and the feature extraction module calculates the process control variables for the compliance with associated regulations. The tool kinematic model based on a solo IMU sensor can not only retrieve the historical construction process, it can also segment the construction process for quality assessment of manual efforts at each stage. According to the two experimental results, given a cyclic repetitive pattern, this model semi-automatically conducts the data processing and analysis for the assessment of quality with a high accuracy. Moreover, ML-based approach for segmentation is also tested in the experiment to show the feasibility of applying AI techniques to automatize quality control and monitoring completely.
- How to combine the non-intrusive data collection and the smart data analysis model to automatically generate a traceable structure framework for quality evaluation and root cause analysis?

- A smart construction tool gadget and a construction traceability chain model are developed and proposed respectively to represent the framework of non-intrusive and automated quality evaluation and root cause analysis. The tool-based prototype is made up of an IMU and a BLE module, which validates the proposed data collection in practice. The construction traceability chain model formulates the collected data and quality information as a Bayesian network to conduct the quality analysis and management quantitatively. The two lab experiments proves that the combined framework of a non-intrusive tool-based data collection and a construction traceability chain model enables a clear vision of responsibilities and a structure record for quality evaluation and root causes analysis.

This thesis has answered the research questions and validated these answers by practical experiments. Hence, the developed prototype and proposed method has fulfilled the research purpose and generated both theoretical and practical contributions.

11.2 Theoretical contributions and practical implications

This research firstly introduces the traceability concept into the construction industry, it therefore theoretically contributes to the research area of the construction quality management and practically contributes to the stake holders in the construction industry. These theoretical contributions are listed as follows:

- This thesis has contributed to the research field with a detailed introduction of traceability concept to the construction industry. This concept and its associated management framework have tested and analyzed to be feasible for the current construction quality management.

- The kinematic tool data model makes contributions to the research field of activity recognition in many scenarios since it provides an effective and efficient alternative to the collect associated data instead of tracking the workers directly. Compared with the traditional ways, the proposed method is simple that can be transferred to various applications.
- The traceability chain model theoretically contributes to the research area of the structural record of the construction process. It provides a new alternative to briefly capture the construction process as a flight box for air crafts. The recorded network is more effective and efficient than the manual reports.

This thesis has also shown the practical implications by the rebar connection task and the concrete consolidation task, which are listed as follows:

- The first practical implication is that the stake holders involved in the construction industry should increase the understanding of traceability concept for the quality management. They can gain a clear vision of responsibility due to the established traceability and transparency.
- The second practical implication is that the contractors can apply the tool-based construction activity capture system instead of wearable devices and surveillance cameras to avoid offending personal privacy and enhance the relations between employees and employers.
- The third practical implication is related to the public government. The construction associations and communities can apply the tool-based construction activity data collection to concealed projects in order to gain a

systematic view of the construction quality and outwit the anxiety in public. In addition, the regulations that govern the construction progress can also obtain a quantitative feedback for improvement in the next version.

11.3 Future research

This thesis within the area of the construction quality is limited due to the assumptions of working repetitive patterns and the two simple but typical experiments, but the framework of the construction traceability can serve as a starting point for future research in the research area of construction quality management. There are still a body of areas and techniques where researchers need to investigate and develop before the traceability concept widely implemented in the construction industry. These future researches contain, but not limited to the following areas:

- The current IMU-based data collection only contains spatial parameters, such as the acceleration, the angular velocity, the magnetic field and the temperature. However, the construction process is not only affected by human behaviors but also by environmental factors, such as the humidity and illumination. Data from a variety of resources need to be added in future research to enrich the existing data and improve the robustness and reliability of the system.
- A GPS connected with an antenna is wired and must be exposed to the outdoor environment to receive data from satellites, resulting in low accuracy for indoor environments. More state-of-the-art technologies need to be applied and used in the future to realize a wireless global localization.

- The energy of the developed system is supported by batteries. Thus, the sensors need to be charged over time. Biomechanical and passive tags should be investigated for future implementations to avoid frequent intervention.
- In the future, the Standard Method of Measurement used in measurement of the quantities in construction projects will be investigated. The proposed methods can be integrated to achieve an automated and non-intrusive measurement in practices.
- To construct a realistic traceability chain, a number of field experiments are required to generate the appropriate conditional and prior distribution parameters in the network. Only under this condition can the accuracy, as well as the determined prediction and cause, be inferred.

