

A method of track starting point identification for tram based on integral algorithm

Yimin Sun, Cheng Wu, Yiming Wang

Abstract—With the development of intelligent driving technology, the unmanned technology of rail vehicles has also made great progress. How to determine the front limit region in the driving vehicle is a very important topic in the unmanned technology of the rail vehicle. In this paper, a method of Track-Starting-Point(TSP) identification for tramway based on integral algorithm is proposed in this paper. The method is based on the special morphological characteristics of the tramway, and takes the gray mean of column pixels as the processing basis, and uses integral operation to detect the TSP. In order to achieve accurate detection of TSP under various weather conditions, illumination conditions and terrain features, the accurate boundary extraction is finally achieved, providing a guarantee for subsequent tramway obstacle detection.

Keywords—tram, integral operation, image processing

I. INTRODUCTION

WITH the development of intelligent driving technology, the fully automatic driverless technology is attracting more and more attention. For rail transmit, fully driverless ability functions such as wakeup, sleep, start and stop, door opening and closing, and train operation under emergency condition are all automatically controlled by the system, without any staff participation. The realization of fully automatic driverless operation can greatly reduce operation cost, and also can avoid accidents caused by fatigue or negligence. In various rail vehicles, modern tram is more and more popular among big and medium-sized cities because of their large capacity, comfortable, low energy consumption and low pollution [1]. The biggest difference between the tram and other rail vehicle is that it has no independent right of way, although mixed right can effectively save the space of the city, but also makes the tram running in the complex environment, as shown in Fig 1. According to the data released by China Urban Rail Transit Association, by the report of 2014, the total mileage of modern tram in Nanjing, Dalian, Changchun, Shanghai and other 8 cities has reached 180.3 kilometers, which is developing rapidly. According to statistics, there are more than 100 cities in the country planning to build trams. By 2020, the total mileage of tramway will reach 2500 km [2]. At present, the obstacle detection of trams mainly depend on the naked eye of drivers. Drivers suffer from long time driving fatigue or bad weather and light environment. Therefore, it is of

great practical significance to realize the complete automatic driverless of the tram. The unmanned vehicle system of the general vehicle is perceived by the surrounding environment, the intelligent behavior decision and the vehicle control system. In actual operation, the system needs to carry out the route planning and vehicle posture readjustment at any time. As a result of the single route of the track vehicle, the system can focus more attention on the obstacle detection and avoidance in front of the vehicle. It also provides the development space for the accuracy and real time of the obstacle detection system of the rail vehicle on the objective condition. In the obstacle detection system, the concept of "limit region" is very important, and the main energy of the system is in the area where the target may appear. The establishment of a suitable recognition limit region can greatly reduce the amount of computation and reduce the possibility of misreporting of the system itself.

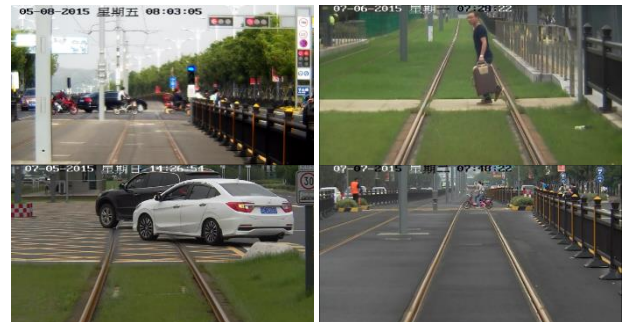


Fig 1 complex environment of tram operation

Starting from the driverless technology of trams, this paper studies the determination of the possible boundary start points of obstacles in front of tracks, and proposes a method based on integral algorithm to identify the starting point of trams. This method is suitable for the extraction of track starting points in complex environments. At present, no one has studied the problems in the related fields determined by the starting point of the track. This is an important basis for the development of this method.

This paper is organized as follows: Section 2 reviews the current research status of obstacle detection at home and abroad, and the overview of research carried out by the author's group. At the same time, it describes the environment applicable to this method. In Section 3, the TSP identification method of tram based on integral algorithm is briefly introduced. The average intensity of column pixels is introduced as the "intensity" of image processing, and then the integral algorithm is conducted through the analysis of its gradient mean. In addition, the starting point of tram track is established. This part also contains the experimental results. Finally, the analysis of the

Yimin Sun is with School of Rail Transportation, Soochow University, Suzhou, China. (e-mail: 948253398@qq.com).

