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

THE DEVELOPMENT AND EVALUATION OF AN ON-SITE CONSTRUCTION AND DEMOLITION WASTE RECYCLING ROBOT

WANG ZELI

PhD

The Hong Kong Polytechnic University

2021

The Hong Kong Polytechnic University

Department of Building and Real Estate

The Development and Evaluation of an On-Site Construction and Demolition Waste Recycling Robot

Wang Zeli

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

July 2020

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 materials previously published or written, nor materials that has been accepted for the award of any other degree or diploma, except where due acknowledgement has been made in the text.

_______________(Signed)

Wang Zeli (Name of student)

ABSTRACT

Worldwide, the demolition and construction waste generated by construction activities has caused a large number of environmental pollution problems. Although more and more countries are currently adopting laws and regulations to encourage manufacturers to increase the recycling rate of demolition and construction waste, it has actually achieved little effect for various reasons. Many builders still send mixed construction and demolition waste to landfills for disposal. The purpose of this study is to develop a robot for sorting and picking up waste for construction and demolition, and to evaluate the feasibility of the robot prototype in a real environment. In order to achieve these goals, we have designed and evaluated the robot patrol system and the pick-up system separately, in order to achieve the following objectives: (1) to realize the automatic patrol of the robot prototype in complex construction sites; (2) to realize the automatic sorting and recycling of heterosexual construction and demolition waste Pick up; (3) confirm the feasibility of the robot prototype.

First of all, due to the less application of robot path planning in the construction industry, we built a robot platform suitable for use on construction sites. Ensure the accuracy of the robot through technologies such as map segmentation and relocation. An advanced path planning algorithm is also used to ensure the efficiency of robot patrol tasks in any environment. Secondly, in order to automatically collect demolition and construction waste scattered on the ground, this study introduced a computer vision algorithm. However, there is currently no database for demolition and construction waste, so we built and expanded the database of target objects based on COCO format. Through experiment and optimization, the pixel-level target recognition system is completed. Thirdly, we first developed strategies for picking up demolition wastes of different shapes. In this study, we realized that the usual picking strategies sometimes produce errors when faced with small objects, and the success rate for special-shaped construction waste is even lower. Therefore, we have developed a set of picking strategies for elongated objects and curved objects, which can pick up water pipes and cables very well. The strategy can also be applied to other similar objects. Fourth, considering that the testing of robot prototypes in the laboratory does not well evaluate the feasibility of the real environment, an evaluation was conducted to investigate the accuracy and success rate of robot patrolling, positioning, target detection, and object pickup. The research shows that the prototype of the manufactured robot can be accurately located in the real environment, complete the patrol task and establish a real-time point cloud map, which is conducive to the management work on the construction site. In addition, in order to improve the accuracy of the computer vision system, different CNN backbones and transfer learning sources are compared and verified.

Overall, this research work provides an innovative method of collecting construction and demolition waste to solve the current problems encountered in the recycling of construction and demolition waste and increase its recovery rate.

LIST OF PUBLICATIONS

Refereed Journal Papers: Published or Accepted

[1] **Zeli Wang**, Heng Li, Xiaoling Zhang, Construction waste recycling robot for nails and screws: Computer vision technology and neural network approach, Automation in Construction, Volume 97, 2019, Pages 220-228, ISSN 0926-5805, https://doi.org/10.1016/j.autcon.2018.11.009.

[2] **Zeli Wang**, Heng Li, Xintao Yang. Vision-based robotic system for on-site construction and demolition waste sorting and recycling, Journal of Building Engineering, 2020, Volume 32, 101769, ISSN: 2352-7102, https://doi.org/10.1016/j.jobe.2020.101769

[3] Zhihong Zhang, Dongdong Chen, **Zeli Wang***, Heng Li, Lu Bai, Edwin R. Hancock, Depth-based subgraph convolutional auto-encoder for network representation learning, Pattern Recognition, Volume 90, 2019, Pages 363-376, ISSN 0031-3203, https://doi.org/10.1016/j.patcog.2019.01.045.

[4] Zhihong Zhang, Chen Xu, Zhonghao Zhang, Guo chen, Yide Cai, **Zeli Wang***, Heng Li, Edwin R. Hancock, Single Image Super Resolution via Neighbor Reconstruction, Pattern Recognition Letters, 2019, 125: 157-165, https://doi.org/10.1016/j.patrec.2019.04.021.

ACKNOWLEDGEMENT

Four years of exploration and learning have brought me countless benefits and good memories. This thesis is a summary of my PhD research with the help and encouragement of my supervisor, collaborators, friends and family. I am deeply indebted to them.

I would first like to express my deepest gratitude to my supervisor, Professor Heng Li. When I started my research career, young and naive, Professor Li taught me the method of research and guided me into the right direction. During four years, Professor Li has continuously supported and encouraged me with his rich experience and unique insights in research. More important, his selfless help and guidance also have a profound and positive impact on my personal life. I sincerely appreciate all his effort.

I would also like to sincerely thank the Hong Kong Polytechnic University, Department of Building and Real Estate, the Smart Construction Laboratory and all my colleagues and friends. I am very happy to receive academic training in these institutions and to meet people with different cultural backgrounds and research directions here. I will not forget the good old times I spent with my colleagues and friends in Hong Kong.

Many thanks to the financial support of the following two grants from Environment Conservation Funds: 1) “Construction waste sorting and recycling robot” (ECF 70/2017) and 2) “Automated airborne drone for beach wastes recycling” (ECF 99/2018).

Last but not least, I want to thank my family, my parents, and my girlfriend. Thank them for supporting me with love and companionship. They gave me confidence and courage to face all the ups and downs during my PhD study.

TABLE OF CONTENTS

LIST OF FIGURES

LIST OF TABLES

CHAPTER 1 INTRODUCTION

1.1 RESEARCH BACKGROUND

1.1.1 The situation and influences of construction and demolition waste

Construction and demolition waste (CDW) is defined as the surplus and damaged materials produced during construction and demolition progress [1,2]. Since construction is an indispensable part of human society, CDW has a wide range of influences on a global scale. According to government reports, CDW accounts for more than 25 percent of Hong Kong’s solid waste in 2016 and 2017 [3]. In China, a large amount of CDW is continuously generated because of the economic development [4]. Similarly, construction processes in developed countries such as the United States have also generated hundreds million tons of CDW [5]. In Australia, waste generated from the construction sector constitutes about 44% of the total amount of annual waste across all industry sectors [6]. A 2016 report in Europe stated that construction waste accounts for 36.4% of all waste generated by economic activities and households [7]. With the population growth and the economic development globally, the number of buildings will continue to increase and old buildings will be demolished, inevitably leading to the generation of CDW [8]. Generally, construction waste is a mixture of inert, non-inert, harmless and harmful materials, which means that effective sorting is an essential step in the disposal of CDW [9]. However, recent studies have shown that construction merchants usually transport mixtures directly to landfills without distinction [10]. In this case, CDW not only causes serious air, water, and soil pollution, but also puts tremendous pressure on limited landfills [11].

Previous research has shown that the amount of construction waste generated is affected by various factors. For example: legislation is conducive to reducing the generation of construction waste and has a positive effect on the effectiveness of construction waste management; however, poor communication, coordination, awareness, and behavior, combined with the time and cost of classification are clearly some of the culprits that lead to inefficient and unmotivated construction waste management [12]. Governments around the world have formulated corresponding policies and regulations to enforce or encourage construction merchants to recycle CDW [13]. Unfortunately, the results have not been satisfactory. The Hong Kong Government implemented the "Construction Waste Disposal Charge Scheme" (CWDCS) in 2005, which used economic incentives to encourage CDW producers to reduce waste and implement reuse and recycling [14]. However, three years after the implementation of this regulation, a survey showed that many people believed the reduction amount of CDW in Hong Kong to be less than 5% [15]. In Europe, EU and Member States also issued related laws and policies in order to reduce the influences of CDW, but recent report shows that the recycling work of CDW is still a vast challenge in Spain [16].

On-site recycling of construction waste, one of the most important CDW recycling methods, increases the proportion of reused and recycled building materials, which not only reduces land resource consumption and landfill pollution, but also reduces waste transportation and disposal costs [17]. Previous research indicated that separating and recycling different types of CDW is an important factor in the success of CDW recycling [17]. However, limited site space, management work, labor, costs, interference with normal site activities, and many other reasons collectively lead to builders directly mixing landfill with CDW [18]. Therefore, we believe that the efforts to reduce pollution generated by CDW should not only focus on issuing new policies, but also on developing new technological solutions to reduce the cost of time and money.

1.1.2 Problems and possible solutions in construction industry

Comparing with other industries, labor productivity in the construction industry has been decreasing since 1990s [19]. Boke believes that the characteristics of the investment in the construction industry, the harsh working environment, and the consumption of large amounts of raw materials are problems that the traditional construction industry cannot temporarily solve. At the same time, there are many phenomena which indicate that traditional building technology may have reached its limit, so the introduction of new technologies is even more necessary now. In the future, the problem of population aging will be very serious [20]. Studies have shown that by 2050, nearly one-third of the workforce will be aged 50 and over [21]. Therefore, according to previous research on factors affecting work efficiency, the aging of the population will have a negative impact on labor productivity [22]. In addition, as a high-risk industry with frequent casualties, in addition to implementing existing regulations, the construction industry also needs more technical means to reduce the chances of workers facing danger [23].

Regarding the issue of labor productivity, we believe that the promotion of new technologies may be one of the most likely ways to increase productivity in construction industry. Chen et al. declare that construction automation (CA) can improve the production efficiency of the construction industry in different ways, such as automated management systems and robots [24]. Experiments have proved that in the wall-building work, the efficiency of existing robots has different performances under different conditions compared with humans [25]. In simple wall-building work, humans are more efficient. However, when the complexity of the wall increases, the efficiency of the robot will gradually exceed that of human workers. Moreover, a study of human-machine cooperative glazing robots shows that robots can speed up work while reducing the number of participants [26].

At the same time, CA can also reduce the possibility of worker injuries. Research in this area usually uses non-contact methods to regulate workers' behavior, such as reminding workers to stay away from vehicles and wear safety helmets [27,28]. Of course, using robots instead of workers to work on the construction site can also greatly reduce risk.

1.2 KNOWLEDGE GAP AND RESEARCH OBJECTIVES

1.2.1 Knowledge gaps

Due to the rapid development of automation technology in recent decades combined with the outstanding performance in other fields, people's interest in building automation research is increasing. In the field of construction, exploration of automation technology focuses on automated worker management systems and automated assembling robots, as described in Chapter 2 [29–31]. These studies have either improved the efficiency of management and freed up expensive labor costs from real-time monitoring of the construction site or reduced the number of workers required for repetitive and dangerous works. As construction activities inevitably generate waste, research on the use of automation technology in waste management can greatly promote the efficiency and reduce the cost of CDW recycling. However, existing construction waste recycling robots only function to classify the collected CDW, without considering how to collect it [32]. In fact, although automation technology has been widely used in the construction industry, most on-site CDW collection and sorting work is still handled manually, which is inefficient and costly [33].

A robot with a similar function, the floor cleaning robot, can do a good job of cleaning up dust, debris, etc., but it cannot meet the requirements of construction sites in terms of path planning, collection methods, and classification capabilities. Firstly, the path planning systems of traditional cleaning robots are usually based on random coverage path planning algorithms. This algorithm can cover any workplace with a high coverage rate after a certain period of time. However, the random coverage path planning algorithm cannot ensure full coverage of the workplace, because the coverage efficiency gradually decreases as the coverage rate increases. Therefore, we believe that designing a successful path planning algorithm can ensure that the robot efficiently and completely covers the workplace.

In terms of collection methods, the cleaning robot does not need to consider the classification problem since the collection of dust and debris is more convenient. Contrastingly, in a construction site, the amount of waste is large, the shape different, and waste would need to be picked up by a mechanical gripper. Therefore, a properly designed pickup system needs to be developed in order to accurately collect CDW. At the same time, the classification task of CDW is also one of the important functions of recycling robots.

In general, there are three main gaps for developing an on-site construction waste robot. First, a navigation system is needed to assist the robot to successfully search the entire construction site. We are faced with challenges such as unknown environments, obstacles and rough roads. After solving the navigation problem, this research needs to develop a high-precision vision system to recognize the target object. We are facing the difficulty of lack of data and need to consider the accuracy, calculation speed, computing resource consumption and other issues. For picking up CDW of different shapes, an effective picking system is also essential.

1.2.2 Research objectives

Based on the above background and research gaps, this study aims to explore the use of path planning algorithms and computer vision algorithms to identify and pick up construction waste on construction sites. With the help of existing path planning algorithms and visual algorithms, this study aims to develop a CDW sorting and recycling robot prototype suitable for complex building construction sites, which is a new solution for on-site CDW picking and sorting. We believe that the developed prototype can promote the development of building automation and increase the willingness of builders to recycle CDW. The specific objectives established for this research work are as follows:

1. Construction and demolition waste is common on construction sites, but existing systems and methods cannot encourage builders to sort and recycle construction waste. In order to provide a new automated on-site CDW recycling method, this study aims to develop a robot prototype, which can automatically patrol, sort, and recycle construction waste.

2. Due to the complex road conditions on the construction site, existing path planning algorithms cannot well meet the needs of the CDW recycling robot working on the construction site. It is a possible solution to improve existing algorithms and introduce other algorithms to assist positioning. Therefore, this study aims to develop a new robotic patrol system for complex building construction sites based on existing algorithms, including automatic navigation and automatic positioning.
3. After solving the problem of robot patrol, the success rate of identifying and picking up CDW determines the efficiency and feasibility of the overall robot. Therefore, this study aims to build a CDW database and train a computer vision model that meets the needs. After using computer vision technology to identify different CDWs, design picking schemes for different objects.
4. In order to evaluate the feasibility of the developed robot prototype, this study finally carried out actual tests and compared the efficiency of robot picking with manual picking.

1.3 ORGANIZATION OF THE THESIS

The rest of the thesis is organized as follows. Chapter 2 reviews the relevant literature on building automation and outlines the relevant technologies, such as computer vision technology, robot path planning algorithms, and positioning technology that support this research. Chapter 3 illustrates the design of this research. Chapter 4 describes the overall design of the robot mobile module, which not only outlines the overall hardware configuration of the robot, but also details the positioning and path planning algorithms. Based on the robot motion system introduced by Chapter 4, Chapter 5 carries out the algorithm design of recognition system and grab system. Next, Chapter 6 evaluates the robot prototype developed in this study. Chapter 7 summarizes the main findings, discusses the main contributions, and outlines the direction of future research.

CHAPTER 2 LITERATURE REVIEW

2.1 INTRODUCTION

In order to review the literature that laid the foundation for this study, this chapter is organized as follows. Section 2.2 outlines the existing construction robots and explains the main trends of the research. Since the construction and demolition waste sorting and recycling robots are divided into mobile systems and pick-up systems, we have reviewed related research separately. Section 2.3 specifically reviews the research on path planning algorithms. Section 2.4 further studies the problem of robot relocation in complex environments. Then, Section 2.5 outlines the computer vision technologies that underpin this research. The analysis and discussion of existing algorithms are then summarized in Section 2.6.

2.2 OVERVIEW OF CONSTRUCTION ROBOTICS

The construction industry faces many problems and challenges. The construction industry is dangerous, and a large number of fatal accidents occur on construction sites every year [34]. Methods to reduce worker injuries and deaths have been extensively studied. At the same time, several reports pointed out that the construction industry is facing a shortage of workers[35,36]. As a labor-intensive industry, construction sites rely heavily on human capital. However, the problem of an aging population is plagued by many countries. The poor construction site environment, low salary, and high skill requirements cause this problem to be particularly serious. [21]. Compared with other industries, the low labor productivity of construction sites further increases the severity of the shortage of workers in the construction industry [19].

It is within this context that people began to study the application of automation in the construction industry to solve these problems. Construction robots are expected to increase labor productivity, improve the quality of buildings, improve the working environment of workers, and reduce the cost in the construction industry [37]. When searching for “construction industry” and “robot” on Scopus, the results show that research on construction robots has gradually increased in the past decade.

This phenomenon indicates that construction robots are receiving more and more attention. Therefore, this section selects a representative part of research related to construction robots for overview and analysis.

The first type of construction robot is a robot used to replace humans for repetitive labor. The most iconic one is the bricklaying robot. In the 1990s, in order to meet the challenges caused by the reduction of skilled workers in the construction field and the development of the construction industry, Pritschow et al. designed a mobile bricklaying robot that can grab bricks from the prepared pallets and accurately install them on the designated position [38]. The robot developed in this research can build a planned wall in an offline environment according to the set procedures. In order to solve the problem of versatility, this robot can handle bricks of different sizes, and can deal with the tolerance of materials. In order to improve the accuracy, the robot needs to calibrate the position of the brick according to the Tool Center Point. Therefore, this robot integrates calibration, measurement, bonding, as well as other functions, and has proved its feasibility through experiments. This research is not only an exploration of the application of robots and automation technology in the construction industry, but also serves as a preliminary exploration of object grasping methods. However, due to the immature automation technology, many tasks need to be done manually, such as the initial setting of the robot, real-time supervision, and accurate placement of building materials, which all require skilled workers to operate. On this basis, Dörfler et al. proposed an automated wall-building robot prototype based on 3D point cloud and Robot Operating System (ROS) system[39]. The research used a robot called The In situ Fabricator (IF) developed by the Federal Institute of Technology in Zurich [40]. Studies have shown that IF is used to manufacture complex Mesh Mould Walls, and has higher efficiency than traditional manufacturing [25]. In bricklaying tasks, the proposed robot has additional functions on top of the basic functions of IF. The robot can first use the 3D point cloud to compare and feedback the real size and design size, greatly improving the success rate of building walls. After confirming the precise geometry, the robot can automatically design the order, position, and orientation of each brick. Finally, the robot can automatically complete all the work. The research results show that the time for placing each brick in the wall-building work of the robot is about 40 seconds, and the error of the brick position is within 7 mm. The robot has reduced human intervention as much as possible, proving the feasibility of a completely autonomous construction robot with the aid of modern computer technology.

Considering the wide application of 3D printing in aerospace, automotive, and medical industries, some researchers have begun to explore the feasibility of 3D printing in the field of construction [41]. For example, Lim et al. took inspiration from fused deposition modeling technology, using cement or gypsum as a material, and built large-scale building components according to a given 3D computer-aided design and drafting (CAD) model through three steps of material preparation, delivery, and printing [42]. The study described the components and principles of the printer in detail and verified the feasibility through several tests. Although the research of Lim et al. still has some shortcomings in printing scale and accuracy, it fully demonstrates the potential of 3D printing technology in the field of architecture.