REFERENCE

Alexiev, Kiril, and Iva Nikolova. 2013. "An algorithm for error reducing in IMU." 2013 IEEE INISTA.

Aly, Nael A., Venetta J. Maytubby, and Ahmad K. Elshennawy. 1990. "Total quality management: An approach & a case study." *Computers & Industrial Engineering* 19 (1):111-116. doi: https://doi.org/10.1016/0360-8352(90)90087-3.

Armand V. Feigenbaum. 2004. *Total Quality Control*. 4th ed: McGraw-Hill Professional.

Aryal, Ashrant, Ali Ghahramani, and Burcin Becerik-Gerber. 2017. "Monitoring fatigue in construction workers using physiological measurements." *Automation in Construction* 82:154-165.

Awolusi, Ibukun, Eric Marks, and Matthew Hallowell. 2018. "Wearable technology for personalized construction safety monitoring and trending: Review of applicable devices." *Automation in construction* 85:96-106.

Azar, Ehsan Rezazadeh. 2015. "Construction equipment identification using marker-based recognition and an active zoom camera." *Journal of Computing in Civil Engineering* 30 (3):04015033.

Benoussaad, Mourad, Benoît Sijobert, Katja Mombaur, and Christine Azevedo Coste. 2016. "Robust Foot Clearance Estimation Based on the Integration of Foot-Mounted IMU Acceleration Data." *Sensors* 16 (1):12.

Bosche, Frederic, Carl T Haas, and Burcu Akinci. 2009. "Automated recognition of 3D CAD objects in site laser scans for project 3D status visualization and performance control." *Journal of Computing in Civil Engineering* 23 (6):311-318.

Caldas, Carlos H, David Grau Torrent, and Carl T Haas. 2006. "Using global positioning system to improve materials-locating processes on industrial projects." *Journal of Construction Engineering and Management* 132 (7):741-749.

Chen, Shenen, Howard Chung, and Youngjin Park. 2013. "LiDAR scan and smart piezo layer combined damage detection." Nondestructive Characterization for Composite Materials, Aerospace Engineering, Civil Infrastructure, and Homeland Security 2013.

Cheng, Kris. 2018. MTRC top official unsure why contractors cut corners during Hung Hom MTR station expansion.

Cheng, T, M Venugopal, J Teizer, and PA Vela. 2011. "Performance evaluation of ultra wideband technology for construction resource location tracking in harsh environments." *Automation in Construction* 20 (8):1173-1184.

Cheng, Tao, Giovanni C Migliaccio, Jochen Teizer, and Umberto C Gatti. 2012. "Data fusion of real-time location sensing and physiological status monitoring for ergonomics analysis of construction workers." *Journal of Computing in Civil engineering* 27 (3):320-335.

Cheok, Geraldine S, William C Stone, Robert R Lipman, C Witzgall, and Javier Bernal. 2001. "Laser scanning for construction metrology." Proceedings of the American Nuclear Society 9th International Topical Meeting on Robotics and Remote Systems, Seattle, WA: Cambridge University Press.

Cho, Yong K, Thaddaeus Bode, Jongchul Song, and Jin-Hoon Jeong. 2011. "Thermography-driven distress prediction from hot mix asphalt road paving construction." *Journal of Construction Engineering and Management* 138 (2):206-214.

Creydt, M., and M. Fischer. 2019. "Blockchain and more - Algorithm driven food traceability." *Food Control* 105:45-51. doi: https://doi.org/10.1016/j.foodcont.2019.05.019.

Crosby, Philip B. 1983. "Don't be defensive about the cost of quality." *Quality Progress* 16 (4):38-39.

Davis, Kent, W. B. Ledbetter, and James L. Burati. 1989. "Measuring Design and Construction Quality Costs." *Journal of Construction Engineering and Management* 115 (3):385-400. doi: doi:10.1061/(ASCE)0733-9364(1989)115:3(385).

Eghtesadi, Shahrzad, and Michelle Nokken. 2017. "Effect of Cracking and Improper Consolidation as Important Concrete Defects on Water Absorption and Electrical Conductivity." *Journal of Materials in Civil Engineering* 29 (11):04017201. doi: doi:10.1061/(ASCE)MT.1943-5533.0002050.

Environment Transport and Works Bureau. 2003. Trade classification in the construction industry.

Georgiou, Jim, PED Love, and Jim Smith. 1999. "A comparison of defects in houses constructed by owners and registered builders in the Australian State of Victoria." *Structural Survey* 17 (3):160-169.