Cheng Wu is with School of Rail Transportation, Soochow University, Suzhou, China. (corresponding author, e-mail: cwu@suda.edu.cn).

Yiming Wang is with School of Rail Transportation, Soochow University, Suzhou, China. (e-mail: ymwang@suda.edu.cn).

results of the experiment is summarized in Section 4 and the future work is expected.

II. RELATED WORK

A. Present status of related research

Since the 80s of the last century, many countries have begun to study the automation and intelligent operation of rail vehicles. At the 1994 world conference held in Paris, France, experts from all over the world agreed to apply the system of transportation operation, management and security service developed by communication, information and control to Intelligent Transportation System (ITS) [3]. And its derivative RITS in rail vehicles has been studied for nearly 20 years under the guidance of European and American countries. At present, the technology of RITS has been developing continuously, and it has been gradually developed into a real-time, accurate and funny traffic and transportation integrated management and control system. With the continuous development of rail vehicles, their types are gradually diversified, and there are different categories of railway[4], subway, light rail and tram. Because of the difference in the running environment and running speed of these rail vehicles, the challenges they face in the intelligent operation are not the same. But similarly, a reliable and safe driving system or unmanned system is indispensable. In recent years, with the rapid development of robotic cars[5], the driverless technology of track vehicle has also made progress. The obstacle detection system in front of the track vehicle is the most important part of the driving auxiliary system and the unmanned system. There are two main obstacle detection systems used to track vehicles at present:

1) Physical contact detection method. At present, it is more common to detect vehicles by using a single track, detect the track regularly, including detection of foreign objects and obstacles, usually including two kinds of automatic detection vehicle and manned vehicle detection. In particular, the rail vehicles operating in the subway, which have more closed operating environment, have higher requirements for the driving limit. At present, the British Railway Institute, located at the Derby, has developed a track limit test vehicle capable of running at the speed of 70km/h. An obstacle detection device is also installed on the running vehicle, for example, an obstacle detection device suitable for the subway ring proposed by Hou Xiaoxuan [6], is used to detect obstacles in front of vehicles at any time during vehicle running.

2) Sensor detection method. Using camera, radar, thermal imager and other sensors to detect obstacles in the front environment of rail cars, it has the advantages of non-contact and real-time. The researchers have done a lot of work in sensor obstacle detection. In the field of multi-sensor fusion, S. Scholz [7] and other researchers used the fusion method of laser radar, video and millimeter wave radar to modularized multi-sensor fusion, and realized the obstacle detection method suitable for high-speed rail. Sinha, D. and Feroz, F [8] uses vibration sensors and signal filtering methods to detect track obstacles. While also such as Zhiguo Bai, Sung-Hwan and Jung [9] using single sensor multi arrangement of body in different parts of the

obstacle detection method, and according to the different parts of the possible problems of sparks, obstacles and nut loss are put forward the corresponding algorithm to detect. In practical field, the Japanese Shinkansen has developed a set of automatic detection system for rail, equipped with xenon lamp and high scanning CCD camera, using the template matching method to track the contour contrast has been in the database to determine the objects in front of obstacles or track infrastructure. In the research field of the adjacent, also for obstacle detection, Ding, X., Yan, L., Liu, J., Kong, J. and Yu, Z [10] to put forward a kind of the thermal image and video image fusion based on the detection of dark infrared radar illumination method may appear under the condition of fire hazard in the forest. Matthew Coombes, William Eaton, Wen-Hua Chen[11] use the machine vision in road detection in UAV Ground Operations. Abdelkader Dairi, Fouzi Harrou, Mohamed Senouci, Ying Sun[12] apply deep-learning-based stereovision in unsupervised obstacle detection in driving environments.

At present, with the rapid development of intelligent driving technology, sensor obstacle detection technology has also made considerable progress and has gradually become the mainstream of obstacle detection.

B. Completed work

At present, the subject group of the author has also been studied in the detection of tram obstacles. According to the actual operation situation, the project team proposed a set of track tram obstacle identification system based on machine vision. In this system, the selection of the recognition limit region is very important. The track recognition method based on multi threshold and pixel tracking is proposed by Xiang Qiang and Zhaoyang Zhang[13], two members of author's subject group. It can cut out the trapezium clearance of obstacle recognition adaptively based on the given track starting point, as shown in Fig 2.1. However, the starting point of track method is adopted for calibration, with certain subjective errors, in (1) for calibration is not accurate (2) pavement jitter (3) frequently lost in the starting point will appear heavy rain snow and other inclement weather conditions, leading to the trapezoidal limit choice deformation, serious influence image processing efficiency, bring some security risks, as shown in Fig 2.2.