Since the traditional 3D printing technology works in a fixed-size space, product size is limited by the mechanical size. However, since buildings are usually large-scale projects, the cost and structure limit the application of 3D printing technology on the construction site. In order to solve this problem, Zhang et al. proposed a large-scale 3D printing technology combined with mobile robots [43]. In hardware, the proposed system uses a robotic arm, stereo camera, pump, and mobile robot platform. In terms of algorithm, this study uses simultaneous localization and mapping algorithm for map construction, and then uses adaptive Monte Carlo localization for positioning. Based on precise positioning, the proposed robot system performs motion planning for multiple robots. Multi-robot collaborative work greatly increases the efficiency and expandability of 3D printing. At the same time, the use of a 6-degree-of-freedom manipulator for printing allows more flexibility for the robot. There is also research devoted to solving the problem of insufficient strength regarding 3D printed structures. The combination of shotcrete 3D printing technology and new concrete materials allows 3D printing technology to be used to construct reinforced concrete structures, including columns, walls, and ceilings [44]. Compared to the traditional 3D printing method, this technology has higher design freedom and saves concrete materials.

In addition to the aforementioned construction robots, robot technology is also used in the field of building tiles, paint coating, material handling, automatic inspection, and many other fields.

2.3 RESEARCHES ON PATH PLANNING OF KNOWN AND UNKNOWN ENVIRONMENTS

Many coverage path planning algorithms have been widely applied to the automation control of terrain scanner robots, demining robots, floor cleaning robots, painter robots, lawn mowers, automated harvesters, window cleaners, inspection of complex underwater structures, etc. [45–49]. Since information relating to the entire workspace is given before path planning, the algorithms used are multitudinous off-line planning algorithms, such as classical exact cellular decomposition methods (trapezoidal decomposition [50], boustrophedon decomposition [51,52], Morse decomposition [53] and distance transforms algorithms [54]). However, there are many uncertain factors on construction sites. Although the border of the entire workspace can be accurately represented by construction drawings, such drawings cannot authentically reflect the details of workspaces due to the continual dismantling, rebuilding, and fitting of spaces. Therefore, using complete coverage path planning (CCPP) algorithms for uncertain environments could provide a feasible approach to assist a floor-tiling robot, for instance. Many methods have been applied to path planning in uncertain environments during the last two decades, such as disk covering [55], bioinspired neural networks [56], cellular decomposition [57,58], sensor-based coverage approaches [51,59] and finite state machines (FSM) [60].

Obstacle avoidance by the disk covering algorithm was first proposed in 2004, as an early trial of the CCPP algorithm. This solution assumes that the working area can be represented by an arbitrary closed curve. Therefore, the entire workspace can be encased by a minimum-area rectangle using an optimized method proposed in 1945 [61]. They can decompose the quadrate workspace into several circular regions using the method proposed by Kershner and ensure a minimum number of disks at the same time. After the decomposition work, the patrolling robot is expected to go through every center of disks from the boundaries of the entire workspace. Though the decomposition method of this solution is convincing, we did not consider the obstacle avoidance method for the unknown barriers inside the workspace as it is still far from practical application.

The second solution uses neural network technology. The main principle of this algorithm is to make the uncleaned area global thus attracting the cleaning robot, while making the barriers local thus rejecting the robot. In contrast with other solutions, this CCPP algorithm represents the workspace by using the triangular cell decomposition method proposed by Joon Seep Oh et al. (2004) to expand potential directions of the robot. The neural network algorithm then determines the coverage priority of robot. However, the complexity of neural networks allows the computational complexity of this algorithm to be higher than other methods. A similar approach has been used in underwater vehicles [62], which extends the 2D path planning algorithm to 3D underwater environments. Similarly, Guo and Balakrishnan proposed a coverage solution for nonholonomic mobile robots by integrating neural network technology and the circular region decomposition method [63].

Boustrophedon decomposition is one of the cellular decomposition methods that have been widely used in CCPP research both for certain and uncertain environments. Batsaikhan et al. proposed the method to decompose the workspace into easily covered rectangles using the detected characteristic bindery of obstacles. This method is able to cover the single region with a traditional zig-zag path, which can work well to cover uncertain workspaces [51]. Although this method was used in a certain workspace by Choi et al. in given environments, there are many differences between certain and uncertain environments. More importantly, this algorithm may cause dead zones in extreme situations, and the overlap rate of coverage path is primary determined by the location of obstacles. Recently, there has been another method based on boustrophedon motion, which was combined with advanced point-to-point path planning algorithms to reduce the distance of the backtracking path [52]. This method performs a lower overlap rate when comparing to other CCPP algorithms based on boustrophedon motion. However, due to the disadvantage of boustrophedon motion, the algorithm needs to find the backtracking path multiple times in a complex environment, resulting in a wastage of time and computational power.

Another CCPP algorithm proposed by Caihong Li et al. claimed that the algorithm based on the Finite State Machine (FSM) approach and rolling windows approach could cover unknown environments completely without causing too much overlap [60]. Their result shows that the algorithm will cause an 11.98% overlap rate, which is about 40% of the random CCPP approach when supposing the coverage rate is about 98%. This online path-planning algorithm is a step-by-step method for coverage planning. The robot detects adjacent environmental information and updates the rolling window every time it shifts to another area. The size of the rolling window is very small and makes the computational complexity of this algorithm relatively low. Hence, the robot decides the direction of its next motion using the ‘greedy strategy’, meaning that the robot will cover only those grids with the highest possibility of being unvisited. This algorithm successfully proved that the FSM approach, rolling windows approach, and greedy strategy could be effective and efficient in solving CCPP problems in uncertain environments. Therefore, it is used with some modifications and improvements to fit the requirements of a floor tiling robot. This research provided reliable proof of the effectiveness of the FSM approach, rolling windows approach, and the greedy strategy while solving path-planning problems in complicated unknown environments. The characteristics of this algorithm are in good agreement with such requirements of floor tiling works as low repetition rate, orderly work, and controllable coverage rate. Therefore, the path-planning algorithm described in the present paper learns from this algorithm and improves its shortcomings.

2.4 RESEARCHES ON SIMULTANEOUS LOCALIZATION AND MAPPING

Endres et al. proposed the first RGB-D Simultaneous Localization And Mapping（SLAM) system that uses dense color and depth images provided by RGB-D cameras [64]. Comparing with previous SLAM algorithms, this algorithm introduces several extensions to improve accuracy and stability. By conducting extensive experiments, they demonstrated that the RGB-D

SLAM system could accurately track robot poses over long distance trajectories and challenging situations. The algorithm extracted visual key points from color images and used depth images to position them in three dimensions. Then, they used Random sample consensus (RANSAC) to estimate the transition between the relevant key points and used nonlinear optimization to optimize the pose map. Finally, the algorithm generated a 3D environment map that could be used for robot positioning, navigation, and path planning.

The BundleFusion algorithm uses local small block optimization and global optimization to solve the drift and loop detection problems of pose solving; this solves the problem of reconstructing the scene update after pose optimization by means of integration and de-integration [65]. The algorithm shows excellent performance in 3D reconstruction. This algorithm may be a good choice in 3D scanning of small scenes. However, excellent performance also implies having a large computational burden.

The algorithm has high hardware requirements and is not suitable for use in outdoor environments.

AJ Glover et al. developed an appearance-based SLAM method and tested it in different lighting environments for up to 3 weeks [66]. However, the change of the dynamic environment caused the map generated by the algorithm to become increasingly larger, thus repeatedly generating the existing map and resulting in an unnecessary waste of computing power. Many studies have tried to solve this problem, but in a highly dynamic environment, their results have been equally unsatisfactory [67,68]. This problem has been plaguing people M Labbe et al [69] developed an algorithm.

Labbe's SLAM approach to large-scale, long-term positioning and mapping needs may be able to meet the realities of large construction sites. However, the evaluation of the algorithm is only tested indoors, and the construction site has more complex ground conditions and the surrounding environment. Therefore, whether the algorithm can perform well at the construction site is still unknown.

2.5 RESEARCHES ON TARGET DETECTION

Many previous studies have focused on the application of computer vision technology in the construction industry, proving the feasibility of computer vision technology on construction sites: Hamledari et al. introduced a computer vision-based algorithm for detecting components of internal partitions and inferring their current state[70]. On construction sites, computer vision can also be used to assist worker management. Park et al. proposed a video frame detection algorithm designed specifically for construction workers for automatic initialization of visual trackers [71]. Luo et al. developed a system that integrates computer vision technology for detection and visualizing dynamic workspaces [72]. This system can help managers improve worker productivity and site safety. Computer vision technology can also be combined with biomechanics to detect construction workers' fatigue and protect workers' health in real time on construction sites [73].

In the field of computer vision, convolutional neural networks (CNN) were widely used in the 1990s and has since received attention again in 2012 [74,75]. In this section, we will review the advanced computer vision technologies based on CNN and discuss their advantages and disadvantages.

Regions with CNN features (R-CNN) are a milestone in the application of the CNN method for object detection, which was proposed by Ross Girshick and his team in 2014 [76]. The input image is processed in four steps:

1) Firstly, 1k ~ 2k candidate areas are generated using Selective Search method.
2) Secondly, a CNN feature extraction operation is performed for each candidate region to obtain a fixed-dimensional output.

3) Thirdly, the SVM classifier is responsible for analysis and classification.
4) Finally, in order to obtain an accurate target position while avoiding repeated detection, the algorithm processes the data and outputs the final result by using bounding-box regression.

R-CNN has made a huge contribution to the advancement of target detection technology. However, although the algorithm is effective, its efficiency is not satisfactory, since analyzing a large number of candidate areas is extremely time consuming.

The fast R-CNN is based on R-CNN, which classifies objects more quickly and efficiently [77]. Fast R-CNN is superior to both R-CNN and spatial pyramid pooling (SPP) net in training, testing, and mean average precision. In short, compared to R-CNN, faster R-CNN speeds up recognition while increasing the success rate. Since fast R-CNN does not achieve the desired recognition speed, a faster R-CNN was developed. Real-time object recognition is possible because faster R-CNN can achieve higher efficiency.

The faster R-CNN has been widely used in various fields, and the construction industry is of no exception. At the construction site, builders use the faster R-CNN to detect and manage personnel safety [78]. Fang et al. used the faster R-CNN to identify workers without helmets and workers with helmets and evaluated the effectiveness of the system through extensive testing. Other methods of building safety management also mention this approach. Yang et al. used faster R-CNN to detect the bounding box of the object, and proposed an algorithm to convert the 2D relationship between the worker and the vehicle on the construction site to a 3D result, which has been used to issue a warning when the worker is positioned too close to the vehicle [28]. Wang et al. have also introduced the faster R-CNN to construction waste recycling filed previously [79]. In the previous study, in order to reduce the chance of worker injury, we used nails and screws as the target objects for pickup. However, we have not considered the common pickup method for all building materials. Therefore, when the experiment was applied to other target objects, sometimes we found that the ordinary picking method could not successfully pick up the pipe and the bent cable. Faster R-CNN, as an excellent target detection algorithm, has high calculation efficiency and accuracy, and it also performs very well in the complex environment of construction sites. Conclusively, it is a target detection algorithm that is very suitable for construction sites.

MASK R-CNN is an advanced algorithm developed based on faster R-CNN [80]. The main purpose of this algorithm is to provide precise pixels when detecting each distinct target object, which is called instance segmentation. This function is achieved by adding a new branch for object mask prediction in faster R-CNN, which leads to a high efficiency result in inference and training. Experiments show that this algorithm performs well in human pose estimation. However, although authors have announced that the algorithm can run at 5fps, the computational burden of instance segmentation is much higher than boding box detection, and ultimately affects fps and hardware costs. Therefore, instance segmentation and bounding box recognition have their own benefits in practical applications. Benefiting from the relationship between Faster R-CNN and MASK R-CNN, only one model is required to use them independently, which will significantly reduce the time cost of training process.

There are also other algorithms, for instance segmentation such as DWT, SAIS, DIN, SGN, etc. [81–84]. One of the best performers is the Sequential Grouping Networks (SGN) algorithm, which detects horizontal and vertical breakpoints, and form some line segments. Next, the boundary and class of each block in the picture can be judged by those line segments. Finally, the SGN algorithm can combine the non-adjacent blocks of the same object to output a reliable instance segmentation result. However, after training with the COCO dataset, Mask R-CNN far surpassed these algorithms in terms of accuracy in various categories [80].

2.6 SUMMARY OF REVIEW

In general, several main findings can be drawn from the reviews in this chapter; the details are as follows.

(1) Robot technology has emerged in the construction industry, and construction robots have played a huge role in many construction and demolition tasks. The problems of high accident rate and shortage of skilled workers in the construction industry can be solved by introducing corresponding robots. In particular, studies have shown that mobile machines can play an irreplaceable role in construction sites with a wide working environment. Today, robots have been used in the field of construction waste sorting. However, like 3D printed construction robots, the introduction of mobile platforms can expand the scope of the robot's work, reduce the need for human participation, and make the robot more scalable.

(2) The path planning algorithms for mobile robots have been fully studied in the past few decades. The simplest zig-zag path developed into a more complex boustrophedon decomposition algorithm, which eventually developed into a path planning algorithm that introduces a neural network. These algorithms have played a good role in their

respective environments. However, the efficiency and feasibility of full-coverage path planning in different environments require more testing. At the same time, for different tasks, the design and optimization of the neural network is also essential.

(3) The survey on the SLAM algorithm found that despite the continuous development of the algorithm, the choice of algorithm differs in different environments. Due to the lack of testing and development of the SLAM algorithm in the construction field, choosing an appropriate algorithm is particularly important for the efficiency and success rate of robot prototypes.

(4) In recent years, as the application of computer vision in the field of construction has gradually increased, computer vision algorithms have also been evolving. Since the CNN algorithm was introduced into the field of computer vision, more accurate and efficient algorithms have been proposed. In the field of computers, many studies continuously pursue the improvement of algorithms and evaluate their pros and cons through the

training and testing of several standard data sets. In fact, it is not only the algorithm that determines the accuracy of computer vision, but also the extremely high requirements for the data set’s accuracy. However, in the field of construction, the lack of data sets is often the biggest factor that hinders the application of computer vision in the construction industry. The COCO data set is marked with dozens of sample labels, but no one has collected and marked the CDW data set. At the same time, in different environments, the training and recognition parameters of computer vision algorithms will greatly affect the quality of the results. Therefore, it will be relatively difficult to construct an appropriate data set and optimize the entire recognition system to improve the object recognition rate on the construction site.

CHAPTER 3 RESEARCH DESIGN

3.1 INTRODUCTION

The purpose of this article is to develop a CDW recycling robot to automatically patrol construction sites in an efficient and effective manner, detect and automatically pick up construction waste, so as to increase the recycling efficiency and recovery rate of construction waste. In order to solve this problem, this research adopts a quantitative analysis method, so that the author can measure and count the effectiveness of the robot.

In order to achieve the established research goals, this research mainly carried out the design, development and verification of the robot. This chapter is divided into two parts: 1) Research framework 2) Research methods.

3.2 RESEARCH FRAMEWORK

This research is mainly divided into two parts, the first part is the navigation system, and the second part is the picking system.

The main purpose of navigation system is to complete the robot moving tasks, including the robot's complete coverage path planning and the robot real-time positioning system. In the path planning algorithm, in order to enable the robot to analyze and judge the work site, this research first designs the representation method of the map. After proposing an innovative map expression method that meets actual needs, this research improves the neural network algorithm for full coverage path planning, so that the robot can cover a site with unknown obstacles at the fastest speed. Next, in order to assist the robot in avoiding errors in a complex environment, this research uses the RGB-D camera to establish a relocation system.

The picking system is an important part of completing the CDW collection. This research first collected the image data of the target CDW, processed and amplified it, and then identified different types of construction waste through a computer vision system. At the same time, in order to enable the robot to successfully determine the detailed position and posture of the construction waste, this study uses the instance segmentation algorithm to analyze the special-shaped construction waste. Finally, based on the above data, this research proposes an innovative picking scheme that can successfully pick up CDWs with different poses and different shapes.

In order to verify the feasibility of the robot prototype developed in this research, a series of experiments, including laboratory experiments and field experiments, were organized.

3.3 RESEARCH METHOD

3.3.1 data collection method

This research involves multiple data sources, including data from literature, laboratory experiments and field experiments. In order to verify the feasibility of the robot system, laboratory experiments and field trials are usually organized, and the test data is collected by RGB cameras and RGB-D cameras. The details of the literature and experimental data are as follows:

This research initiates a literature review by searching for relevant background knowledge of specific keywords, including construction robots, path planning, Simultaneous localization and mapping, and computer vision. Most of the data comes from academic journals and books.

Experiments are the main method for verifying the feasibility of robots in this study, and one of the main methods for scientific research. In this study, two experiments were implemented, laboratory experiment and field experiment. Laboratory experiments are organized in the Intelligent Building Laboratory of Hong Kong Polytechnic University. We set the scope of the entire laboratory as a working area, arranged obstacles such as sofas, tables and chairs, and tested the robot's ability to patrol the environment many times. At the same time, we arranged a CDW randomly placed on the ground to test the robot's recognition and pickup capabilities. Similarly, in field experiments, we test each system separately in an outdoor environment. First, we tested that the robot can automatically patrol, relocate, and identify construction waste. We also tested the CDW of the robot picking up different posture targets in an outdoor environment. Taking into account the impact of different lighting on the visual system, we also compared the accuracy of computer vision algorithms under different environments and different lighting.

3.3.2 data analysis method

Data processing and data analysis accompany the entire experiment process. We checked the validity of the data before analyzing the data and cleared the data that might affect the results of the experiment before each experiment. The data analysis in this study includes not only the evaluation of experimental results, but also the comparative evaluation of experimental results under different conditions.

3.4 CHAPTER SUMMARY

This chapter briefly describes the overall research framework of this study, as well as the data collection and analysis methods, which are used to empirically examine the framework. In order to have a more comprehensive understanding of the existing related technologies, this study conducted a literature review of various aspects. At the same time, this research uses a variety of experimental methods to verify the feasibility of the robot.

CHAPTER 4 AN AUTONOMOUS PATROL SYSTEM IN COMPLEX CONSTRUCTION SITES

4.1 INTRODUCTION

As demonstrated by the robot prototypes proposed in many previous studies, robots incorporating mobile units can be well adapted to large construction sites [40,43]. Therefore, this study uses self-assembled mobile robots for related research. Traditionally, the movement of mobile robots in complex environments requires manual operation by workers. In order to improve the level of automation and reduce dependence on workers, the research of robots has derived the research field of path planning algorithms. In order to better complete the CDW recycling task, it is necessary to first design an automated patrol system for the construction site. As stated in Section 2.3, a variety of path planning algorithms have been proposed in previous studies, and they all have their own advantages and disadvantages. However, there is no full coverage path planning algorithm for construction site design to date. Therefore, in variable and complex construction sites, improving and designing a suitable full-coverage path planning algorithm based on existing algorithms is very valuable for the application of construction robots on construction sites. At the same time, due to the complexity of the road surface at the construction site, we need an automated relocation method to reduce errors in robot movement. The SLAM algorithm has been applied to construction sites as a positioning method to assist multi-robot collaborative work, which is described in Section 2.2 [43].