Gibson, Kathleen R, Kathleen Rita Gibson, and Tim Ingold. 1994. *Tools, language and cognition in human evolution*: Cambridge University Press.

Gomez-de-Gabriel, Jesus M, Juan A Fernández-Madrigal, Antonio Lopez-Arquillos, and Juan Carlos Rubio-Romero. 2019. "Monitoring harness use in construction with BLE beacons." *Measurement* 131:329-340.

Gordon, Chris, Frank Boukamp, Daniel Huber, Edward Latimer, Kuhn Park, and Burcu Akinci. 2003. "Combining reality capture technologies for construction defect detection: A case study." EIA9: E-Activities and Intelligent Support in Design and the Built Environment, 9th EuropIA International Conference.

Greene, Jennifer C, Valerie J Caracelli, and Wendy F Graham. 1989. "Toward a conceptual framework for mixed-method evaluation designs." *Educational evaluation and policy analysis* 11 (3):255-274.

Grejner‐Brzezinska, Dorota A, Yudan Yi, and Charles K Toth. 2001. "Bridging GPS gaps in urban canyons: The benefits of ZUPTs." *Navigation* 48 (4):216-226.

Guo, Hongling, Yantao Yu, Tian Xiang, Heng Li, and Dan Zhang. 2017. "The availability of wearable-device-based physical data for the measurement of construction workers' psychological status on site: From the perspective of safety management." *Automation in Construction* 82:207-217.

Guo, Qinghua. 1998. "Yingzao Fashi: twelfth-century Chinese building manual." *Architectural History* 41:1-13.

Hallak, Juan Carlos. 2006. "Product quality and the direction of trade." *Journal of international Economics* 68 (1):238-265.

Harris, Frank, and Ronald McCaffer. 2013. *Modern construction management*: John Wiley & Sons.

Huang, Jincheng, Zhu Liu, Yao Wang, Yu Chen, and Edward K Wong. 1999. "Integration of multimodal features for video scene classification based on HMM." 1999 IEEE Third Workshop on Multimedia Signal Processing (Cat. No. 99TH8451).

Hubbard, Bryan, Heng Wang, Michael Leasure, Tim Ropp, Tamara Lofton, Sarah Hubbard, and Shiyuan Lin. 2015. "Feasibility study of UAV use for RFID material tracking on construction sites." Proc., ASCE Annual International Conference.

Hughes, Josie, Jize Yan, and Kenichi Soga. 2015. "Development of wireless sensor network using bluetooth low energy (BLE) for construction noise monitoring." *International Journal of Smart Sensing and Intelligent Systems* 8 (2):1379-1405.

Hunaidi, Osama, and Peter Giamou. 1998. "Ground-penetrating radar for detection of leaks in buried plastic water distribution pipes." International Conference on Ground Penetrating Radar.

Ibrahim, YM, Tim C Lukins, X Zhang, Emanuele Trucco, and AP Kaka. 2009. "Towards automated progress assessment of workpackage components in construction projects using computer vision." *Advanced Engineering Informatics* 23 (1):93-103.

International Organization for Standardization. 2015. Quality management systems — Requirements (ISO 9001:2015).

Jang, Won-Suk, and Mirosław J Skibniewski. 2009a. "Cost-benefit analysis of embedded sensor system for construction materials tracking." *Journal of Construction Engineering and Management* 135 (5):378-386.

Jang, Won-Suk, and Mirosław J Skibniewski. 2009b. "Embedded system for construction asset tracking combining radio and ultrasound signals." *Journal of Computing in Civil Engineering* 23 (4):221-229.

Jang, Won-Suk, and Miroslaw J Skibniewski. 2008. "A wireless network system for automated tracking of construction materials on project sites." *Journal of civil engineering and management* 14 (1):11-19.

Jebelli, Houtan, Sungjoo Hwang, and SangHyun Lee. 2017. "Feasibility of field measurement of construction workers' valence using a wearable EEG device." In *Computing in Civil Engineering 2017*, 99-106.

Josephson, P-E, and Yngve Hammarlund. 1999. "The causes and costs of defects in construction: A study of seven building projects." *Automation in construction* 8 (6):681-687.

Josephson, Per-Erik, Bengt Larsson, and Heng Li. 2002. "Illustrative benchmarking rework and rework costs in Swedish construction industry." *Journal of Management in Engineering* 18 (2):76-83.