Fig 2.1 Trapezoidal limit region Fig 2.2 Loss of starting points

The method proposed in this paper can be applied to the following two cases:

1) When the obstacle detection system start in the first time, the system automatically searches for the starting point to start the follow-up detection step.

2) When the bad weather or light conditions cause the track start to lose, the system enables the algorithm to get the starting point of interested area in a short time, so as to ensure driving safety.

III. BRIEF INTRODUCTION OF METHOD

The tram is mainly run in the city and its surrounding area, which is different from the concave rail of the general railway. The cross section diagram of the track, as shown in Fig 3.1 (a), is shown by the overlook Fig 3.1 (b). Through observation, it is found that there are two characteristics below:

- (I) The concave rail groove inside is dark, the groove outside is brighter, and the difference of gray level is obvious.
- (II) Directly adjacent to the brighter and darker part.



(a) Cross section diagram of the track (b) Track overlook map of tram
Fig 3.1 Concave track structure of tram

A. Picture preprocessing

The image obtained by the sensor contains a lot of useless information, so it is necessary to preprocess the whole image and reduce the amount of operation. The preprocessing of this method consists of two blocks: 1) the extraction of the possible region of interest (ROI) that may exist at the starting point. 2) grayscale.

The extraction of the starting point of interest is to cut the original image in the region that may appear according to the starting point, reducing the amount of computation required by the whole method. According to the prior knowledge, this article intercepts the block of the 1050*40 pixel size at the bottom of the original image as a region of interest, as shown in Fig 3.2(a).

Grayscale is a common preprocessing method in image processing. In the process of obstacle recognition, the color component on the image is actually not important. The commonly grayscale methods include the component method, the maximum value method, the mean value method and the weighted mean method. In this paper, the weighted average method which is generally recognized as the best result is adopted. The RGB component $R(i, j)$, $G(i, j)$ and $B(i, j)$ in the original image are weighted average. The implementation is shown in Fig 3.2(b). Because the human eye has the highest sensitivity to the green component $G(i, j)$, the sensitivity of the blue component $B(i, j)$ is the lowest, and the gray level formula of the image is as follows:

$$f(i, j) = 0.30R(i, j) + 0.59G(i, j) + 0.11B(i, j) \quad (1)$$



Fig 3.2(a) Region of interest (Blue frame)



Fig3.2(b) Region of interest after grayscale

B. The realization of the method based on integral operation

In this method, the focus of processing is placed on the morphological features of "bright-dark-bright" in the image of the track area on the image at the end of the preprocessing. In order to highlight this morphological feature, this method introduces the definition of the gray value of column pixels, and takes it as the "intensity" of the image, and becomes the main basis for subsequent processing. Finally, the starting point of the orbit is determined by the integral method. The specific process is as follows:

1) The calculation of the mean value of the gray level of the column pixels. The preprocessed images are defined as $f(x, y)$, in which x and y are the abscissa and ordinates of the preprocessed images respectively. Here, this paper introduces the definition of the \bar{T}_n as the column coordinates mean gray level, namely image $f(x, y)$ after preprocessing in the gray $T_{f(x,y)}$ pixels in the column. The formula is as follows:

$$\bar{T}_n = \frac{1}{40} \sum_{i=1}^{40} T_{f(n,i)} \quad (2)$$

The mean value of the column pixel gray level of each column of $f(x, y)$ is obtained and the corresponding histogram is made, as shown in Fig 3.3.

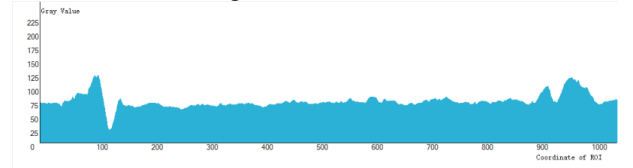


Fig3.3 Histogram of gray mean value of column coordinate

Through the analysis of histogram, it can be found that the gray mean value of TSP will have a great change, which is also consistent with the "bright-dark-bright" morphological characteristics presented at the beginning of track, as shown in the red frame in Fig 3.4.