On the basis of the studies mentioned in Section 2.3 and Section 2.4, this section will provide a method for automatic path planning in complex and changing construction sites. We first elaborated the software and hardware structure of the self-assembled robot, which forms the basis of the entire study. Then the floor plan of the construction site is reasonably divided into as few areas as possible by circles, which is also called a node. SLAM algorithm is used for robot relocation and three-dimensional environment information collection on the construction site, aiming to improve the accuracy of robot movement and reduce the generation of accumulated errors. Next, we use a neural network-based path planning algorithm to perform full-coverage path planning for the robot in an unknown and known environment. Then, a laboratory test shows the feasibility of the algorithm in a laboratory environment. Section 4.7 summarizes this chapter.

4.2 HARDWARE DESIGN

Different robots adapt to different tasks, so the first task of this study is the design of robot hardware. As described in Chapter 2, mobile robots can greatly expand the working range of robots, and high-degree-of-freedom robotic arms can increase the freedom of design [43]. Although the robot hardware structure design is the basic unit of related research, and in most cases will affect the algorithm design and final evaluation of the algorithm, the robot structure design does not have a perfect answer.

The approach described in this thesis is tested on a self-made robot which runs on a Kinetic version of the Robot Operating System (ROS).

The developed robot possesses a shape size of 610mm*520mm*220mm, neglecting the sensors installed on it, and is powered by a 24V rechargeable lithium battery.

To maximize its working load, the developed robot is built on a four-wheel drive mobile platform designed for outdoor applications requiring terrain maneuverability. The mobile platform is able to drive at a speed of 1.0m/s when it is fully loaded. The mobile platform is configured with large torque stepper motors and 8-inch pneumatic wheels which ensure a carrying capacity of 50kg while running with full speed. In this research, its working speed is reduced to 0.6m/s to comply with the controlling frequency published by NVIDIA Jetson TX2, a power-efficient embedded supercomputer specialized for AI computing and vision-based solutions. While Jetson TX2 acts as the electronic brain of the robot, a ZED stereo camera by Stereolabs and a RPLIDAR A2 by Slamtec constitute its eyes.

Mounted on top of the robot through a monopod, the ZED stereo camera is used to capture RGB images, as well as depth data covering the area straight ahead. It is capable of providing colored point clouds with depth perception up to 20 meters in outdoor environment, which is perfect as sensor source of the SLAM approach. The RPLiDAR A2 is a 2D laser scanner and it provides real-time plane range information up to 8 meters. Data provided by ZED stereo camera and RPLiDAR A2 enable the robot to make action plans and evade obstacles in the way. Moreover, the ZED stereo camera is also exerted to generate visual odometry necessary for robot navigation.

As for recognition system, a high definition RGB camera is mounted on the robot arm to find CDW. The real-time video frames are uploaded to a host with GTX 1080 for image processing.

Based on the above hardware, we designed and developed a software system for automatic patrol and CDW pickup. The patrol system, the picking system, and the computer vision system are independent of each other, but the patrol system suspends and continues the patrol work based on the signal of the image processing system, whereas the picking system works based on the result of instance segmentation. In order to make the entire workflow easier to understand, the flowchart of the software system is shown in Fig.1.

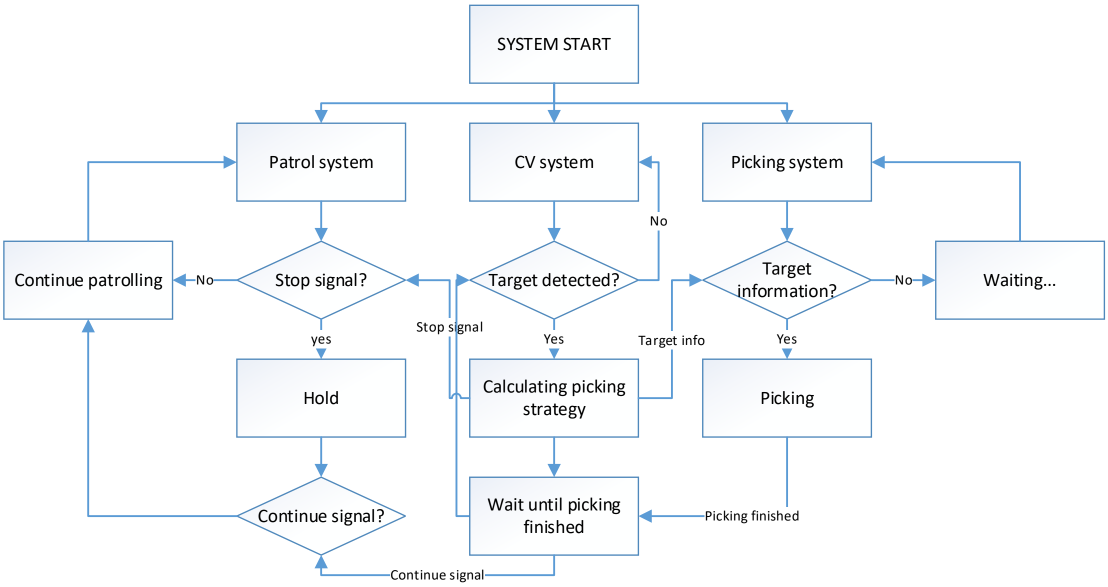


Figure 1. Recycling system workflow

The detection device of the robot is a video camera. The camera is placed at the front of the robot at a fixed angle and scans the ground ahead of the robot in real time. As Figure 2 shows, the ground being scanned is trapezoidal due to the camera function and placement.

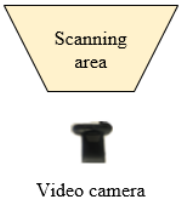


Figure 2. Video camera working range

The number of nodes in the neural network algorithm directly affects its computational complexity. Therefore, increasing the area of a single neuron can reduce the number of neurons in the neural network and thus reduce the computational burden. Hence, we designed the robot scanning process as two steps. In the first step, the robot shifts from the initial region to the next region and the camera sweeps through a rectangular area. Then, the robot rotates in place and sweeps the camera across an annular area. As shown in Figure 3, the entire circular area can be cleaned by the two steps.

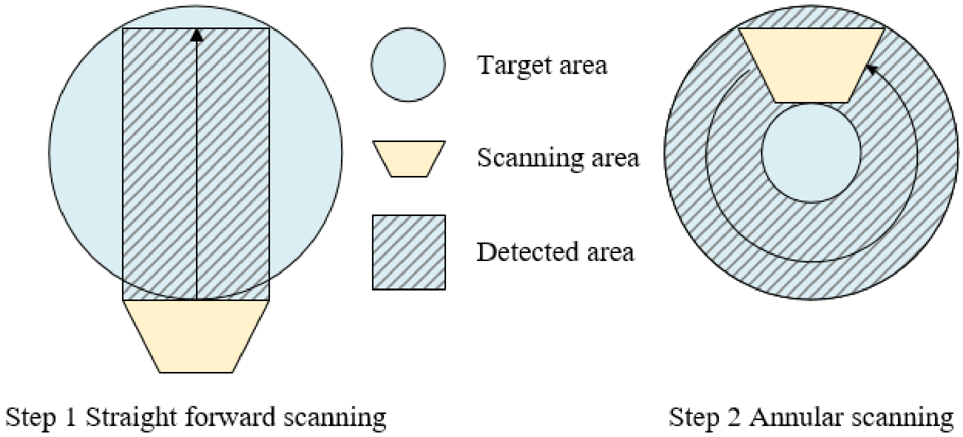


Figure 3. Scanning process of a single neuron

4.3 MAP REPRESENTATION

According to the initial solution of decomposing a rectangle by circles [85], the algorithm encases a limited area by a minimum-area rectangle [61] and, as presented by Yi and Qu [55], the map of workspace can be easily represented by a minimum number of circles whose area is determined by the detection distance of the video camera.

Firstly, this study encases the given workspace using a minimum encasing rectangle (MER) - defined as the rectangle of minimum area that can enclose the given area. Although the MER is calculated by various methods, the method used here is based on the theorem that the MER must be collinear with a side of the given polygon [61]. Since the common boundaries of the construction sites will not be complicated curves, the computational complexity will not be too high. A typical example is shown in Figure 4.

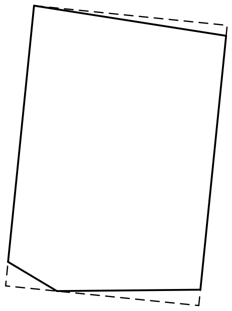


Figure 4. Encasing the given workspace using a minimum encasing rectangle

Therefore, an irregular polygon workspace can be decomposed into circular areas. Due to the theorem proposed by Kershner, the distance between adjacent circles is $\sqrt{3}R$, which determines the position of the circles. The result is shown in Figure 5, where R is the detection distance mentioned above.

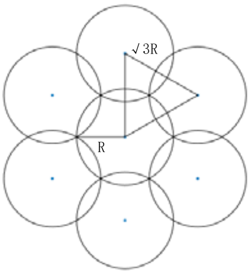


Figure 5. Pattern of decomposing a rectangle by circles

Based on the structure of the barrier detection area recognition area, the network planning of node i is represented in Figure 6, where each node has six adjacent nodes.

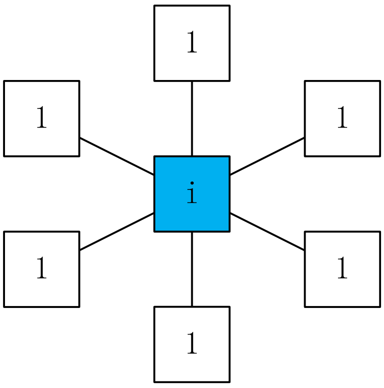


Figure 6. Adjacent nodes to node i

Moreover, as a common standard, we assume that the circular center coordinates of the lower left corner are (0.5R,0), which has been proven valid in a previous study [55]. The workspace represented by the circular areas is shown in Figure 7. Obviously, over 95% of the workspace will be covered if the robot goes through every node inside the workspace.

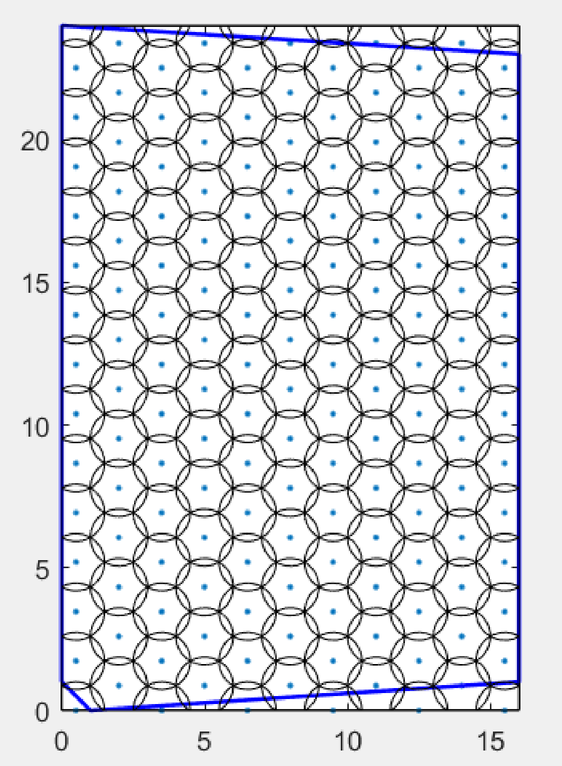


Figure 7. Workspace represented by circular areas

4.4 POSITIONING AND COMMUNICATION SYSTEMS

Similarly with most path planning algorithms, a common robot path planning system assumes that the robot's orientation and movement distance are known and controllable, which is not always feasible on construction sites [50,53–55,58,86,87]. In fact, in complex construction sites, robotic system based on the angle of rotations and the number of turns of the wheel is inaccurate. Since the site surface is rarely flat, the real length of a path is always longer than its projection on the plan. Fig.8 shows the difference of moving distance in different surfaces. Therefore, the re-localization method is significantly important for robot path planning in complex environments.

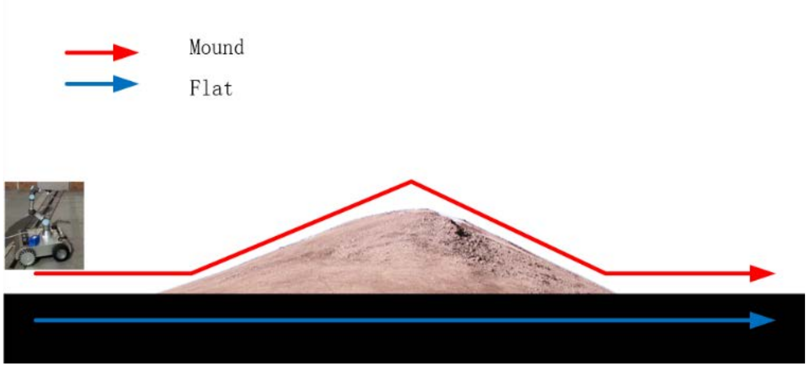


Figure 8. The moving distance increases when the surface is uneven

Robot Operating System (ROS) is an open source system for manipulating robots on computers. Generally speaking, the control method of the ROS system is to establish nodes and operate through mutual communication between the nodes. Taking the CDW recycling robot as an example, the depth camera is a node that publishes the perceived RGBD information at any time, which allows the positioning system to read the RGBD information of the node for processing and publishing the location information.

The developed robot utilizes ROS to organize all the SLAM and navigation functions. With all the data from the mounted sensors, the running ROS is able to locate the robot, continuously conduct path planner to find an optimum route, and generate building models. Fundamental key running nodes include zed_wrapper_node, rplidarNode, rtabmap, move_base ， patrol_tree, base_core, and model_export_node. The relationship between the above-mentioned key nodes is shown in Fig.9.

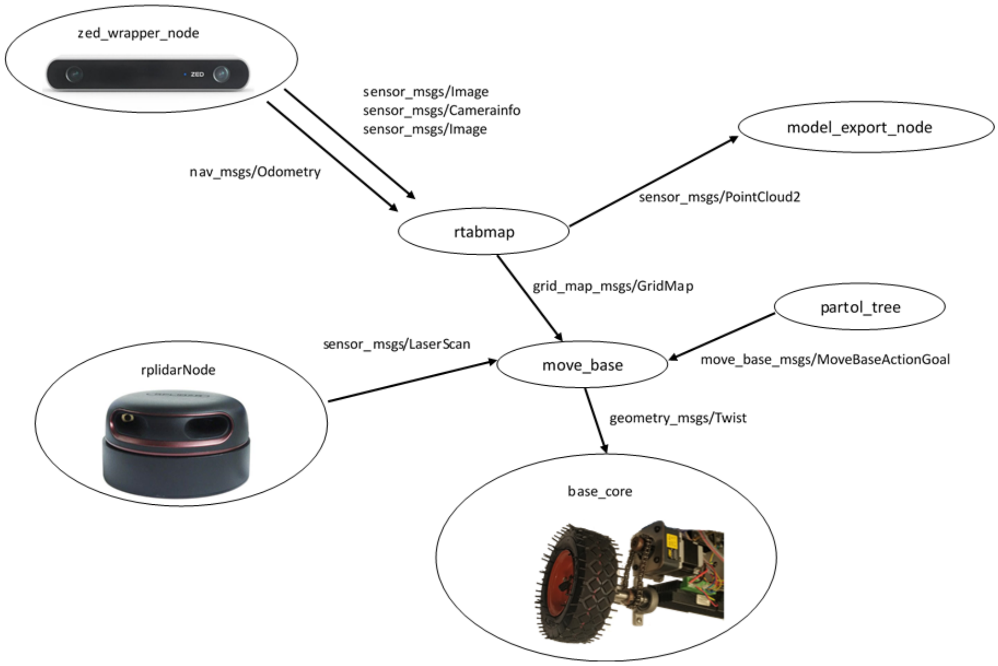


Figure 9. Construction of ROS key nodes

To enable the robot to conduct complex multi-tasks including periodic patrolling, pi_trees, a framework of behavior trees, is introduced to build its tasks hierarchy. All the tasks are arranged through pi_trees framework to compose a well-organized and efficient workflow.

The robotic diagram for behavior tree implementation is shown in Fig.10.

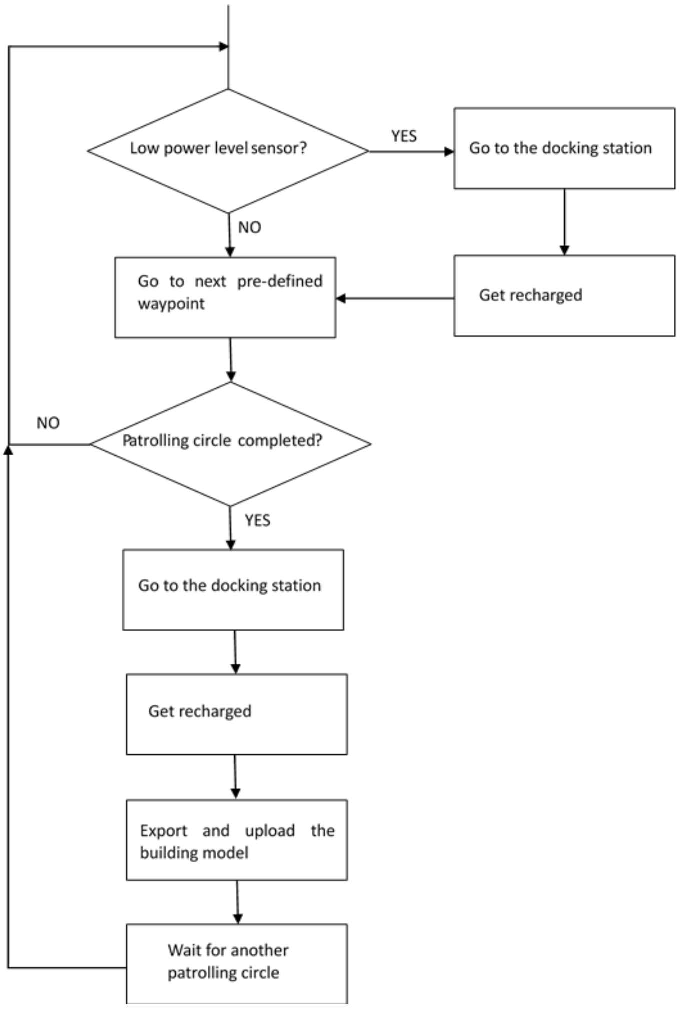


Figure 10. Program flow chart

4.5 NAVIGATION STRATEGY

An improved neural network model was proposed by Luo and Yang (2008), in which the dynamics of each neuron is calculated by the shunting equation, derived from Hodgkin and Huxley's membrane equation [43]. In contrast with Luo and Yang's approach, we integrate the spiral filling motion because of its robustness, as proved in previous studies [57,58,88,89]. The basic idea of this neural network approach is to make the neurons, which are surrounded by more obstacle and cleaned areas, more attractive to the robot, while the obstacles are excluded from the robot to avoid collision through the dynamic neural network landscape.