Juran, Joseph, and A Blanton Godfrey. 1999. "Quality handbook." *Republished McGraw-Hill*:173-178.

Kanji, Gopal K. 1990. "Total quality management: the second industrial revolution." *Total Quality Management* 1 (1):3-12. doi: 10.1080/09544129000000001.

Kendall Jones. 2017. Top Causes of Construction Accident Injuries and How to Prevent Them.

Koch, Christian, Kristina Georgieva, Varun Kasireddy, Burcu Akinci, and Paul Fieguth. 2015. "A review on computer vision based defect detection and condition assessment of concrete and asphalt civil infrastructure." *Advanced Engineering Informatics* 29 (2):196-210.

Kubal, Michael T. 1994. "Engineered Quality in Construction. Partnering and TQM."

Labres, Henrique, Maria Fernanda de Oliveira, Fernanda Pacheco, Jorge Patrício, and Bernardo Tutikian. 2018. "Acoustic performance of brick masonry walls: Construction defects and influence of installations." *Building Acoustics* 25 (4):351-362.

Lai, WL, T Kind, and H Wiggenhauser. 2011. "Using ground penetrating radar and time–frequency analysis to characterize construction materials." *NDT & E International* 44 (1):111-120.

Lee, Seonah, and Carrlo A. M. Smith. 2012. "Criteria for Quantitative and Qualitative Data Integration: Mixed-Methods Research Methodology." *CIN: Computers, Informatics, Nursing* 30 (5):251-256. doi: 10.1097/NXN.0b013e31824b1f96.

Lepar, Vasilica, and Prakash P. Shenoy. 2013. "A comparison of Lauritzen-Spiegelhalter, Hugin, and Shenoy-Shafer architectures for computing marginals of probability distributions." *arXiv preprint arXiv:1301.7394*.

Li, Chunxia, and SangHyun Lee. 2011. "Computer vision techniques for worker motion analysis to reduce musculoskeletal disorders in construction." In *Computing in Civil Engineering (2011)*, 380-387.

Li, Heng, Zhen Chen, Liang Yong, and Stephen C. W. Kong. 2005. "Application of integrated GPS and GIS technology for reducing construction waste and improving construction efficiency." *Automation in Construction* 14 (3):323-331. doi: https://doi.org/10.1016/j.autcon.2004.08.007.

Li, Yan, and Chunlu Liu. 2019. "Applications of multirotor drone technologies in construction management." *International Journal of Construction Management* 19 (5):401-412.

Liu, Tianming, Hong-Jiang Zhang, and Feihu Qi. 2003. "A novel video key-frame-extraction algorithm based on perceived motion energy model." *IEEE transactions on circuits and systems for video technology* 13 (10):1006-1013.

Liu, Xuesong, Matineh Eybpoosh, and Burcu Akinci. 2012. "Developing as-built building information model using construction process history captured by a laser scanner and a camera." Construction Research Congress 2012: Construction Challenges in a Flat World.

Lu, Ming, Wu Chen, Xuesong Shen, Hoi-Ching Lam, and Jianye Liu. 2007. "Positioning and tracking construction vehicles in highly dense urban areas and building construction sites." *Automation in construction* 16 (5):647-656.

Lu, Weisheng, George Q. Huang, and Heng Li. 2011. "Scenarios for applying RFID technology in construction project management." *Automation in Construction* 20 (2):101-106. doi: https://doi.org/10.1016/j.autcon.2010.09.007.

MathWorks. 2019. "IMU simulation model: For Use with MATLAB." MathWorks. https://ww2.mathworks.cn/help/fusion/ref/imusensor-system-object.html.

McKinsey Global Institute. 2017. Reinventing construction through a productivity revolution.

Mishra, Gopal. 2017. Quality in Construction Industry - Objectives, Factors Affecting Quality.

Moselhi, Osama, and Tariq Shehab-Eldeen. 1999. "Automated detection of surface defects in water and sewer pipes." *Automation in Construction* 8 (5):581-588. doi: https://doi.org/10.1016/S0926-5805(99)00007-2.

Müller, Meinard, and Tido Röder. 2006. "Motion templates for automatic classification and retrieval of motion capture data." Proceedings of the 2006 ACM SIGGRAPH/Eurographics symposium on Computer animation.