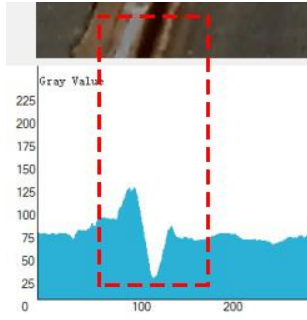


Fig3.4 Comparison of histogram and gray scale

2) The calculation of the absolute value of the gradient. In image processing, there are many ways to highlight the change of image. Considering the complexity and computation complexity of the algorithm, this paper introduce the definition of gradient G_n of adjacent column pixel mean:

$$G_n = \overline{T_n} - \overline{T_{n+1}} \quad (3)$$

In order to avoid the normalized results, due to the influence of gradient sign brings, the method using $|G_n|$ histogram, as shown in Fig 3.5.

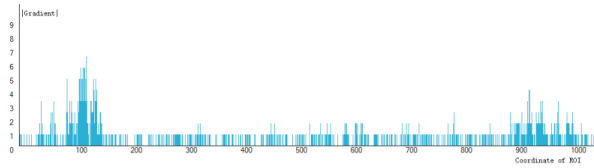


Fig3.5 Gradient absolute value histogram

2) Interference rejection. A large number of small gradient absolute values are contained in the histogram obtained by step 2). According to a large number of experiments, this method remove the histogram components of $|G_n| = 1$ and improve the efficiency of operation under the premise of guaranteeing the accuracy of operation results. As shown in Fig 3.6, the following methods are applied:

$$|G_n^*| = \begin{cases} |G_n|, & |G_n| > 1 \\ 0, & |G_n| \leq 1 \end{cases} \quad n = 0, 1, 2 \dots 1049 \quad (4)$$

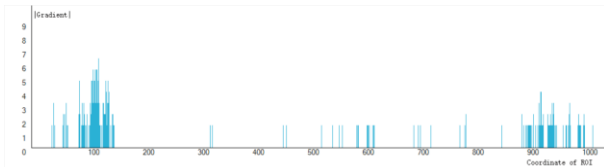


Fig3.6 result after improvement

3) Realization of integral algorithm. In the gradient histogram, the starting point of the orbit is still not intuitive. The starting point of the track determined by the two peaks in the histogram will often cause serious error due to unpredictable abnormal pixel interference. For this reason, the concept of integral is introduced to balance the interference of abnormal pixels, and the maximum value of absolute value of gradient in fixed integration domain is found as a possible area for starting point. According to the pixel track starting point width, the method selects 10 pixels as the integral domain width,

of the histogram every 10 continuous gradient absolute value summation $|G_n|$:

$$S_n = \sum_{i=n}^{n+10} |G_i| \quad (5)$$

This process is repeated until a strike on the abscissa of integral value of each point. Then, the left TSP coordinate value is X_{left} , the right track TSP coordinate value is X_{right} , and the TSP is in the each half of gradient absolute value, which is the maximum value of S_n in histogram area:

$$\begin{aligned} X_{left} &= S_{n1}, S_{n1} = \max\{S_0, S_1, S_2 \dots S_{524}\} \\ X_{right} &= S_{n2}, S_{n2} = \max\{S_{525}, S_{526}, S_{527} \dots S_{1049}\} \end{aligned} \quad (6)$$

As shown in Fig 3.7(a), the two peaks after the integral operation have been identified with the red frame. In the final experimental results, the starting point X_{left} and X_{right} are identified with the red frame in the diagram. The results of the experiment are shown in Fig 3.7(b).

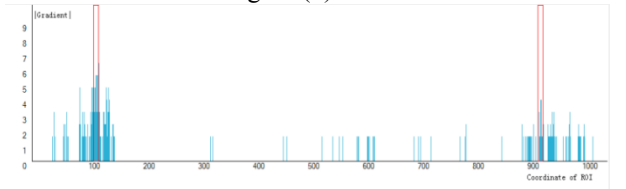


Fig3.7(a) Two peaks after integral operation



Fig3.7(b) experimental result

C. Algorithm running result

The material selected from the algorithm is from the actual operation environment of tram in Suzhou hi tech Zone, and the experimental results under various weather conditions are shown in Fig 3.8(a)-(e).



Fig3.8(a) Artificial grassland



Fig3.8(b) Rainy day



Fig3.8(c) Asphalt road



Fig3.8(d) Natural grassland



Fig3.8(e) Snowy day

This method is integrated into an obstacle detection system that is developed before the members of the subject group. The experimental results are shown in Fig 3.9 (a).