Since we want to encourage robots to scan from the boundary to the center, thus reducing the return distance at the completion of all tasks, the shunting equation is defined as:

$$dx_i/_{dt} = -\mathrm{A}x_i + (B - x_i)\left\{[I_i]^+ - \sum_{j=1}^{j=k} \omega_{ij}\left[x_j\right]^+\right\} - (D + x_i)[I_i]^- \quad (1)$$

where i and j are the number of neurons; I_i is the external input and ω_{ij} is the connection weight between neuron i and j; A, B, and D represent nonnegative constants describing the passive decay rate and upper and lower bounds respectively. Affected by this equation, neural activity of the obstacle will be less than zero and neural activity of the area near the obstacle and cleaned area will be slightly higher than the area away from the obstacle.

The value of the external input is determined by whether the neuron is occupied or not. In order to avoid collision, the value of I_i is set to $-E$ when the neuron is occupied. In contrast, the value of I_i is set to E when the neuron is free. The value of I_i is set to 0 when the neuron is cleaned to ensure that the cleaned area neither excludes nor attracts the robot. The equation is

$$I_i = \begin{cases} -E & obstacle \\ E & free \\ 0 & cleaned \end{cases} \tag{2}$$

The connection weight ω_{ij} is determined by the Manhattan distance of two region. In this case, the Manhattan distance of an adjacent neuron is set to 1. Therefore, the connection weight can be calculated by equation (3), where d_{ij} is the Manhattan distance of neuron i and neuron j - the value of ω_{ij} being is inversely proportional to d_{ij}. In order to decrease computational complexity, farther neuron will be ignored. This is controlled by variable α.

$$\omega_{ij} = \begin{cases} {}^{\mu}/_{d_{ij}} & 0 \le d_{ij} \le \alpha \\ 0 & d_{ij} > \alpha \end{cases} \tag{3}$$

Similarly, when the robot performs point-to-point motion, the neuron activities are calculated by

$$^{dx_i}/_{dt} = -AX_i + (B - x_i)\left\{[I_i]^+ + \sum_{j=1}^{j=k} \omega_{ij}\left[x_j\right]^+ + \varphi cos\delta_{it}\right\} - (D + x_i)[I_i]^- \qquad (4)$$

In contrast with shunting equation (1), this equation adds a parameter $\varphi cos\delta_{ij}$, which guarantees that the robot tends to approach the target neuron. φ is a positive coefficient and δ_{it} is the angle between the vector from robot to neuron i and the vector from robot to target neuron t. Meanwhile, the parameter $\sum_{j=1}^{j=k} \omega_{ij}\left[x_j\right]^+$ ensures that the robot moving path will be far away from the obstacles.

We divide the robot into five states in FSM as shown in Fig. 11. S1 is the initial state, S2 is the state of existing uncovered free neuron adjacent to the robot, S3 is the state of without uncovered free neuron adjacent to the robot, S4 is the state the nearest uncovered neuron has been found, and S5 is the end of the entire process. S6 is the state that the robot went to the appointed place when lacking power or with a full load. The strategies marked F1, F2, and F3 are illustrated in Fig.11. F1 is the strategy that the robot is searching for the neuron with maximum neural activity, F2 is the strategy that the robot is searching for the nearest uncovered free neuron using the Dijkstra algorithm. Dijkstra algorithm is an algorithm for calculating the shortest path. The robot traverses all neurons from near to far, until it scans uncovered neuron. F3 is the strategy that the robot is shifting to the target uncovered free neuron.

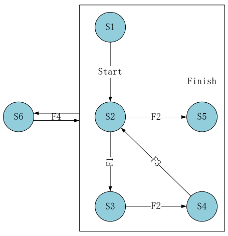


Figure 11. Structure of the Finite State Machine (FSM)

In the F1 strategy, the path-planning algorithm decides the next working neuron of the robot based on the rolling windows as Fig.12 shows. The degree of attraction of the robot's peripheral nerve neurons to the robot can be calculated by the previously mentioned shunting equations. In order to reduce the energy and time costs of the robot, the coverage pattern is generated from the neural network model as well as the previous situation of the robot. The following movement direction is firstly determined by the neural activity and secondly determined by the degree of swerving. Therefore, the next neuron $\boldsymbol{N_{next}}$ is obtained by

$$N_{next} \leftarrow x_{N_{next}} = MAX(x_j + \beta \times COS\theta,\ j = 1,2,\dots,k\,) \tag{5}$$

where $\boldsymbol{\beta}$ is a small positive constant and $\boldsymbol{k}$ is the number of adjacent neurons of the current neuron; $\boldsymbol{\theta} \in [\mathbf{0}, \boldsymbol{\pi}]$ is defined as the turning angle between the current orientation and the next moving direction.

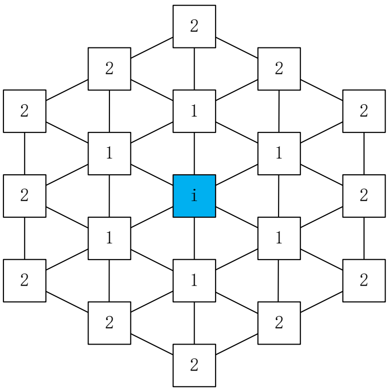


Figure 12. Network planning of neuron **i**

When the neuron in the first layer are either visited or occupied, the robot is in the S3 state. In this state, the control system uses the Dijkstra algorithm to search for the nearest uncovered free neuron. The neuron information record in F1 strategy will be used. With the Dijkstra algorithm, the system searches the nearest unvisited neuron in the neural network topology from near to far with regard to the central neural, where the robot is located. The robot can subsequently move closer to the nearest unvisited point as soon as possible using equation (5).

Strategy S5 indicates that the robotic package is full and needs to be moved to the item collection point. Similarly, the robot uses equation (5) to determine its own movement path. When no neuron is detected that has not been visited, the system enters the S6 state. In this state, the robot is expected to return to its initial position.

4.6 FEASIBILITY VERIFICATION

To evaluate the feasibility of the patrol system, we tested the robot mobile system in a laboratory environment. The laboratory covers an area of about 25 square meters and is equipped with obstacles such as tables and chairs, as shown in Fig.13.

Figure 13. Experiment environment for SLAM system

In the laboratory, we set the path and tried to artificially hinder the normal route of the robot to evaluate the robustness of the patrol system. Experiments show that RTAB-map can accurately determine the obstacle while changing the travel path and reaching the next target point. At the same time, because the SLAM algorithm used in this paper determines the position by comparing the original 3D information and the new 3D information, we tried to change the position and appearance of some objects to create obstacles. Experiments prove that a small amount of change will not affect the judgment, and that the SLAM system will automatically update the three-dimensional information. The RGBD image and the final 3D point cloud information during the operation are shown in FIG.

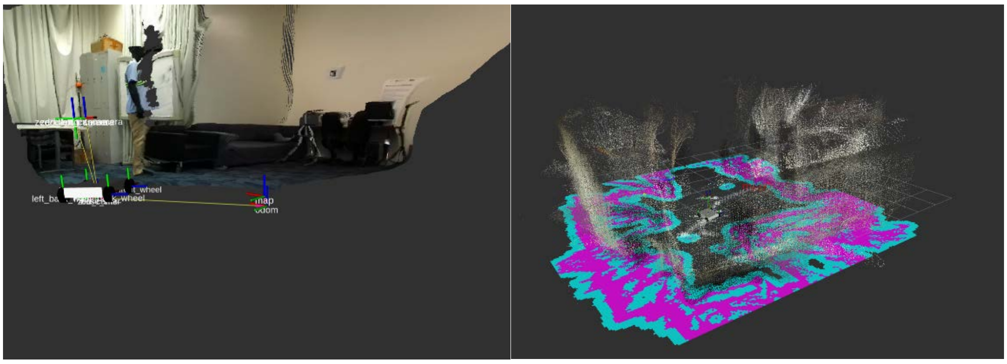


Figure 14. Experiment result of SLAM system

We also evaluated the path planning algorithm based on neural network. This study compares the results and efficiency of the developed path planning algorithm and traditional Zig-Zag path in laboratory environment, respectively. The results are shown in Fig.15. Obviously, when there is no obstacle, the results of the two path planning algorithms are the same, which is also the most efficient way. However, after encountering obstacles, the two paths diverged. The traditional path planning algorithm continued to follow the original plan after encountering obstacles until it entered a dead end, and then returned to fill the uncovered places. Therefore, the path planning algorithm based on the neural network will avoid the creation of uncovered places as much as possible, such that there are no positions to be filled in this simple test map; thus we can avoid the duplication of patrolling path.

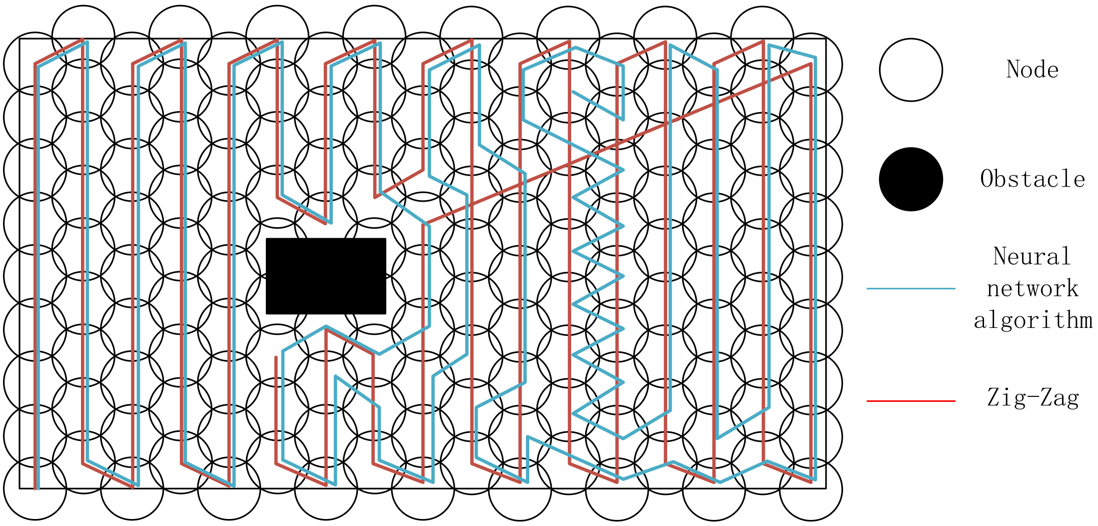


Figure 15. Different path planning results under different algorithms

This result shows that in a simple environment, the algorithm successfully planned the path according to the expected rules, and the efficiency is the same as the traditional algorithm. When the complexity of the environment rises, the algorithm can well avoid the path overlap problem caused by the traditional algorithm, which can improve the efficiency of robot patrol.

4.7 CHAPTER SUMMARY

Based on many previous path planning and positioning algorithms, this chapter elaborated on the hardware and software components of the automated patrol system of the CDW recycling robot. This chapter describes the characteristics of the patrol system from the following aspects: how to build a suitable hardware system; how to deal with a flat map of the working environment; how to reduce the errors caused by the non-ideal working environment, such as covering the entire working environment with the shortest path. The test results show that the robot system can well perform the designated patrol tasks in the laboratory environment. At the same time, as a "by-product" of the SLAM system, the system can collect the three-dimensional information of the latest environment, which will play an auxiliary role in construction management. In the test, we checked the accuracy of robot movement by repeating the test many times. Facts have proved that the positioning system can reduce the difference between the robot movement trajectory and the design trajectory. Since the positioning system repositions the robot's position in every movement, no errors have been found after multiple tests. This will greatly aid the longevity of the CDW recycling robot on construction sites. Regarding the path planning system, experiments show that in the laboratory environment, the developed path planning algorithm not only completes the work well, but also improves the efficiency compared with the traditional zig-zag path planning algorithm.

Through the research in this chapter, we believe that the robot mobile system has good scalability. By changing the parameter value of the neural network function, the robot's tendency to move can be adjusted to control reasonable route planning. This can be applied not only to CDW recycling robots, but also to any objects that need to be moved in complex environments, such as the automatic driving of construction vehicles in construction sites. However, the neural network algorithm only considers the movement planning of a robot; in reality, in order to improve efficiency, it usually requires multiple robots to work collaboratively, which greatly increases the complexity of the network. In future research, we will further study the multi-robot collaborative path planning algorithm to make the robot mobile system more versatile.

CHAPTER 5 COMPUTER VISION AND PICKING STRATEGIES

5.1 INTRODUCTION

The developed CDW recycling robot needs to be able to automatically identify and pick up construction waste. Therefore, the application of computer vision technology is essential. In previous research, computer vision technology has been widely used in the field of construction, mainly in worker management, such as determining whether workers wear safety helmets. Generally speaking, this type of application does not have high requirements for the accuracy of object recognition, and reasonable accuracy is sufficient. However, for the CDW recycling robot, the target recognition module not only needs to recognize the CDW in the visible range, but also needs to improve the recognition accuracy to ensure the success of the pickup. In Section 2.5, we reviewed a series of computer vision algorithms, in which Faster RCNN has excellent performance in target recognition and Mask RCNN is one of the representative examples of instance segmentation.

Data sets are the foundation of computer vision technology. So far, all computer vision algorithms have been designed and tested based on a large number of reliable data sets. For example, the Detectron computer vision platform uses COCO and IMAGENET datasets [90]. These open source data sets have a large number of calibrated data tags, such as people, cars, animals, etc. [91]. However, there is no data set of building materials suitable for use on construction sites. Therefore, in order to apply computer vision technology in the field of construction waste management, a complete data set needs to be established first. This study does not plan to establish a data set suitable for all building materials in the built environment. Instead, this study establishes and improves the data set for specific objects in different environments so that the computer vision algorithm can be applied to the developed robot. With the support of a complete data set, the accuracy of computer vision can reach a value that meets expectations. At the same time, the fine-tuning of parameters will also affect the results of target recognition, which will be explained and demonstrated in detail in this chapter.

Based on the existing computer vision algorithm and the robot mobile module we introduced in Chapter 3, this section will focus on the construction of the computer vision module and the strategy of CDW pickup. In Section 5.2, we completed the preliminary target recognition, using nails and screws as representatives, and demonstrated the preliminary application of target recognition in the field of CDW management. Through many experiments, it was found that despite the small size of the nails and screws, the ordinary picking method may still fail due to the angle of the object. At the same time, target recognition can only mark the approximate location of the object. For soft objects such as cables, the recognition results are of limited use for picking up. Therefore, in the next section, we further introduce the instance segmentation algorithm, which is a technology that can identify the target object at the pixel level. Through instance segmentation, we can accurately know the posture of the target object on the plane. In this study, we assume that these construction wastes are all on the ground, so we can calculate the position of the target object in space, and design the corresponding pickup method for processing, which is described in Section 5.4.

5.2 OBJECT RECOGNITION

Of all kinds of construction waste, nails and screws are common objects on construction sites and are hard to find. Injuries from construction materials can also result in workers having to take time off, medical costs, being maimed, and suffering fractures [10]. Construction workers also face the risk of stepping on a nail or screw [11], which may cause such serious infection, such as tetanus. Therefore, recycling nails and screws can reduce the risks of injury on construction sites, as well as saving money. However, workers usually ignore and nails and screws lying around construction sites as being too small and insignificant to look for.

Faster R-CNN, as the most reliable computer vision object detection technology, is used here to detect the location of objects. This section illustrates the training, testing, and application process of the model. A large amount of diverse training and testing data has been established to ensure the reliability and stability of the model. At the same time, three common types of nails and screws are used as prototype recycling targets. The practical application experiment is completed by a fixed robot to verify the reliability of the model.

5.2.1 Training the model

We placed the different kinds of nails and screws separately on the cement floor, sand, and marble, and collected the required data through many cameras. The data covers a variety of possible scenarios and has ample dataset size, including various backgrounds and perspectives.

After collecting the data, we manually annotated the data through the graphical image annotation tool Labeling [46]. The preprocessing of the prepared data set is shown in Fig.16. Then, we saved the file in VOC2007 format in the specified directory and trained the ZF model using faster R-CNN in CAFFE [47]. To ensure the reliability of the model, we set the first and second stage of RPN, as well as the first and second stage of faster R-CNN to 40,000 and 20,000 iterations respectively. The result shows that the model's mean average precision (AP) for nails and screws is 0.891.

Figure 16. Preprocessing the training dataset

5.2.2 Model testing

We tested the model repeatedly with video and images. Some results are shown in Fig.17.

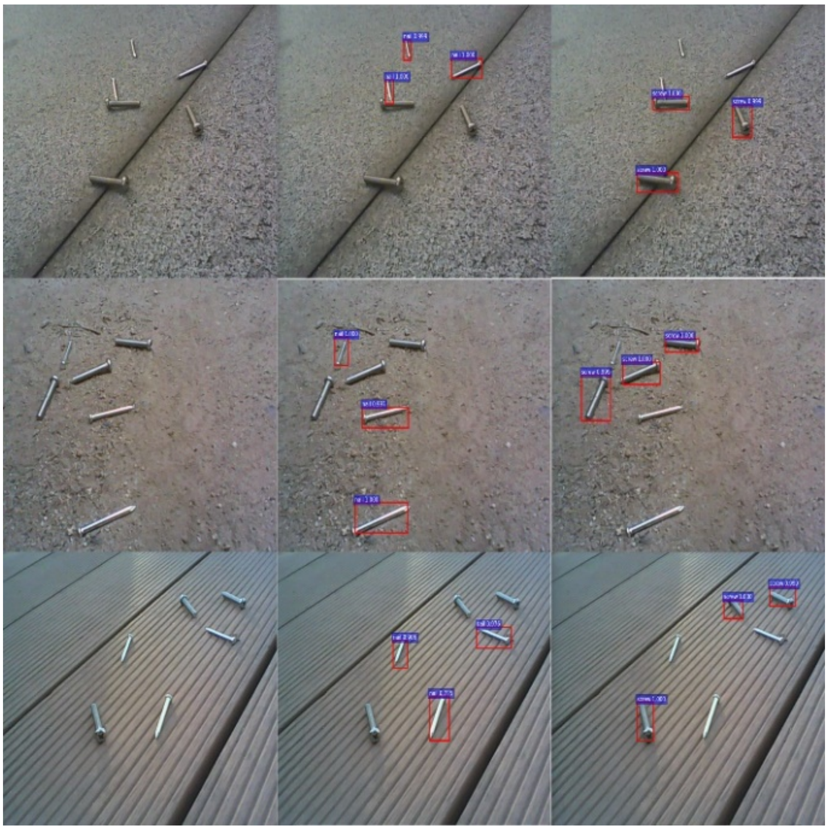


Figure 17. Object detection testing result

Using the faster R-CNN technology, the camera can accurately identify the target object and provide an accurate relative position. Hence, we can convert the relative position into the absolute position of the object and control the robot to pick it up. Since the position of the camera is fixed and we assume that the prototype is on the same plane as the detected object, the coordinates in the video can easily be converted to the difference in position between the detected object and the prototype in the working plane.