Nakamura, Eduardo F, Antonio AF Loureiro, and Alejandro C Frery. 2007. "Information fusion for wireless sensor networks: Methods, models, and classifications." *ACM Computing Surveys (CSUR)* 39 (3):9.

Nandakumar, P., S. M. Datar, and R. Akella. 1993. "Models for Measuring and Accounting for Cost of Conformance Quality." *Management Science* 39 (1):1-

16. doi: 10.1287/mnsc.39.1.1.

Oliver J. Woodman. 2007. An introduction to inertial navigation. Computer Laboratory, University of Cambridge.

Omar, Tarek, and Moncef L. Nehdi. 2016. "Data acquisition technologies for construction progress tracking." *Automation in Construction* 70:143-155. doi: https://doi.org/10.1016/j.autcon.2016.06.016.

Oyama, Yutaka, Li Zhen, Tadao Tanabe, and Munehito Kagaya. 2009. "Sub-terahertz imaging of defects in building blocks." *NDT & E International* 42 (1):28-33. doi: https://doi.org/10.1016/j.ndteint.2008.08.002.

Park, JeeWoong, Kyungki Kim, and Yong K Cho. 2016. "Framework of automated construction-safety monitoring using cloud-enabled BIM and BLE mobile tracking sensors." *Journal of Construction Engineering and Management* 143 (2):05016019.

Park, Man-Woo, Christian Koch, and Ioannis Brilakis. 2011. "Three-dimensional tracking of construction resources using an on-site camera system." *Journal of computing in civil engineering* 26 (4):541-549.

Pease, Brad J, Gregor A Scheffler, and Hans Janssen. 2012. "Monitoring moisture movements in building materials using X-ray attenuation: Influence of beam-hardening of polychromatic X-ray photon beams." *Construction and Building Materials* 36:419-429.

Pedley, Mark. 2013. "Tilt sensing using a three-axis accelerometer." *Freescale semiconductor application note* 1:2012-2013.

Philipe miranda de moura. 2018. "Position estimation by emerging low cost IMU and camera data using the extended Kalman filter." Master.

Pieraccini, Massimiliano, Daniele Mecatti, Linhsia Noferini, Guido Luzi, Giorgio

Franchioni, and Carlo Atzeni. 2002. "SAR interferometry for detecting the effects of earthquakes on buildings." *NDT & E International* 35 (8):615-625. doi: https://doi.org/10.1016/S0963-8695(02)00047-6.

Plunkett, JJ, and Barrie G Dale. 1988. "Quality costs: a critique of some ‘economic cost of quality’models." *The International Journal of Production Research* 26 (11):1713-1726.

Porter, Leslie J, and Paul Rayner. 1992. "Quality costing for total quality management." *International Journal of Production Economics* 27 (1):69-81.

Pradhananga, Nipesh, and Jochen Teizer. 2013. "Automatic spatio-temporal analysis of construction site equipment operations using GPS data." *Automation in Construction* 29:107-122. doi: https://doi.org/10.1016/j.autcon.2012.09.004.

Pratt, Donald, and Mary Sansalone. 1992. "Impact-echo signal interpretation using artificial intelligence." *Materials journal* 89 (2):178-187.

Razavi, Saiedeh N., and Osama Moselhi. 2012. "GPS-less indoor construction location sensing." *Automation in Construction* 28:128-136. doi: https://doi.org/10.1016/j.autcon.2012.05.015.

Richter, Christian. 2009. "Visualizing sensor data." Media Informatics Advanced Seminar on Information Visualization.

Saarenketo, Timo, and Tom Scullion. 2000. "Road evaluation with ground penetrating radar." *Journal of applied geophysics* 43 (2-4):119-138.

Sansalone, Mary, and Nicholas J Carino. 1988. "Impact-echo method." *Concrete International* 10 (4):38-46.

Sansalone, Mary J, and William B Streett. 1997. "Impact-echo. Nondestructive evaluation of concrete and masonry."

Schiff, Jeremy, Marci Meingast, Deirdre K Mulligan, Shankar Sastry, and Ken Goldberg. 2009. "Respectful cameras: Detecting visual markers in real-time to address privacy concerns." In *Protecting Privacy in Video Surveillance*, 65-89. Springer.

Schiffauerova, Andrea, and Vince Thomson. 2006. "A review of research on cost of quality models and best practices." *International Journal of Quality & Reliability Management* 23 (6):647-669.