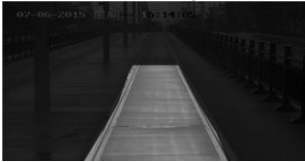


Fig3.9(a) Improvement results

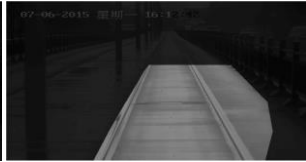


Fig3.9(b) Original result

IV. CONCLUSION

In this paper, an algorithm for detecting track starting point of tram based on integral is proposed. The algorithm is based on the morphological characteristics of the track of trams, and judging from the local gray level changes of the images. It can achieve the function of adaptive detection in different weather, light and road conditions, and has good robustness. The proposed track recognition method based on integral starting point is still inadequate, especially in the snow covered conditions, pavement intensity changes greatly, will have a certain impact on the starting point of the track detection. And the time spent on single frame images is more than 500ms, and it can not meet the 10 frames per second video processing requirements. The next step of the author is to optimize the algorithm and reduce the time required to deal with the algorithm.

ACKNOWLEDGEMENT

This research was supported by the Science and Technology Development Foundation of Suzhou (No. SYG201715).

REFERENCES

- [1] Wang yancai, A preliminary study on the applicability of modern tram [D]. Nanjing Forestry University, 2011, 2-3.
- [2] The national tram mileage is 5 years or 13 times more. NetEase Finance and Economics. <http://money.163.com/15/1104/10/B7IQBBV500253B0H.html>. 2015.
- [3] Shi tianyun, Zhang hongyu, Jia limin. (2003) Intelligent transportation system of Japanese railway (RITS). CHINA RAILWAY SCIENCE, pp. 82-88.
- [4] Xavier Gibert, Vishal M. Patel, Rama Chellappa. (2017). Deep Multitask Learning for Railway Track Inspection. IEEE TRANSACTIONS ON INTELLIGENT TRANSPORTATION SYSTEMS.
- [5] Jian-ru XUE, Di WANG, Shao-yi DU, Di-xiao CUI, Yong HUANG, Nan-ning ZHENG. (2017). A vision-centered multi-sensor fusing approach to self-localization and obstacle perception for robotic cars. Frontiers of Information Technology & Electronic Engineering, pp. 122-136.
- [6] Hou xiaoxuan. (2013). The Design of Metro Obstacle Detector and Key Technology Research. Peking University
- [7] S. Scholz. (2017). An Innovative System to Detect Obstacles on Rail Tracks. Automated People Movers and Automated Transit Systems 2016. pp. 146-155.

- [8] Sinha, D. and Feroz, F. (2016). Obstacle Detection on Railway Tracks Using Vibration Sensors and Signal Filtering Using Bayesian Analysis. IEEE Sensors Journal, 16(3), pp. 642-649.
- [9] Bai, Z. and Jung, S. (2015). Image-based Subway Security System by Histogram Projection Technology. Journal of Korea Multimedia Society, 18(3), pp. 287-297
- [10] Ding, X., Yan, L., Liu, J., Kong, J. and Yu, Z. (2013). Obstacles Detection Algorithm in Forest based on Multi-sensor Data Fusion. Journal of Multimedia, 8(6).
- [11] Matthew Coombes, William Eaton, Wen-Hua Chen. (2017). Machine Vision for UAS Ground Operations - Using Semantic Segmentation with a Bayesian Network classifier. J Intell Robot Syst.
- [12] Abdelkader Dairi, Fouzi Harrou, Mohamed Senouci, Ying Sun. (2018). Unsupervised obstacle detection in driving environments using deep-learning-based stereovision. Robotics and Autonomous Systems, pp. 287-301.
- [13] Qiang xiang, Zhang zhaoyang. (2015). Track recognition based on multi threshold and pixel tracking. Electronic Design Engineering, 23(23), 149-150.

Yimin Sun was born in 1993. He received his B.S in 2016 from Soochow University. Now, he is a graduate student of the School of Rail Transportation, Soochow University. His main research directions include image processing and pattern recognition.

Cheng Wu was born in 1976. He graduated from the computer engineering major of Northeastern University and received his doctorate. He is now an associate professor of Soochow University. His researches include computer engineering, artificial intelligence, and image processing.

Yiming Wang, was born in 1956. She is a professor and doctoral tutor of Soochow University. She is also a senior member of China Electronics Society, a member of IEEE, and a leader of communication and information system in Soochow University. The current research interests are wireless communication network, cognitive radio, ultra wideband communication and so on.