Then, we test the recycling robot model with real nails and screws. As shown in Fig.18, the robot can not only successfully pick up screws, but also put them in the correct box.

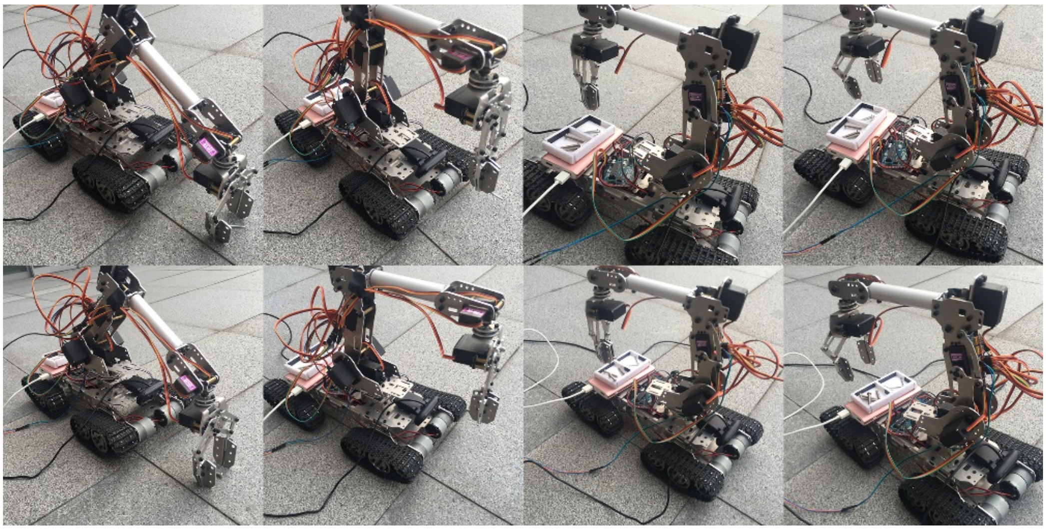


Figure 18. Picking up and sorting process

Since the experiment is supported by a video camera, some of the video frames gathered by the camera is shown in fig 13. With faster R-CNN model, the robot can recognize the target object in high probability, which is shown in Fig.19.

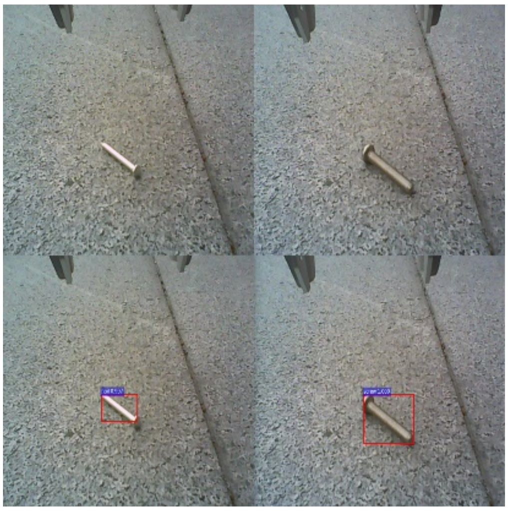


Figure 19. Video frame and detection result in experiments

Although the CDW recycling robot based on Faster RCNN performed well in this test, it sometimes fails due to the posture of the target object. This phenomenon does not often occur when the target objects are nails and screws. However, when we tried more target objects, it was found that the limited information provided by the target recognition algorithm was often unable to assist the CDW recycling robot to successfully complete the task, which reduced the universality of the robot. Some special shapes of construction materials may cause failure when picking, such as pipes and cables. As shown in Fig.20, a gripper with limited size does not guarantee a successful grip in all directions. This situation will also occur when picking up other various shapes of CDW.

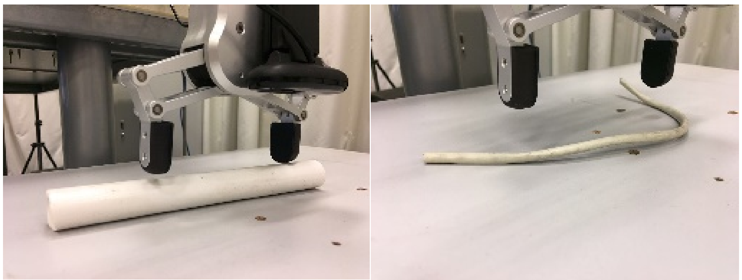


Figure 20. Failure occurred when only one gripping method is set

To solve this problem, we introduced the strength segmentation algorithm introduced in Section 2.5, and designed and tested picking strategies for different types of building materials.

5.3 INSTANCE SEGMENTATION

In this research, we applied mask R-CNN, a semantic segmentation algorithm based on faster R-CNN algorithm, for construction waste detection. Different from target recognition methods, mask R-CNN provides a detailed pixel range of the target object instead of a bounding box. Therefore, while we assume that the target object is placed on the floor where the robot stands, the orientation of target object can be calculated.

The basic structure of MASK R-CNN is shown in fig. 7. Firstly, the input image will be reshaped to a fixed size and sent to the convolutional layers. Then the generated feature maps will be sent to region proposal network (RPN) and output the proposals. Finally, after processing by region of interest (ROI) align layer, the classification, bounding box generation, and instance segmentation will be finished synchronously. The total Loss (L) value is the sum of L values of the three branches.

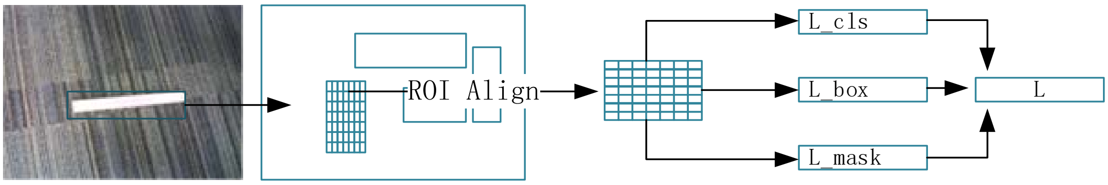


Figure 21. Processing flow of mask R-CNN

The Mask R-CNN has three advantages over other methods used to detect construction waste in previous studies. Firstly, Mask R-CNN is an algorithm developed on the basis of Faster R-CNN, which means that they can perform model training at the same time. This saves time and makes it easier for robots to use two different vision algorithms depending on their needs. Secondly, Mask R-CNN is an instance segmentation algorithm that provides more information than the Faster R-CNN, used in previous studies, to allow the robot to calculate the pose of the object and pick it up. Finally, the high precision and high computational efficiency of Mask R-CNN makes it suitable for practical engineering applications. Therefore, in this study we developed a more powerful prototype of a construction waste recycling robot using Mask R-CNN.

We created a data set containing 7000 images, of which 6000 images were used as the training set and the rest were used as the test set. Since different backgrounds and lighting conditions affect the judgment of computer vision, we collect thousands of data in different environments. Initially, we collected photos on the ground including tile floor, sand bottom, cement floor, stone pavement, land, during daytime and evening. Later, in order to expand the robot's ability to recognize objects in dynamically blurred pictures, we expanded the data set by adding motion blur effects. Simultaneously, we also use Gaussian noise, sharpening, white balance adjustment, etc. to further enlarge the data set. Fig.22 shows a small part of the dataset, including target objects with different backgrounds and light conditions.

Figure 22. Data examples in training sets

Then, we process the data using labelme [92], as shown in Fig.23. The output calibration file is trained using the DETECTRON2 platform after editing and distinguishing according to the COCO dataset format [90].

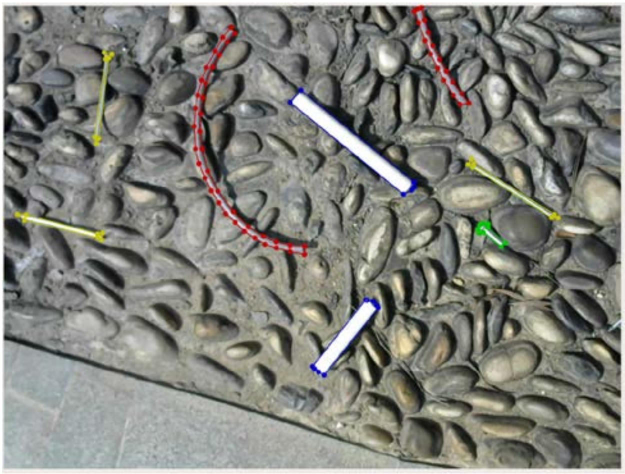


Figure 23. Data processing examples

After training, we obtained a file, which is called the model. Generally, the quality of a model can be evaluated by several metrics such as pixel accuracy (PA), average precision (AP), average recall (AR), and intersection over union (IOU). We use AP and AR, one to measure the accuracy of predictions, and another to measure the ability of finding all the positives pixels, in order to evaluate the quality of the model, as shown in equation (6).

$$\begin{cases} Precision = \frac{TP}{TP+FP} \\ Recall = \frac{TP}{TP+FN} \end{cases} \tag{6}$$

where True (T) indicates areas that the prediction is correct while False (F) indicates other areas. Positive (P) indicates the area is predicted belonging to this category, and Nagative (N) indicates other areas. Generally, AP and AR will be affected by the confidence thresholds, respectively. Therefore, F_β Scores were introduced to evaluate which confidence value performs best, as shown in equation (7).

$$F_\beta = (1+\beta^2)\frac{Precision + Recall}{\beta^2 * Precision + Recall} \tag{7}$$

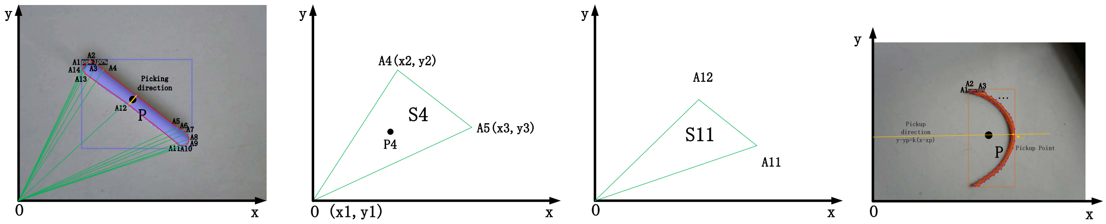
Since the wrong prediction result will make the pickup position deviate from the real target, and not completely predicting the entire target will not cause a very large deviation, we decided to use the $F_{0.5}$ score to evaluate the model.

5.4 PICKING STRATEGIES

We have established different picking strategies for pipes and cables. Normally, the identified boundary of pipes are convex polygons. For a uniform object, picking from the center of gravity will be stable and convenient. Therefore, this study uses the following algorithm to convert the boundary points provided by MASK R-CNN algorithm to the center point of objects. Mask R-CNN will use polygons to mark the pixels where the object is located, as shown in Fig.24 (a). Here we simply mark the polygons as A1, A2, A3...A14. To deal with this n-sided object (n=14). Next, Associate the adjacent vertices into a group and form a triangle with the origin point. The triangle formed by A4 and A5 is shown in Fig.24 (b). Therefore, we get 14 triangles with area of $\{S_1, S_2 \ldots S_{14}\}$, which is calculated by $S = (x_1 * y_2 - x_1 * y_3 + x_2 * y_3 - x_2 * y_1 + x_3 * y_1 - x_2 * y_2)$. Since the center point of a triangle is $P((x_1 + x_2 + x_3)/3, (y_1 + y_2 + y_3)/3)$, we can easily get the center point of all triangles, which is mark as $\{P_1, P_2 \ldots P_{14}\}$. At the same time, we introduce the parameter $\{K_1, K_2 \ldots K_n\}$. We suppose that there is a triangle $0A_mA_{m+1}$. When A_{m+1} is to the left of vector $\overrightarrow{OA_m}$, the parameter $K_m = -1$, otherwise $K_m = 1$. For example, as shown in Fig.24 (b) and (c), $K_4 = 1$ and $K_{11} = -1$. Finally, according to the equation 8, we can calculate the position of the center of gravity of the polygon. At the same time, area of the polygon can be calculated as equation 9.

$$P = (K_1 * P_1 * S_1 + K_2 * P_2 * S_2 + \ldots\ K_n * P_n * S_n)/(S_1 + S_2 + \ldots\ S_n) \tag{8}$$

$$S = K_1 * S_1 + K_2 * S_2 + \ldots\ K_n * S_n \tag{9}$$



(a) (b) (c) (d)

Figure 24. Center point calculation

Due to the limited size of the robotic gripper, we chose to pick through the cross-sectional direction of the center of gravity. Assuming that the center of gravity is P(x_p, y_p), there is a set of straight lines that passes through the center of gravity: $\mathrm{y} - y_p = k(x - x_p)$,where $\mathrm{k} = \tan\theta, \theta\epsilon[0,90) \cup (90,180)$. When $\theta = 90°$, we have the line $\mathrm{x} = x_p$. Therefore, in order to facilitate calculation, we traverse θ from 0° to 180°and each θ can generate a straight line and be cut into a line segment by the polygon. We select the θ of shortest line segment as the picking direction and P as the pickup point.

Since the cables are easy to bend, the boundary identified in most cases is a concave polygon. In this case, the calculated center point may be outside the polygon. Therefore, we use a different strategy to pick up cables. Similarly, we use straight lines and polygons that pass-through point P to generate a set of line segments. Each line segment can divide the polygon into two polygons. Therefore, we can calculate the area of two polygons through equation 4 and find the θ value that can divide the polygon into two polygons with the closest area. At this time, the midpoint of the line segment is taken as the pickup point. A result is shown in Fig.24 (d).

5.5 FEASIBILITY VERIFICATION

In order to initially verify the feasibility of the method described in this chapter, we conducted simple tests on visual and laboratory grabbing. First of all, we conducted a preliminary training with part of the data. The initial learning BASE_LR is set to 0.025, the number of iterations is 1000 times and the default values are used for other parameters. After a short training period, the output model was tested and found: faster RCNN mAP=70.55, Mask RCNN mAP=45.45. The output of the model under the default parameters is shown in the Fig.25.

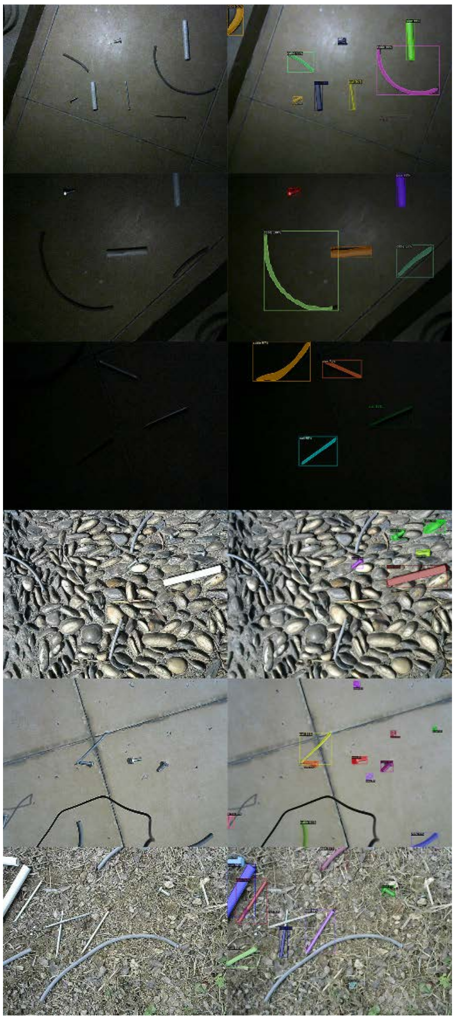


Figure 25. Results of the test model

Undoubtedly, there are obvious errors in the identification of the model in all environments. The target recognition algorithm can find many target objects, but there are a lot of wrong recognition and omissions. Currently, the robot cannot successfully recover most of the target objects and may enter an error state. However, the instance segmentation algorithm is not ideal in terms of data or results. The recognized contours greatly deviate from the actual contours of the object, which may make subsequent pickup actions unsuccessful.

Before further training and augmenting the training set, we also tested the success rate of the robotic arm pickup. Because the background is simple in the laboratory environment, computer vision can play a good role. Therefore, it is optimal to test the picking strategy in the laboratory.

We tested separately on the test bench and on the ground. After many tests, it was found that the robot can pick up the target objects at different angles well, basically meeting the experimental requirements, as shown in Fig.26. However, the test also found that, due to the accuracy of the computer vision, occasionally there appeared to be a wrong gripping position. These problems can be solved by further training in computer vision, and the specific results will be described in Chapter 6.

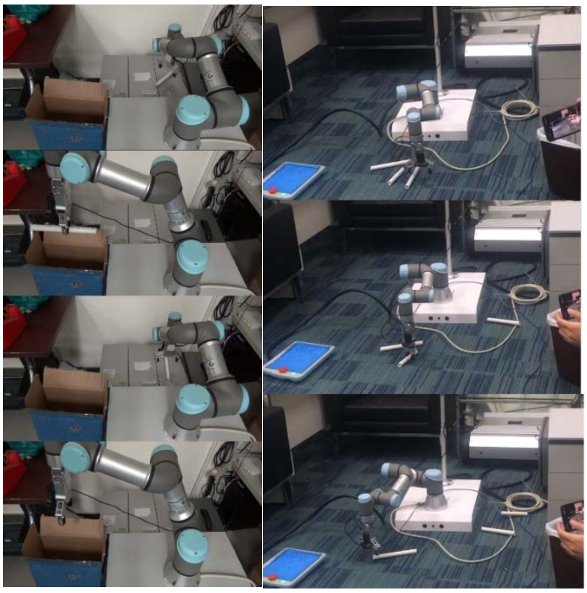


Figure 26. Pick-up result in laboratory experiments

5.6 CHAPTER SUMMARY

The last chapter mainly developed and tested a robot automatic patrol system. On this basis, the main content of this chapter is to design and test the main working modules of the CDW recycling robot. The goal is to discover the target building materials and accurately determine the posture of the target object during the patrol, so that the robotic arm can successfully grip and classify the object.