Schwabe, K, M König, and J Teizer. 2016. "BIM applications of rule-based checking in construction site layout planning tasks." ISARC. Proceedings of the International Symposium on Automation and Robotics in Construction.

Seel, Thomas, Jörg Raisch, and Thomas Schauer. 2014. "IMU-Based Joint Angle Measurement for Gait Analysis." *Sensors* 14 (4):6891-6909.

Seo, JoonOh, SangUk Han, SangHyun Lee, and Hyoungkwan Kim. 2015. "Computer vision techniques for construction safety and health monitoring." *Advanced Engineering Informatics* 29 (2):239-251.

Shahi, Arash, Afrooz Aryan, Jeffrey S. West, Carl T. Haas, and Ralph C. G. Haas. 2012. "Deterioration of UWB positioning during construction." *Automation in Construction* 24:72-80. doi: https://doi.org/10.1016/j.autcon.2012.02.009.

Shan, Junjie, and Srinivas Akella. 2014. "3D human action segmentation and recognition using pose kinetic energy." 2014 IEEE international workshop on advanced robotics and its social impacts.

Shewhart, Walter Andrew. 1931. *Economic control of quality of manufactured product*: ASQ Quality Press.

Shewhart, Walter Andrew, and William Edwards Deming. 1986. *Statistical method from the viewpoint of quality control*: Courier Corporation.

Son, Hyojoo, Changwan Kim, and Kwangnam Choi. 2010. "Rapid 3D object detection and modeling using range data from 3D range imaging camera for heavy equipment operation." *Automation in Construction* 19 (7):898-906.

Song, Jongchul, Carl Haas, Carlos Caldas, and Katherine Liapi. 2005. "Locating Materials on Construction Site Using Proximity Techniques." In *Construction Research Congress 2005*, 1-10.

Srewil, Yaseen, and Raimar J. Scherer. 2013. "Effective Construction Process Monitoring and Control through a Collaborative Cyber-Physical Approach." Collaborative Systems for Reindustrialization, Berlin, Heidelberg, 2013//.

Stukhart, George. 1989. "Construction Materials Quality Management." *Journal of Performance of Constructed Facilities* 3 (2):100-112. doi: doi:10.1061/(ASCE)0887-3828(1989)3:2(100).

Su, YY, Youssef MA Hashash, and Liang Y Liu. 2006. "Integration of construction as-built data via laser scanning with geotechnical monitoring of urban excavation." *Journal of construction engineering and management* 132 (12):1234-1241.

Tang, SL, Syed M Ahmed, Raymond T Aoieong, and SW Poon. 2005. *Construction quality management*. Vol. 1: Hong Kong University Press.

Tarng, JH, and DW Perng. 1997. "Modelling and measurement of UHF radio propagating through floors in a multifloored building." *IEE Proceedings-Microwaves, Antennas and Propagation* 144 (5):359-363.

Taylor, Frederick W. 1911. "The principles of scientific management." *New York* 202.

Taylor, Tim, John Counsell, and Steve Gill. 2014. "Combining thermography and computer simulation to identify and assess insulation defects in the construction of building façades." *Energy and Buildings* 76:130-142.

Tazarv, Mostafa, and M. Saiid Saiidi. 2016. "Seismic design of bridge columns incorporating mechanical bar splices in plastic hinge regions." *Engineering Structures* 124:507-520. doi: https://doi.org/10.1016/j.engstruct.2016.06.041.

Titman, DJ. 2001. "Applications of thermography in non-destructive testing of structures." *NDT & e International* 34 (2):149-154.

Tsai, Ping-Sing, Mubarak Shah, Katharine Keiter, and Takis Kasparis. 1994. "Cyclic motion detection for motion based recognition." *Pattern Recognition* 27 (12):1591-1603. doi: https://doi.org/10.1016/0031-3203(94)90079-5.

Tua, PS, ST Quek, and Q Wang. 2004. "Detection of cracks in plates using piezo-actuated Lamb waves." *Smart Materials and Structures* 13 (4):643.

Van Leeuwen, Jérémy, Michaël Nahant, and Samuel Paez. 2011. "Study of pulsed phase thermography for the detection of honeycombing defects in concrete structures." *Proc. CompNDT*.

Wang, Di, Jiayu Chen, Dong Zhao, Fei Dai, Changjian Zheng, and Xiaobing Wu. 2017. "Monitoring workers' attention and vigilance in construction activities through a wireless and wearable electroencephalography system." *Automation in Construction* 82:122-137.