In the past ten years, computer vision technology has been widely used in different fields. Whether it is classification, recognition, or segmentation algorithms, it has its own unique features. However, this technology is based on machine learning, which means that the application of computer vision in the construction field requires a large amount of data to ensure the accuracy of the results, and there is no standardized data set in the construction field. Therefore, the first problem to be solved in this chapter is how to establish an accurate data set for identifying CDW. First of all, we completed data collection and data calibration. According to the results, we used different data amplification techniques to increase the content of the data set. The results also provided a comparison, proving that data amplification techniques can improve the accuracy of the model. This chapter also makes the robot call more suitable algorithms in different working modes according to the actual test situation. Generally speaking, different algorithms need different training, but the computer vision algorithm based on RCNN selected in this study can use the same model, which can greatly reduce the previous work. Based on the above information, this chapter developed picking strategies based on the characteristics of different building materials. The research results in this chapter are for nails, screws, pipes, and cables. However, this chapter clarify the method and process of applying the CDW recycling robot to other target objects. Overall, the recycling system has good scalability and can adapt to different environments and tasks. At the same time, through certain improvements and designs, the system can be applied to the field of automated assembly, which can greatly enhance the degree of automation in the construction industry.

CHAPTER 6 EVALUATION OF THE EFFECTIVENESS AND EFFICIENCY OF THE CONSTRUCTION WASTE RECYCLING ROBOT

6.1 INTRODUCTION

Based on the CDW classification and recycling robot prototypes described in chapter 3 and chapter 4, the main goal of this chapter is to evaluate the performance of the robot through practical experiments. This chapter will evaluate the developed robot from three aspects: first, the positioning system. The feasibility of the positioning system has been completed in laboratory tests, but the outdoor environment poses more complications, and the accuracy of positioning will be more challenged. For example, in a scene with many similar objects, the SLAM algorithm based on comparison may produce errors, which requires actual experiments to be verified. Then, there is the path planning algorithm. The performance of the path planning algorithm in a simple environment has not been fully demonstrated. We will test it in a more complex environment and then demonstrate the advantages and disadvantages of the algorithm by comparison with the traditional algorithm.

As we explained in chapter 4, there are still many problems that need to be improved in computer vision systems. In this chapter, we will test the results of target recognition and instance segmentation in different parameters and data sets, and select and optimize the parameters through experiments to make the accuracy as high as possible. In this process, the method used in this chapter can provide a certain reference for computer vision technology widely used in the construction industry.

6.2 POSITIONING SYSTEM

We evaluated the robustness of robotic mobile systems on flat ground and complex ground conditions. When entering the unfamiliar environment for the first time, we need to scan the environment of the robot patrol. In Fig.27, the first picture shows the real environment information, the second picture is the map boundary information stored after scanning, and the third picture shows the real-time obstacle information. From the comparison between the first picture and the third picture, it can be found that the SLAM algorithm accurately marks the position of the obstacle and the position of the car.

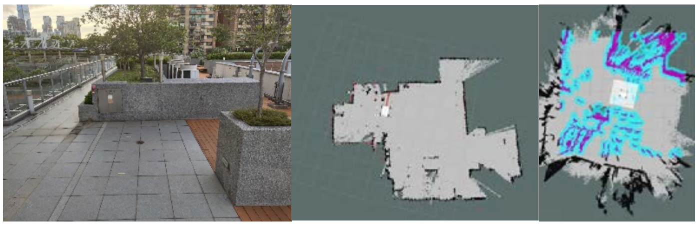


Figure 27. Environment and obstacle information in SLAM system

After that, the robot can successfully patrol the entire workspace when there is no change in the environment. Next, we try to partially change the environment to test the robot. The results show that the robot successfully patrolled the entire site and updated the point cloud information. Fig.28 shows the depth and RGB information collected by the robot when patrolling and the point cloud image generated after patrolling.

During the patrol process, the robot recorded the three-dimensional information of the environment and uploaded it to the server in the form of a point cloud. This can be used not only as a basis for the next patrol, but also to help managers understand project progress information.

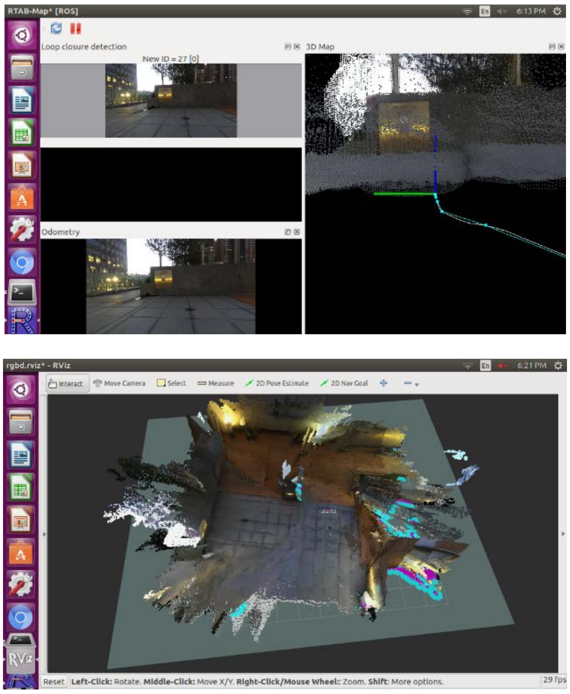


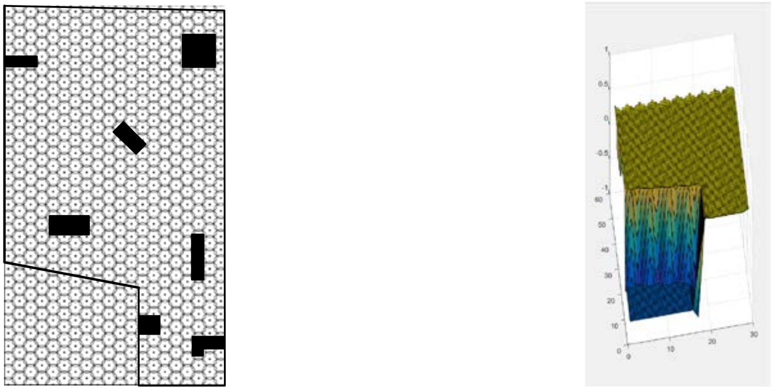
Figure 28. Experiment result of SLAM system

Since obstacles such as workers may appear on the construction site, we try to enter the site to hinder the robot's actions. Results showed that the robot can successfully avoid obstacles and continue to patrol work.

6.3 NAVIGATION SYSTEM

The developed neural network approach is capable of planning a complete coverage path for cleaning robots without any human intervention. In this section, the model is applied in a circular cell decomposition workspace without using any previously known environmental information, although the boundary of the entire workspace is known.

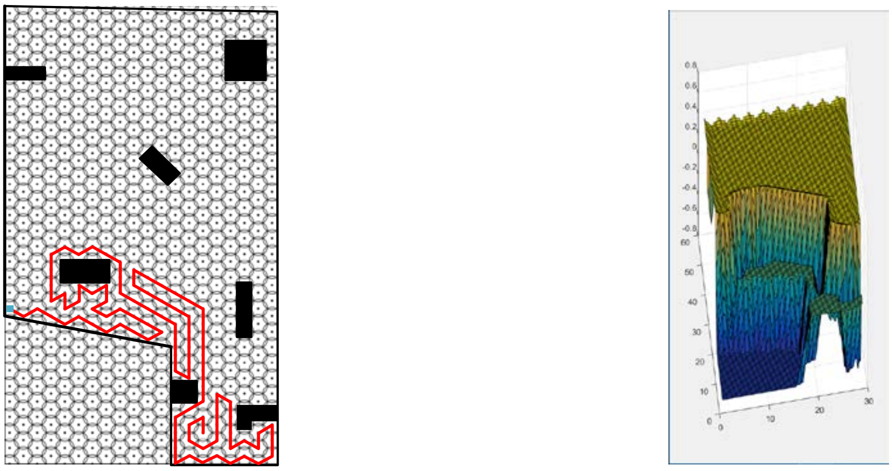
For comparison, the model was applied to a completely unknown outdoor environment. The environment of the entire workspace is assumed totally unknown except for the boundary of the construction site, which can be easily obtained from a drawing and is usually static. The robot can only sense a limited range with a sensor named LIDAR Scanner. The neural network includes 20x30 discretely and topologically organized neurons, where all the neural activities are initialized to zero. The model parameters are set as A=50, B=1, and D=1 for the shunting equation; $\boldsymbol{\mu = 0.05}$ and $\boldsymbol{\alpha = 1}$ for the lateral connections; and E=100 for the external inputs. The robot is initially set in S (1,11) which is the left bottom of the workspace. The boundary of the entire workspace is evidently illustrated by the neural activity landscape, where the unknown area is regarded as an uncleaned area.



(a) (b)

Figure 29. Top view and activity landscape of the neural network upon commencement

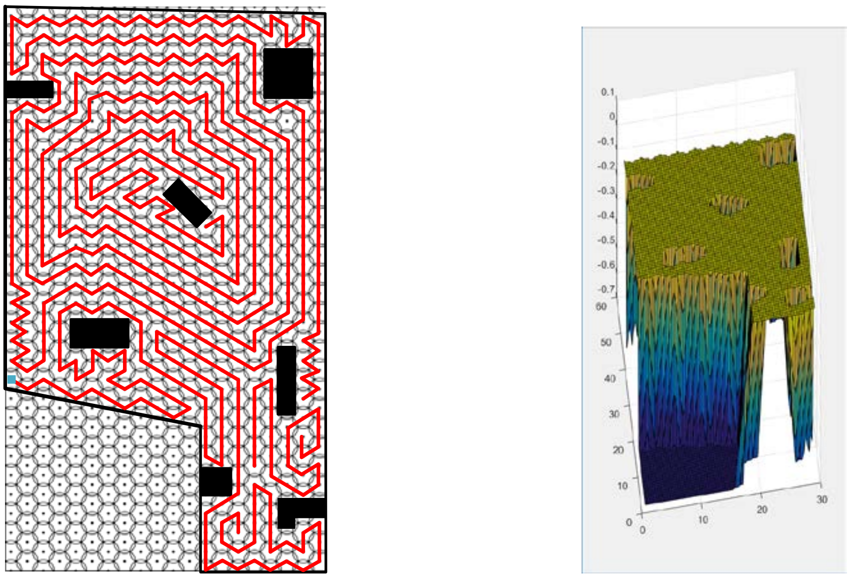
When the robot meets the first deadlock in L (15,3), as shown in Fig.16 (a), the neural activity of the entire workspace is represented in Fig.16 (b). The neural activity of the unknown environment and uncleaned regions is high, while the neural activity of the obstacle area is low, and approximate to zero for the cleaned area.



(a) (b)

Figure 30. Top view and activity landscape of the neural network when meeting the first deadlock

When the entire task is finished, the neural network turns into a static situation, in which the neuron activities of all unoccupied neurons are equal to zero, as illustrated in Fig.31.



(a) (b)

Figure 31. Top view and activity landscape of the neural network on completion

Whether it is for deadlock off or return mode, point-to-point path planning is essential. We assume that the robot is currently in E (16,24), and the coordinate of the target neural is T (1,11). Therefore, the landscape of the neural network is generated as shown in Fig.32. The neural activity of neurons away from the target neuron is much lower than that close to the target neuron. Meanwhile, the neurons near obstacles have a lower degree of neural activity. The neural landscape determines that the movement of the robot will be as straight as possible towards the target point while avoiding obstacles.

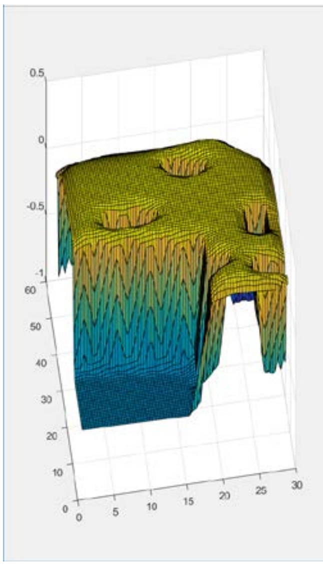


Figure 32. Activity landscape of the neural network for the point-to-point case

The result shows that in this case study, the coverage rate is 100% with a 0.88% repetitive rate. In this case, we assume that the radius of a circle is 2 meters. Therefore, the robot has passed 1828 meters and turned 17700 degrees through the entire process.

In order to demonstrate the advancement of this algorithm, the performance of a recent algorithm is used for comparison. Due to the different ways in which maps are expressed, we improved the algorithms proposed by Khan Amna et al. [22] and tested them on the same map. The result is shown in Fig.33. Although the algorithm reduces the length of the backtracking path compared to the traditional boustrophedon motion algorithm, it still has more backtracking and has a higher repetitive rate. In this case, the coverage is 100% and the repetition rate is over 12%. The total turning angle exceeds 8040 degrees and the total distance is more than 2036 meters by using this algorithm. In this study, the speed of the robot is 0.5 meter per second, and it takes 4 seconds to rotate one revolution. Therefore, the algorithm developed in this study reduces the coverage time by nearly 7.4%. Meanwhile, the efficiency of the algorithm will be more significant in a larger working environment.

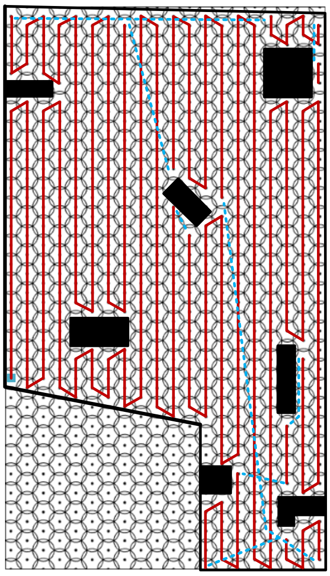


Figure 33. The performance of path planning using two-way proximity search

6.4 DETECTION AND PICKING-UP SYSTEM: LABORATORY EVALUATION AND OUTDOOR EVALUATION

As described in Section 5.5, we first need to optimize the accuracy of the computer vision system. First, we optimized the data set. On the basis of thousands of calibration data, in order for computer vision to cope with complex and changing environment, we first needed to expand the data set. The factors that usually have a greater impact on computer vision are noise, blur, and brightness. We carried out routine operations such as adding Gaussian noise, motion blur, whitening, and sharpening to the photo, as shown in the Fig.34.

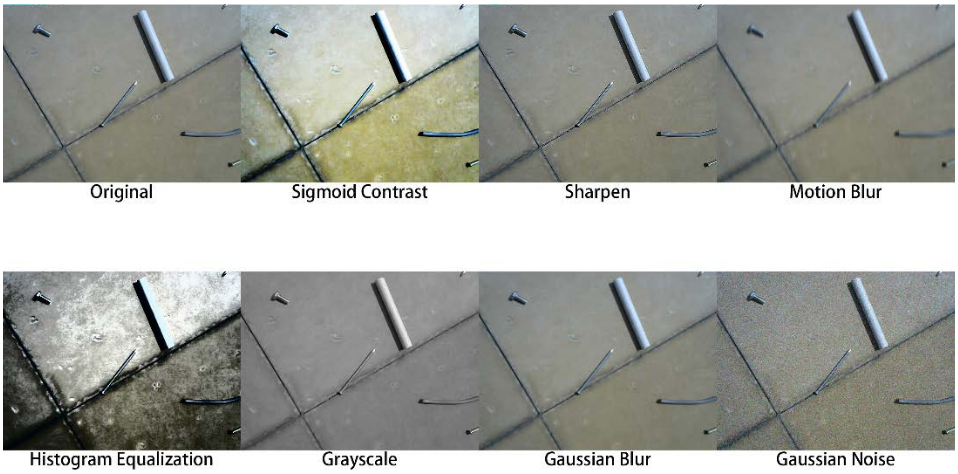


Figure 34. Data augmentation result

Transfer learning can greatly reduce the difficulty of model training, but transfer from different weights will lead to different accuracy of results [93]. Moreover, different CNN Backbone will also affect the accuracy of the computer vision system. Therefore, in order to improve the accuracy as much as possible, we needed to choose the most suitable one from different backbones and transfer learning. After 40,000 iterations, the results of different backbones and transfer learning weights are shown in Fig.35.

After comparison, we decided to use the ResNeXt-101-32x8d as the backbone and the result training by COCO dataset as the transfer learning source.

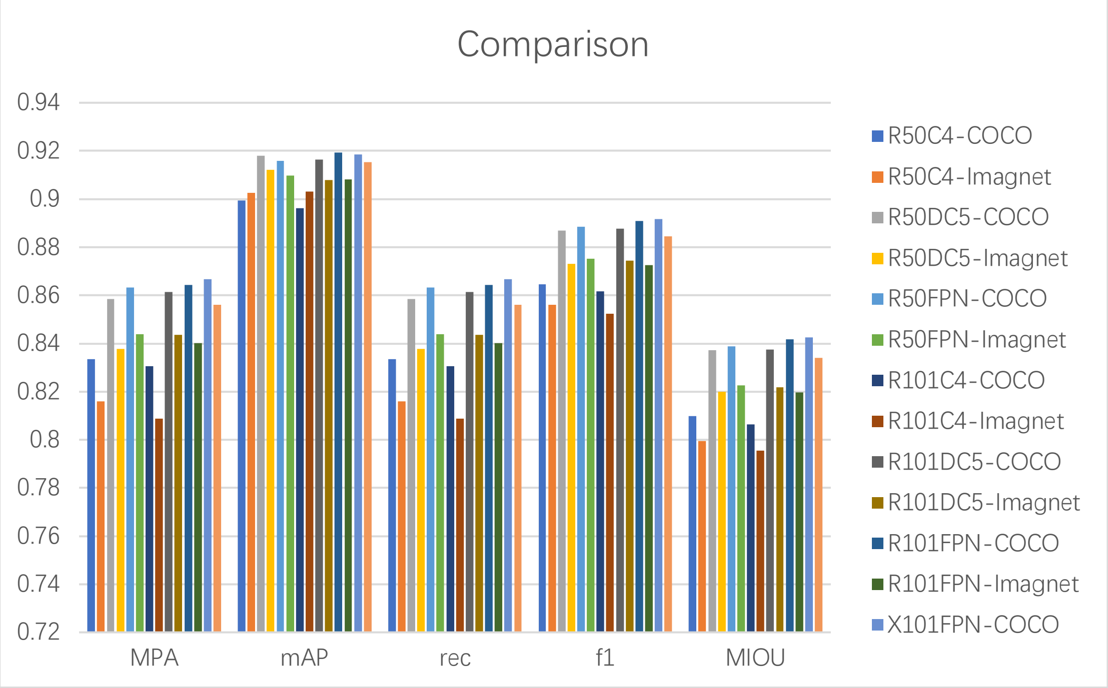


Figure 35. Comparison of different backbones and transfer learning source

The evaluation results of the final model under different threshold values are shown in Fig.36; evidently 0.95 is the best choice. Therefore, the model's evaluation accuracy of different construction wastes is shown in Fig.37.

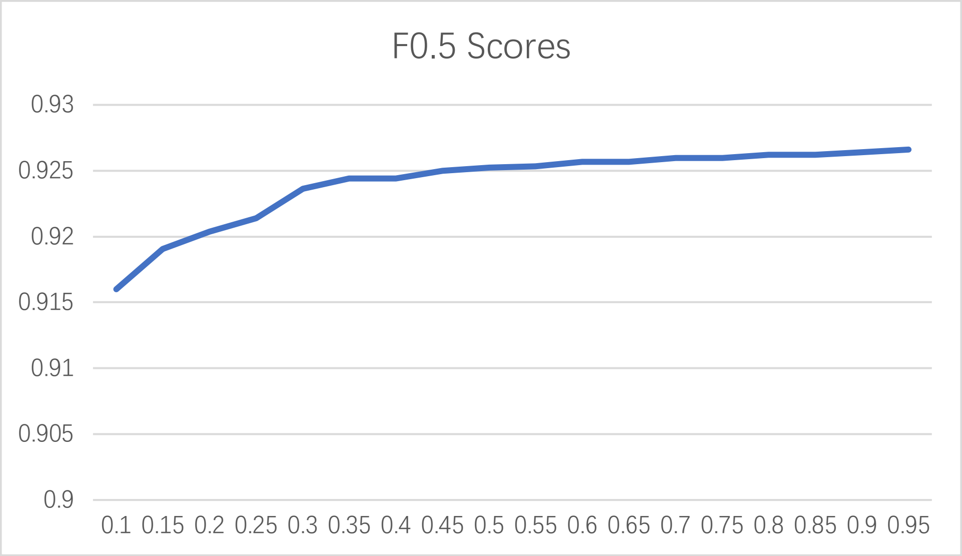


Figure 36. Training result in different thresholds

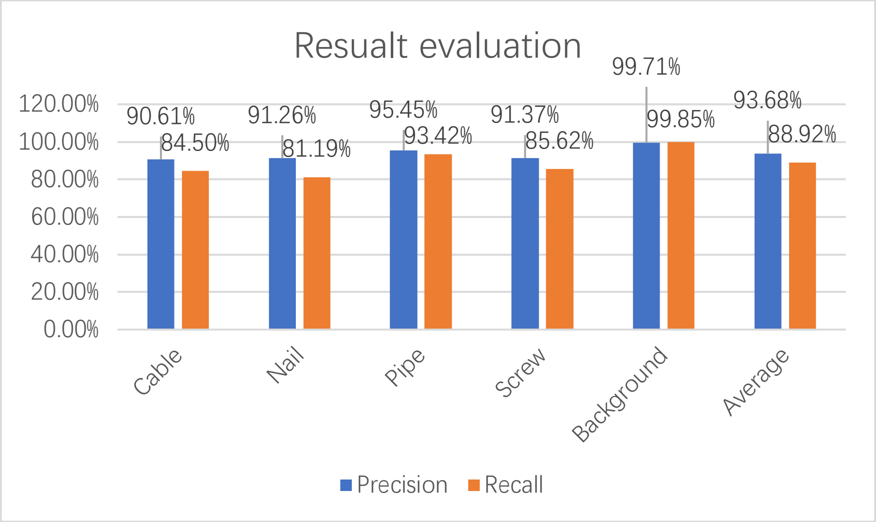


Figure 37. AP and AR results when thresholds = 0.95

From the theoretical and experimental results, the recognition speed of the instance segmentation algorithm is proven to be much slower than that of the target detection algorithm. Therefore, when the object is not recognized, in order to improve the recognition efficiency and increase the fps, we only used the faster R-CNN to detect the object. When an object is detected, we used MASK R-CNN to perform an instance segmentation on the object. In this step, we used the items in different backgrounds to evaluate the reliability of the model. As shown in Fig.38, the trained model exhibited a high degree of precision when detecting the boundaries of the target object in the video frame.

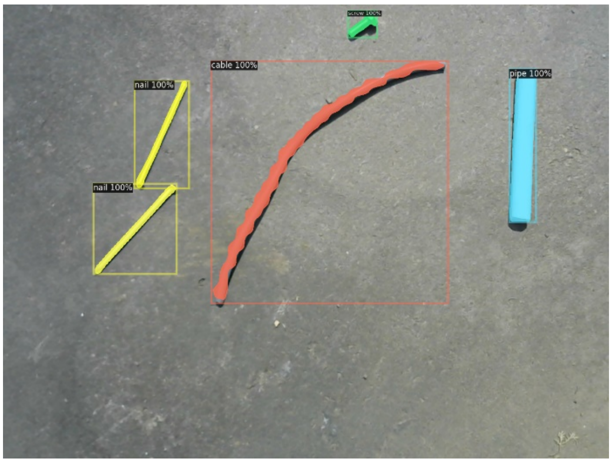


Figure 38. Instance segmentation result of pipe, cable, screw and nails

Based on the accurate instance segmentation results, we try to use the robotic arm to grab the object. This experiment was completed in the laboratory with water pipes and cables as the goal. First place the robot in the starting position to test whether the robot can complete the picking of garbage at random angles while traveling. As shown in fig.39, for target objects in different poses, the robot can change the angle of the gripper and grip target object in the correct direction. At the same time, the robot arm can place the target object in different place according to the classification of the item. In this case the robot set pipes on the right and cables on the left, which is shown in Fig.40.

Figure 39. Gripping the object in the correct direction

The construction site is usually open in an outdoor environment. Changes in weather and lighting may reduce the accuracy of computer vision recognition and affect the reliability of robot picking. Therefore, we tested the robot's robustness to these influencing factors through experiments in an outdoor environment and evaluated whether the robot pick-up success rate and efficiency will be significantly reduced in harsh environments. The classification information of each category is shown in Table 1.

Table 1. Varied experimental environments

Ground conditions	No.	Lighting conditions
Laboratory	1	Normal lighting conditions
	2	One table lamp
Outdoor	3	Noon
	4	Night (with streetlight)

The robustness test results of the robot under different working conditions show that they have little effect on the detection performance. Although the robot can recognize the target object more accurately in the laboratory environment, the robot arm can tolerate certain errors in complex environments; therefore, the final Picking results are not affected. A successful recycling in outdoor experiment is shown in Fig.40.

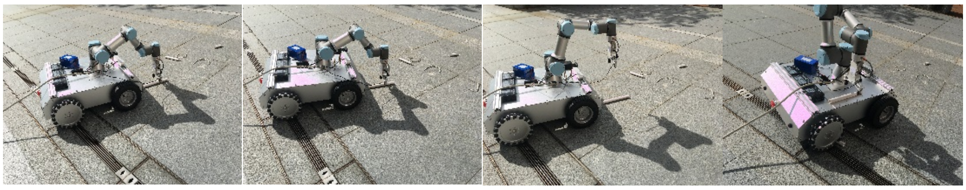


Figure 40. Outdoor experiment result

As a simple evaluation, we tested one hundred random object picking experiments in the laboratory and repeated 5 experiments with 20 randomly placed objects during the field test, for a total of 200 picking tasks. Although more than 98% of the pick-up experiments were successful, we still needed to evaluate the different success rate between the laboratory environment and the actual environment, as well as between different lighting conditions. Therefore, we judged the picking accuracy through the evaluation method of computer vision. As we mentioned in section 5.3, we used $F_{0.5}$ scores to evaluate the performance of this model and the result is shown in table 2.

Table 2. Result in different environments

Conditions	$F_{0.5}$ Scores
Laboratory: Normal lighting conditions	0.9336
Laboratory: One table lamp	0.9507
Outdoor: Noon	0.9232
Outdoor: Night (with streetlight)	0.9183

6.5 CHAPTER SUMMARY

This chapter briefly describes the evaluation method of the developed robot system and the evaluation results of each project. In order to more fully understand the feasibility of each module of the robot, this study separately tested the positioning, path planning, computer vision, and pickup modules. The results show that, as expected, the developed CDW sorting and recycling robot can complete the picking task with high success rate in different environments. At the same time, this study also developed a complete set of methods for applying computer vision technology to the construction site, including data collection, data processing, data augmentation, training methods, result evaluation, and optimization. This will be very helpful for the application of on-site robots in the future.

CHAPTER 7 CONCLUSIONS AND RECOMMENDATIONS FOR FUTURE WORKS

7.1 CONCLUSIONS

The construction industry faces problems such as worker safety, labor productivity, and labor shortage [19,22,23]. This requires the development of building automation technology to improve the future construction industry. Although there are already automated robots used for different jobs in the construction industry, the recycling of construction and demolition waste is still handled manually, which is inefficient and costly [33]. Therefore, this research work explored the method of using robots equipped with neural networks and computer vision technology to automatically patrol, classify, and pick up CDWs. The specific work of this research is to first review the existing construction robots and related technologies. Secondly, based on the conclusion of review, the robot automatic patrol system is designed. The system not only designs a path planning system based on neural networks for complex construction sites, which improves the efficiency of patrols, but also solves the problem of robot accuracy in complex environments on the construction site by using the SLAM algorithm. Third, after establishing a specific CDW image library and performing image processing, this study uses target recognition and instance segmentation techniques according to the requirements of different tasks, and designs different picking strategies based on computer vision results. Finally, the feasibility of the robot is evaluated through practical experiments.

The major contributions of this research project are summarized as follows:

1. First of all, as an exploration of the application of robots in the development of automation in the conservative construction industry, this study has attempted automation in new areas. Many construction robots are used in the fields of prefabricated components and building construction. but automation in the field of construction waste management has received less attention. This study verified the applicability of automation and

robotic technology in the field of construction waste management by developing an advanced waste recycling robot. The research not only provides innovative methods for related fields, but also contributes to the progress of automated management.

2. This study investigated various construction robots in the construction industry. Designed on the basis of mobile robots and high-degree-of-freedom manipulators, a new robot prototype is developed, which can automatically patrol, classify, and pick up CDWs. It provides a new method for builders to recycle construction waste and improve the willingness and efficiency of CDW recycling.

3. This project carried out the research of path planning algorithm. Based on the self-made robot mobile module and ROS system, this study introduces SLAM technology and neural network technology. First, on the basis of the working mode of the robot, the optimal area division method is designed. Based on this method, this study designed and improved the calculation equations of neurons, such that the robot can work well in both

known and unknown environments. Compared with traditional algorithms, the path planning algorithm can automatically avoid obstacles while reducing the repetition rate of the path, thus improving the working efficiency of the robot. At the same time, considering the complex pavement environment of the construction site, we introduced SLAM technology to reduce the errors caused by the robot's long-term work through relocation.

4. From the perspective of the overall building automation field, automated patrols and point cloud generation systems can play an important role in many ways. For example, in the field of scan to BIM, the system can assist the implementation of BIM through the application of point clouds in the BIM model; In terms of on-site supervision, automated patrol robots can assist managers to get real-time progress and work status on the remote construction site.

5. This study firstly established a COCO format data set for CDW and conducted preliminary tests. In order to improve the accuracy of instance

segmentation, a number of data augmentation techniques are used in this study, and the optimal options are determined by comparing different CNN backbones and transfer learning sources. After completing the training, the optimal threshold is selected, and the accuracy of the model is evaluated through actual tests. At the same time, the current construction industry does not have a complete image database. The dataset provided by this research is the first step to establish special dataset for the construction industry, which can be extended to all construction-related researches and works.

5. For different building materials, this study designed special picking methods for pipes and cables, taking into account the posture and position of target objects. This picking strategy improved the picking success rate.

6. A systematic experimental study was conducted to evaluate the feasibility of CDW recycling robots in outdoor environments. By testing and improving each module separately, the robot can adapt to the real environment. Specifically, we first evaluated the accuracy of the

positioning module in different environments. Whether in outdoor or indoor environments, the positioning system can accurately determine the position of the robot and generate a three-dimensional point cloud map of the working environment. Then is the test of the path planning algorithm of the patrol system. A path planning system that combines a new area division method and a neural network algorithm can shorten the working path as much as possible, whether in a complex or simple environment. Finally, a picking system that uses computer vision technology was developed. After a series of improvements and fine-tuning, the robot could accurately identify the specified CDW and successfully pick up the target object with the help of the designed picking strategy.

7.2 LIMITATIONS AND FUTURE RESEARCH

Overall, the research project successfully developed a robot prototype for CDW sorting and recycling, which can improve the current status of CDW recycling in the construction industry. Although the evaluation and experiments prove that the robot is effective in the real environment, there is still room for improvement, as follows:

1. Limited by the function of RGB camera, this study assumes that the target objects are all on the ground. This limits the versatility of the robot. In future research, we consider using multiple cameras to assist in analyzing the spatial position of the target object, so that the robot can be used to grip the target object at any position.

2. The Omnidirectional Multi-Camera System, for instance, which can detect surroundings without robot rotation, may be a better choice for a recycling robot, as the efficiency of cleaning one region could be increased. However, this requires higher accuracy of Omnidirectional Multi- Camera System and higher computation complexity in object detection.

3. Setting up a larger computer vision dataset will make also it possible to identify more types of construction waste in different circumstances.

4. The limited hardware equipment makes the robot prototype developed in this research still far from practical. Therefore, in the future

work, we will improve the prototype of the robot and discuss the improved work efficiency of the robot through comparative experiments.

5. In view of the fact that the robot has hardware equipment suitable for most tasks, in future work, we will explore the possibility of using the robot for other tasks in the construction sites to increase the versatility of the robot. At the same time, the fully automated robot system can greatly improve the construction efficiency of construction projects and reduce costs.

REFERENCES

[1] Z. Chen, H. Li, C.T.C. Wong, An application of bar-code system for reducing construction wastes, in: Autom. Constr., 2002: pp. 521–533. https://doi.org/10.1016/S0926-5805(01)00063-2.

[2] H. Yuan, L. Shen, Trend of the research on construction and demolition waste management, Waste Manag. 31 (2011) 670–679. https://doi.org/10.1016/j.wasman.2010.10.030.

[3] Environmental Protection Department, Monitoring of Solid Waste in Hong Kong - Waste Statistics for 2017, Hong Kong, 2018.

[4] C.Z. Li, J. Hong, F. Xue, G.Q. Shen, X. Xu, L. Luo, SWOT analysis and Internet of Things-enabled platform for prefabrication housing production in Hong Kong, Habitat Int. 57 (2016) 74–87. https://doi.org/10.1016/j.habitatint.2016.07.002.

[5] A.T.W. Yu, C.S. Poon, A. Wong, R. Yip, L. Jaillon, Impact of Construction Waste Disposal Charging Scheme on work practices

at construction sites in Hong Kong, Waste Manag. 33 (2013) 138–146. https://doi.org/10.1016/j.wasman.2012.09.023.

[6] J. Park, R. Tucker, Overcoming barriers to the reuse of construction waste material in Australia: a review of the literature, Int. J. Constr. Manag. 17 (2017) 228–237. https://doi.org/10.1080/15623599.2016.1192248.

[7] File:Waste generation by economic activities and households, EU-28, 2016 (%).png - Statistics Explained, (n.d.). https://ec.europa.eu/eurostat/statistics-explained/index.php?title=File:Waste_generation_by_economic_activities_and_households,_EU-28,_2016_(%25).png (accessed July 5, 2020).

[8] S. Fatemi, R. Imaninasab, Performance evaluation of recycled asphalt mixtures by construction and demolition waste materials, Constr. Build. Mater. 120 (2016) 450–456. https://doi.org/10.1016/j.conbuildmat.2016.05.117.

[9] X. Chen, W. Lu, Identifying factors influencing demolition waste generation in Hong Kong, J. Clean. Prod. 141 (2017) 799–811. https://doi.org/10.1016/j.jclepro.2016.09.164.

[10] H. Duan, J. Li, Construction and demolition waste management: China’s lessons., Waste Manag. Res. 34 (2016) 397–8. https://doi.org/10.1177/0734242X16647603.

[11] H. Yuan, W. Lu, J. Jianli Hao, The evolution of construction waste sorting on-site, Renew. Sustain. Energy Rev. 20 (2013) 483–490. https://doi.org/10.1016/j.rser.2012.12.012.

[12] M. Menegaki, D. Damigos, A review on current situation and challenges of construction and demolition waste management, Curr. Opin. Green Sustain. Chem. 13 (2018) 8–15. https://doi.org/10.1016/j.cogsc.2018.02.010.

[13] S. Giorgi, M. Lavagna, A. Campioli, Guidelines for Effective and Sustainable Recycling of Construction and Demolition Waste, in: Des. Sustain. Technol. Prod. Policies, Springer International

Publishing, 2018: pp. 211–221. https://doi.org/10.1007/978-3-319-66981-6_24.

[14] Environmental Protection Department, Construction Waste Disposal Charging Scheme, (2005). https://www.epd.gov.hk/epd/misc/cdm/scheme.htm (accessed December 31, 2019).

[15] C.S. Poon, A.T.W. Yu, A. Wong, R. Yip, Quantifying the Impact of Construction Waste Charging Scheme on Construction Waste Management in Hong Kong, J. Constr. Eng. Manag. 139 (2013) 466–479. https://doi.org/10.1061/(ASCE)CO.1943-7862.0000631.

[16] G. Rodríguez, C. Medina, F.J. Alegre, E. Asensio, M.I. De Sánchez Rojas, Assessment of Construction and Demolition Waste plant management in Spain: In pursuit of sustainability and eco-efficiency, J. Clean. Prod. 90 (2015) 16–24. https://doi.org/10.1016/j.jclepro.2014.11.067.

[17] J. Wang, H. Yuan, X. Kang, W. Lu, Critical success factors for on-site sorting of construction waste: A china study, Resour. Conserv. Recycl. 54 (2010) 931–936. https://doi.org/10.1016/j.resconrec.2010.01.012.

[18] C.S. Poon, A.T.W. Yu, L.H. Ng, On-site sorting of construction and demolition waste in Hong Kong, Resour. Conserv. Recycl. 32 (2001) 157–172. https://doi.org/10.1016/S0921-3449(01)00052-0.