Wang, Jiang, Zicheng Liu, Jan Chorowski, Zhuoyuan Chen, and Ying Wu. 2012. "Robust 3d action recognition with random occupancy patterns." European Conference on Computer Vision.

Wang, Jun, Weizhuo Sun, Wenchi Shou, Xiangyu Wang, Changzhi Wu, Heap-Yih Chong, Yan Liu, and Cenfei Sun. 2015. "Integrating BIM and LiDAR for Real-Time Construction Quality Control." *Journal of Intelligent & Robotic Systems* 79 (3):417-432. doi: 10.1007/s10846-014-0116-8.

Washburn, Sherwood L. 1960. "Tools and human evolution." *Scientific American* 203 (3):62-75.

Wenyong, Yu, Wang Lihai, Yang Huimin, and Zhang Xidong. 2006. "The Study of Wood Defects Detection Based on Ultrasonic Techniques [J]." *Forest Engineering* 6.

Yan, Zhiguo, Zhizhong Wang, and Hongbo Xie. 2008. "The application of mutual information-based feature selection and fuzzy LS-SVM-based classifier in motion classification." *Computer Methods and Programs in Biomedicine* 90 (3):275-284.

Yang, Huanjia, David A. S. Chew, Weiwei Wu, Zhipeng Zhou, and Qiming Li. 2012. "Design and implementation of an identification system in construction site safety for proactive accident prevention." *Accident Analysis & Prevention* 48:193-203. doi: https://doi.org/10.1016/j.aap.2011.06.017.

Yang, Xincong, Xiaowei Luo, Heng Li, Xiaochun Luo, and Hongling Guo. 2017. "Location-based measurement and visualization for interdependence network on construction sites." *Advanced Engineering Informatics* 34:36-45. doi: 10.1016/j.aei.2017.09.003.

Yu, Tzuyang, Tin Kei Cheng, Ao Zhou, and Denvid Lau. 2016. "Remote defect detection of FRP-bonded concrete system using acoustic-laser and imaging radar techniques." *Construction and Building Materials* 109:146-155.

Yue, Kui, Daniel Huber, Burcu Akinci, and Ramesh Krishnamurti. 2006. "The ASDMCon project: The challenge of detecting defects on construction sites." Third International Symposium on 3D Data Processing, Visualization, and Transmission (3DPVT'06).

Zhang, C, A Hammad, and S Rodriguez. 2011. "Crane pose estimation using UWB real-time location system." *Journal of Computing in Civil Engineering* 26 (5):625-637.

Zhang, Fengshou, Xiongyao Xie, and Hongwei Huang. 2010. "Application of ground penetrating radar in grouting evaluation for shield tunnel construction." *Tunnelling and Underground Space Technology* 25 (2):99-107.

Zhang, Sijie, Jin-Kook Lee, Manu Venugopal, Jochen Teizer, and Charles Eastman. 2011. "Integrating BIM and safety: An automated rule-based checking system for safety planning and simulation." *Proceedings of CIB W099* 99:24-26.

Zhang, Xiao-Guang, Jian-Jian Xu, and Guang-Ying Ge. 2004. "Defects recognition on X-ray images for weld inspection using SVM." Proceedings of 2004 International Conference on Machine Learning and Cybernetics (IEEE Cat. No. 04EX826).

Zhao, Xiaoliang, Huidong Gao, Guangfan Zhang, Bulent Ayhan, Fei Yan, Chiman Kwan, and Joseph L Rose. 2007. "Active health monitoring of an aircraft wing with embedded piezoelectric sensor/actuator network: I. Defect detection, localization and growth monitoring." *Smart materials and structures* 16 (4):1208.

Zhu, Z, and I Brilakis. 2008. "Defects detection and assessment of concrete surfaces." *Intelligent Computing in Engineering*:441-450.