[19] T. Bock, The future of construction automation: Technological disruption and the upcoming ubiquity of robotics, Autom. Constr. 59 (2015) 113–121. https://doi.org/10.1016/j.autcon.2015.07.022.

[20] S. Eaves, D.E. Gyi, A.G.F. Gibb, Building healthy construction workers: Their views on health, wellbeing and better workplace design, Appl. Ergon. 54 (2016) 10–18. https://doi.org/10.1016/j.apergo.2015.11.004.

[21] R. Vos, J. Ocampo, A. Cortez, Ageing and development, (2008).

[22] J. Malara, E. Plebankiewicz, M. Juszczyk, Formula for determining the construction workers productivity including environmental factors, Buildings. 9 (2019) 240. https://doi.org/10.3390/BUILDINGS9120240.

[23] Q. Fang, H. Li, X. Luo, L. Ding, T.M. Rose, W. An, Y. Yu, A deep learning-based method for detecting non-certified work on construction sites, Adv. Eng. Informatics. 35 (2018) 56–68. https://doi.org/10.1016/j.aei.2018.01.001.

[24] Q. Chen, B. García de Soto, B.T. Adey, Construction automation: Research areas, industry concerns and suggestions for advancement, Autom. Constr. 94 (2018) 22–38. https://doi.org/10.1016/j.autcon.2018.05.028.

[25] B. García de Soto, I. Agustí-Juan, J. Hunhevicz, S. Joss, K. Graser, G. Habert, B.T. Adey, Productivity of digital fabrication in construction: Cost and time analysis of a robotically built wall,

Autom. Constr. 92 (2018) 297–311. https://doi.org/10.1016/j.autcon.2018.04.004.

[26] S. Lee, J. Il Moon, Case Studies on Glazing Robot Technology on Construction Sites, n.d.

[27] H. Zhang, X. Yan, H. Li, R. Jin, H. Fu, Real-Time Alarming, Monitoring, and Locating for Non-Hard-Hat Use in Construction, J. Constr. Eng. Manag. 145 (2019) 04019006. https://doi.org/10.1061/(ASCE)CO.1943-7862.0001629.

[28] X. Yan, H. Zhang, H. Li, Computer vision-based recognition of 3D relationship between construction entities for monitoring struck-by accidents, Comput. Civ. Infrastruct. Eng. (2020). https://doi.org/10.1111/mice.12536.

[29] B. Chu, K. Jung, M.T. Lim, D. Hong, Robot-based construction automation: An application to steel beam assembly (Part I), Autom. Constr. 32 (2013) 46–61. https://doi.org/10.1016/j.autcon.2012.12.016.

[30] M.K.A. Ahamed Khan, K.I. Saharuddin, I. Elamvazuthi, P. Vasant, A semi-automated floor tiling robotic system, in: 2011 IEEE Conf. Sustain. Util. Dev. Eng. Technol. STUDENT 2011, 2011: pp. 156–159. https://doi.org/10.1109/STUDENT.2011.6089344.

[31] V. Helm, S. Ercan, F. Gramazio, M. Kohler, Mobile robotic fabrication on construction sites: DimRob, in: IEEE Int. Conf. Intell. Robot. Syst., 2012: pp. 4335–4341. https://doi.org/10.1109/IROS.2012.6385617.

[32] J. Tuomas, T. Lukka, J. V Tossavainen, D. Kujala, T. Raiko, ZenRobotics Recycler-Robotic Sorting using Machine Learning, 2014.

[33] L.Y. Shen, V.W.Y. Tam, C.M. Tam, D. Drew, Mapping approach for examining waste management on construction sites, J. Constr. Eng. Manag. (2004). https://doi.org/10.1061/(ASCE)0733-9364(2004)130:4(472).

[34] J. Wang, P.X.W. Zou, P.P. Li, Critical factors and paths influencing construction workers’ safety risk tolerances, Accid. Anal. Prev. 93 (2016) 267–279. https://doi.org/10.1016/j.aap.2015.11.027.

[35] P.H.K. Ho, Labour and skill shortages in Hong Kong’s construction industry, Eng. Constr. Archit. Manag. 23 (2016) 533–550. https://doi.org/10.1108/ECAM-12-2014-0165.

[36] F.A.M. Rahim, N.S.M. Yusoff, W. Chen, N. Zainon, S. Yusoff, R. Deraman, THE CHALLENGE OF LABOUR SHORTAGE FOR SUSTAINABLE CONSTRUCTION, Plan. MALAYSIA. 14 (2016). https://doi.org/10.21837/pm.v14i5.194.

[37] J. Llale, M. Setati, S. Mavunda, T. Ndlovu, D. Root, P. Wembe, A Review of the Advantages and Disadvantages of the Use of Automation and Robotics in the Construction Industry, in: Constr. Ind. Fourth Ind. Revolut., Springer International Publishing, 2020: pp. 197–204. https://doi.org/10.1007/978-3-030-26528-1_20.

[38] G. Pritschow, M. Dalacker, J. Kurz, M. Gaenssle, Technological aspects in the development of a mobile bricklaying robot, Autom. Constr. 5 (1996) 3–13. https://doi.org/10.1016/0926-5805(95)00015-1.

[39] K. Dörfler, T. Sandy, M. Giftthaler, F. Gramazio, M. Kohler, J. Buchli, Mobile Robotic Brickwork, in: Robot. Fabr. Archit. Art Des. 2016, Springer International Publishing, 2016: pp. 204–217. https://doi.org/10.1007/978-3-319-26378-6_15.

[40] M. Giftthaler, T. Sandy, K. Dörfler, I. Brooks, M. Buckingham, G. Rey, M. Kohler, F. Gramazio, J. Buchli, Mobile robotic fabrication at 1:1 scale: the In situ Fabricator, Constr. Robot. 1 (2017) 3–14. https://doi.org/10.1007/s41693-017-0003-5.

[41] Y.W.D. Tay, B. Panda, S.C. Paul, N.A. Noor Mohamed, M.J. Tan, K.F. Leong, 3D printing trends in building and construction industry: a review, Virtual Phys. Prototyp. (2017). https://doi.org/10.1080/17452759.2017.1326724.

[42] T.T. Le, R.A. Buswell, S.A. Austin, Fabricating construction components using layer manufacturing technology, 2009. https://www.researchgate.net/publication/312919469 (accessed June 19, 2020).

[43] X. Zhang, M. Li, J.H. Lim, Y. Weng, Y.W.D. Tay, H. Pham, Q.C. Pham, Large-scale 3D printing by a team of mobile robots, Autom. Constr. 95 (2018) 98–106. https://doi.org/10.1016/j.autcon.2018.08.004.

[44] H. Kloft, N. Hack, J. Mainka, L. Brohmann, E. Herrmann, L. Ledderose, D. Lowke, Additive Fertigung im Bauwesen: erste 3-D-gedruckte und bewehrte Betonbauteile im Shotcrete-3-D-Printing-Verfahren (SC3DP), Bautechnik. (2019). https://doi.org/10.1002/bate.201900094.

[45] M. Sifyan, H.R. Topcuoglu, M. Ermis, Path planning for mobile sensor platforms on a 3-D terrain using hybrid evolutionary algorithms, in: 2010 IEEE World Congr. Comput. Intell. WCCI

2010 - 2010 IEEE Congr. Evol. Comput. CEC 2010, 2010. https://doi.org/10.1109/CEC.2010.5586378.

[46] E.U. Acar, H. Choset, Y. Zhang, M. Schervish, Path planning for robotic demining: Robust sensor-based coverage of unstructured environments and probabilistic methods, in: Int. J. Rob. Res., 2003. https://doi.org/10.1177/02783649030227002.

[47] T. Oksanen, A. Visala, Coverage path planning algorithms for agricultural field machines, J. F. Robot. (2009). https://doi.org/10.1002/rob.20300.

[48] A. Janchiv, D. Batsaikhan, B. Kim, W.G. Lee, S.G. Lee, Time-efficient and complete coverage path planning based on flow networks for multi-robots, Int. J. Control. Autom. Syst. (2013). https://doi.org/10.1007/s12555-011-0184-5.

[49] E. Galceran, M. Carreras, A survey on coverage path planning for robotics, Rob. Auton. Syst. (2013). https://doi.org/10.1016/j.robot.2013.09.004.

[50] J. Barraquand, J.C. Latombe, Robot Motion Planning: A Distributed Representation Approach, Int. J. Rob. Res. (1991). https://doi.org/10.1177/027836499101000604.

[51] D. Batsaikhan, A. Janchiv, S.G. Lee, Sensor-based incremental boustrophedon decomposition for coverage path planning of a mobile robot, in: Adv. Intell. Syst. Comput., 2013. https://doi.org/10.1007/978-3-642-33926-4_59.

[52] A. Khan, I. Noreen, H. Ryu, N.L. Doh, Z. Habib, Online complete coverage path planning using two-way proximity search, Intell. Serv. Robot. (2017). https://doi.org/10.1007/s11370-017-0223-z.

[53] E.U. Acar, H. Choset, A.A. Rizzi, P.N. Atkar, D. Hull, Morse decompositions for coverage tasks, Int. J. Rob. Res. (2002). https://doi.org/10.1177/027836402320556359.

[54] a Zelinsky, R. Jarvis, J. Byrne, S. Yuta, Planning paths of complete coverage of an unstructured environment by a mobile robot, Proc.

Int. Conf. Adv. Robot. (1993). https://doi.org/10.1107/S1600536810016661.

[55] Y. Guo, Z. Qu, Coverage control for a mobile robot patrolling a dynamic and uncertain environment, in: Proc. World Congr. Intell. Control Autom., 2004. https://doi.org/10.1109/wcica.2004.1343643.

[56] C. Luo, S.X. Yang, A bioinspired neural network for real-time concurrent map building and complete coverage robot navigation in unknown environments, IEEE Trans. Neural Networks. (2008). https://doi.org/10.1109/TNN.2008.2000394.

[57] Y.H. Choi, T.K. Lee, S.H. Baek, S.Y. Oh, Online complete coverage path planning for mobile robots based on linked spiral paths using constrained inverse distance transform, in: 2009 IEEE/RSJ Int. Conf. Intell. Robot. Syst. IROS 2009, 2009. https://doi.org/10.1109/IROS.2009.5354499.

[58] T.K. Lee, S.H. Baek, S.Y. Oh, Y.H. Choi, Complete coverage algorithm based on linked smooth spiral paths for mobile robots, in:

11th Int. Conf. Control. Autom. Robot. Vision, ICARCV 2010, 2010. https://doi.org/10.1109/ICARCV.2010.5707264.

[59] A. Sipahioglu, G. Kirlik, O. Parlaktuna, A. Yazici, Energy constrained multi-robot sensor-based coverage path planning using capacitated arc routing approach, Rob. Auton. Syst. (2010). https://doi.org/10.1016/j.robot.2010.01.005.

[60] C. Li, F. Wang, Y. Song, Z. Liang, Z. Wang, A complete coverage path planning algorithm for mobile robot based on FSM and rolling window approach in unknown environment, in: Chinese Control Conf. CCC, 2015. https://doi.org/10.1109/ChiCC.2015.7260560.

[61] H. Freeman, R. Shapira, Determining the Minimum-Area Encasing Rectangle for an Arbitrary Closed Curve, Commun. ACM. (1975). https://doi.org/10.1145/360881.360919.

[62] J. Ni, L. Wu, P. Shi, S.X. Yang, A dynamic bioinspired neural network based real-time path planning method for autonomous

underwater vehicles, Comput. Intell. Neurosci. (2017). https://doi.org/10.1155/2017/9269742.

[63] Y. Guo, M. Balakrishnan, Complete coverage control for nonholonomic mobile robots in dynamic environments, in: Proc. - IEEE Int. Conf. Robot. Autom., 2006. https://doi.org/10.1109/ROBOT.2006.1641952.

[64] F. Endres, J. Hess, J. Sturm, D. Cremers, W. Burgard, 3-D Mapping with an RGB-D camera, IEEE Trans. Robot. (2014). https://doi.org/10.1109/TRO.2013.2279412.

[65] A. Dai, M. Nießner, M. Zollhöfer, S. Izadi, C. Theobalt, Bundlefusion: Real-time globally consistent 3D reconstruction using on-the-fly surface reintegration, ACM Trans. Graph. (2017). https://doi.org/10.1145/3054739.

[66] A.J. Glover, W.P. Maddern, M.J. Milford, G.F. Wyeth, FAB-MAP + RatSLAM: Appearance-based SLAM for multiple times of day,

in: Proc. - IEEE Int. Conf. Robot. Autom., 2010. https://doi.org/10.1109/ROBOT.2010.5509547.

[67] W. Churchill, P. Newman, Practice makes perfect? Managing and leveraging visual experiences for lifelong navigation, in: Proc. - IEEE Int. Conf. Robot. Autom., 2012. https://doi.org/10.1109/ICRA.2012.6224596.

[68] K. Pirker, M. Rüther, H. Bischof, CD SLAM - Continuous localization and mapping in a dynamic world, in: IEEE Int. Conf. Intell. Robot. Syst., 2011. https://doi.org/10.1109/IROS.2011.6048253.

[69] M. Labbé, F. Michaud, Online global loop closure detection for large-scale multi-session graph-based SLAM, in: IEEE Int. Conf. Intell. Robot. Syst., 2014. https://doi.org/10.1109/IROS.2014.6942926.

[70] H. Hamledari, B. McCabe, S. Davari, Automated computer vision-based detection of components of under-construction indoor

partitions, Autom. Constr. (2017). https://doi.org/10.1016/j.autcon.2016.11.009.

[71] M.W. Park, I. Brilakis, Construction worker detection in video frames for initializing vision trackers, Autom. Constr. (2012). https://doi.org/10.1016/j.autcon.2012.06.001.

[72] X. Luo, H. Li, H. Wang, Z. Wu, F. Dai, D. Cao, Vision-based detection and visualization of dynamic workspaces, Autom. Constr. (2019). https://doi.org/10.1016/j.autcon.2019.04.001.

[73] Y. Yu, H. Li, X. Yang, L. Kong, X. Luo, A.Y.L. Wong, An automatic and non-invasive physical fatigue assessment method for construction workers, Autom. Constr. (2019). https://doi.org/10.1016/j.autcon.2019.02.020.

[74] Y. LeCun, L. Bottou, Y. Bengio, P. Haffner, Gradient-based learning applied to document recognition, Proc. IEEE. (1998). https://doi.org/10.1109/5.726791.

[75] A. Krizhevsky, I. Sutskever, G.E. Hinton, ImageNet classification with deep convolutional neural networks, in: Adv. Neural Inf. Process. Syst., 2012.

[76] R. Girshick, J. Donahue, T. Darrell, J. Malik, Rich feature hierarchies for accurate object detection and semantic segmentation, in: Proc. IEEE Comput. Soc. Conf. Comput. Vis. Pattern Recognit., 2014. https://doi.org/10.1109/CVPR.2014.81.

[77] R. Girshick, Fast R-CNN, in: Proc. IEEE Int. Conf. Comput. Vis., 2015. https://doi.org/10.1109/ICCV.2015.169.

[78] Q. Fang, H. Li, X. Luo, L. Ding, H. Luo, T.M. Rose, W. An, Detecting non-hardhat-use by a deep learning method from far-field surveillance videos, Autom. Constr. (2018). https://doi.org/10.1016/j.autcon.2017.09.018.

[79] Z. Wang, H. Li, X. Zhang, Construction waste recycling robot for nails and screws: Computer vision technology and neural network

approach, Autom. Constr. (2019). https://doi.org/10.1016/j.autcon.2018.11.009.

[80] K. He, G. Gkioxari, P. Dollar, R. Girshick, Mask R-CNN, in: Proc. IEEE Int. Conf. Comput. Vis., 2017. https://doi.org/10.1109/ICCV.2017.322.

[81] M. Bai, R. Urtasun, Deep Watershed Transform for Instance Segmentation, Proc. - 30th IEEE Conf. Comput. Vis. Pattern Recognition, CVPR 2017. 2017-January (2016) 2858–2866. http://arxiv.org/abs/1611.08303 (accessed May 16, 2020).

[82] H. Ding, S. Qiao, W. Shen, A. Yuille, Shape-aware Feature Extraction for Instance Segmentation, (2019). http://arxiv.org/abs/1911.11263 (accessed May 16, 2020).

[83] A. Arnab, P.H.S. Torr, Pixelwise Instance Segmentation with a Dynamically Instantiated Network, Proc. - 30th IEEE Conf. Comput. Vis. Pattern Recognition, CVPR 2017. 2017-January

(2017) 879–888. http://arxiv.org/abs/1704.02386 (accessed May 16, 2020).

[84] S. Liu, J. Jia, S. Fidler, R. Urtasun, SGN: Sequential Grouping Networks for Instance Segmentation, n.d.

[85] R. Kershner, The Number of Circles Covering a Set, Am. J. Math. (1939). https://doi.org/10.2307/2371320.

[86] H. Choset, Coverage of known spaces: The boustrophedon cellular decomposition, Auton. Robots. (2000). https://doi.org/10.1023/A:1008958800904.

[87] Y.H. Choi, T.K. Lee, S.H. Baek, S.Y. Oh, Online Complete Coverage Path Planning for Mobile Robots, IEEE/RSJ Int. Conf. Intell. Robot. Syst. (2009). https://doi.org/10.1109/IROS.2009.5354499.

[88] Y. Gabriely, E. Rimon, Spiral-STC: An on-line coverage algorithm of grid environments by a mobile robot, Proc. - IEEE Int. Conf.

Robot. Autom. (2002). https://doi.org/10.1109/ROBOT.2002.1013479.

[89] E. González, O. Álvarez, Y. Díaz, C. Parra, C. Bustacara, BSA: A complete coverage algorithm, in: Proc. - IEEE Int. Conf. Robot. Autom., 2005. https://doi.org/10.1109/ROBOT.2005.1570413.

[90] R. Girshick, I. Radosavovic, G. Gkioxari, P. Dollár, K. He, Detectron, (2018).

[91] T.Y. Lin, M. Maire, S. Belongie, J. Hays, P. Perona, D. Ramanan, P. Dollár, C.L. Zitnick, Microsoft COCO: Common objects in context, in: Lect. Notes Comput. Sci. (Including Subser. Lect. Notes Artif. Intell. Lect. Notes Bioinformatics), 2014. https://doi.org/10.1007/978-3-319-10602-1_48.

[92] W. Ketaro, labelme: Image Polygonal Annotation with Python, (2016). https://github.com/wkentaro/labelme (accessed December 12, 2019).

[93] J. West, D. Ventura, S.W.-B.Y. University, C. of P. and, undefined 2007, Spring research presentation: A theoretical foundation for inductive transfer, (n.d.).