APPENDIX A NOISE POWER SPECTRAL DENSITY

Noise power spectral density is the noise power per unit of bandwidth over frequency. The power spectral density (PSD) function of each noise in this research is listed as follows:

- Quantization noise's power spectral density function is written by:

$$P_{\Omega} = 4\pi^2 f^2 C_{QN} \tau_c \tag{11.1}$$

- Random walk/white noise's power spectral density function is written by:

$$P_{\Omega} = C_{RW}^2 \tag{11.2}$$

- Correlated noise's power spectral density function is written by:

$$P_{\Omega} = \frac{q^2 \tau_c^2}{1 + 4\pi^2 f^2 \tau_c^2} \tag{11.3}$$

- Sinusoidal noise's power spectral density function is written by:

$$P_{\Omega} = \frac{\Omega_0^2}{2}\left(\delta(f - f_0) + \delta(f + f_0)\right) \tag{11.4}$$

- Bias instability's power spectral density function is written by:

$$P_{\Omega} = \begin{cases} \dfrac{C_{BI}^2}{2\pi f}, f \le f_0 \\ 0, f \ge f_0 \end{cases} \tag{11.5}$$

- Rate random walk's power spectral density function is written by:

$$P_{\Omega} = \frac{C_{RRW}^2}{2\pi f^2} \tag{11.6}$$

- Rate ramp's power spectral density function is written by:

$$P_{\Omega} = \frac{C_{RR}^2}{8\pi^3 f^3} \tag{11.7}$$

Integration of these spectral components yields the total variance in a statistical process like AVAR by:

$$\sigma_y^2(\tau) = 4\int_0^{+\infty} P_{\Omega}\,(f)\,\frac{\sin^4(\pi f \tau)}{\pi^2 f^2 \tau^2}\,df \tag{11.8}$$

where P_{Ω} represents the PSD, f is the frequency, and τ is the time interval. In time domain, the component of each noise in AVAR therefore is calculated by the following equations:

- Quantization noise's component in AVAR is represented by:

$$3C_{QN}^2 \cdot \tau^{-2} \tag{11.9}$$

- Random walk/white noise's component in AVAR is represented by:

$$C_{RW}^2 \cdot \tau^{-1} \tag{11.10}$$

- Correlated noise's component in AVAR is represented by:

$$\begin{cases} C_{CN}^2 \cdot \tau^{-1}, \tau \gg \tau_c \\ \dfrac{C_{CN}^2}{3} \cdot \tau, \tau \ll \tau_c \end{cases} \tag{11.11}$$

- Sinusoidal noise's component in AVAR is represented by:

$$\Omega_0^2 \frac{\sin^4 \pi f_0 \tau}{\pi^4 f_0^4 \tau^4} \tag{11.12}$$

- Bias instability's component in AVAR is represented by:

$$\frac{2\ln 2 C_{BI}^2}{\pi} \cdot \tau^0 \tag{11.13}$$

- Rate random walk's component in AVAR is represented by:

$$\frac{C_{RRW}^2}{3} \cdot \tau \tag{11.14}$$

- Rate ramp's component in AVAR is represented by:

$$\frac{C_{RR}^2}{2} \cdot \tau^2 \tag{11.15}$$

where C_{QN} is the coefficient of QN, C_{RW} is the coefficient of RW, C_{CN} is the coefficient of CN, C_{BI} is the coefficient of BI, C_{RRW} is the coefficient of RRW, C_{RR} is the coefficient of RR.

APPENDIX B NUMERICAL INTEGRATION AND DIFFERENTIATION

Integration and differentiation are basic mathematical operations in IMU data processing. For example, velocity is an integral of acceleration over time, displacement is an integral of velocity, and translational energy is an integral of force with respect to displacement. Also, jerk is a derivative of acceleration with respect to time and snap is a derivative of jerk.

Suppose that f is the direct measurement that is measured at a fixed time interval T, its integral F is approximated by the following equations:

- Trapezoid rule:

$$F(t) \approx \frac{T}{2}[f(t) + f(t+T)] \tag{11.16}$$

- Simpson's rule:

$$F(t) \approx \frac{T}{3}[f(t) + 4f(t+T) + f(t+2T)] \tag{11.17}$$

- Simpson's 3/8 rule:

$$F(t) \approx \frac{3T}{8}[f(t) + 3f(t+T) + 3f(t+2T) + f(t+3T)] \tag{11.18}$$

And its derivative f' is approximated as follows:

- Newton's different quotient/first-order divided difference:

$$f'(x) \approx \frac{f(x+T) - f(x)}{T} \tag{11.19}$$

- Two-point formula/symmetric different quotient:

$$f'(x) \approx \frac{f(x+T) - f(x-T)}{2T} \tag{11.20}$$

- Four-point formula:

$$f'(x) \approx \frac{-f(x+2T) + 8f(x+T) - 8f(x-T) + f(x+2T)}{2T} \tag{11.21}$$