Intelligent Metro Passenger Flow Monitoring and Guidance System

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Abstract. With the rapid development of big data, image analysis technology, and artificial intelligence, the related businesses of smart subways have been gradually realized. Facing the huge passenger flow during peak hours, how to guide passengers to relatively spacious compartments has become a hot issue of concern. This article utilizes big data processing and existing image analysis technology in combination with the original subway system to develop an intelligent subway passenger flow monitoring and guidance system. This system consists of three parts: multi-terminal collection, data analysis, and intuitive guidance. The system has the advantages of high reliability, low cost, and real-time guidance, which is expected to help improve passengers' ride experience and ensure the normal operation of the subway.

Keywords: Smart Subway, Multi-terminal Acquisition, Data analysis, Intuitive Guidance.

1. Introduction

With the acceleration of urbanization, the urban population density is increasing, and more and more passengers are taking the subway to travel[1-3]. The contradiction between the safe and orderly operation of the subway and the growth of passenger travel demand is becoming more and more prominent. How to guide passengers to board the train reasonably on the basis of the existing operation capacity is becoming increasingly important[4,5]. With the rapid development of big data and artificial intelligence technology, especially the rapid development of image processing and computer vision technology, it provides reliable technical support for passenger flow monitoring in the subway.

Through research on the existing technologies at home and abroad, there are mainly three types of passenger flow monitoring in the subway: (1) Passenger flow density data detection at the entry and exit of the station[6-9]. This technology detects the number of passengers who arrive at and leave the station through the entry and exit gates of the station in a unit of time. Then combined with the camera to capture the passenger flow data in a unit of time in the station area, the passenger flow density data in the station is ultimately analyzed. (2) Passenger flow density data detection at the entry and exit of the station security checkpoint. This technology acquires the station's passenger flow data by installing infrared or laser detection equipment on both sides of the entry and exit doors of the station security checkpoint. This technology can accurately obtain the passenger flow data of the station. (3) Passenger flow density data obtained through video image analysis in the station area. This technology analyzes the video images captured by cameras installed in key locations such as hallways, platforms, and concourses to obtain passenger flow data through counting heads. Although these three methods have achieved certain results in practical applications, there is currently a lack of effective methods and means for detecting passenger flow data in subway train compartments, especially during peak passenger hours. Traditional methods that rely solely on video image analysis are subject to many constraints inside the compartment, such as blind angles of cameras, visual occlusions of passengers on cameras, and multiple factors such as passenger vibrations during high-speed operation that affect the final statistical results. It is difficult to accurately count passenger flow data[10,11]. Therefore, it is urgent to research into reliable passenger flow density detection systems.

In this study, we used big data processing and existing image analysis technology combined with the original subway system to design and develop an intelligent subway passenger flow monitoring and guidance system.

2. System Introduction

2.1. System Overview

Figure 1 shows the composition of the system. The purpose of the system is to guide passengers to evenly distribute to all compartments, solving the problem of uneven distribution of compartment occupancy caused by factors such as limited visual range of passengers and delayed staff guidance during high passenger flow periods or at key stations with a large volume of circulation. At the same time, the system can predict the congestion level of stations and lines in advance, providing reference for user travel planning.

When the system is running, it comprehensively considers the passenger density inside and outside the compartments through data collected from multiple terminals, achieving intelligent guidance for passengers from "gate entrance to compartment". At the same time, by periodically collecting data on the passenger capacity of each station and each time period, extracting recurring passenger flow characteristics, assisting staff to make timely adjustments to the travel environment, and helping users better develop travel plans.

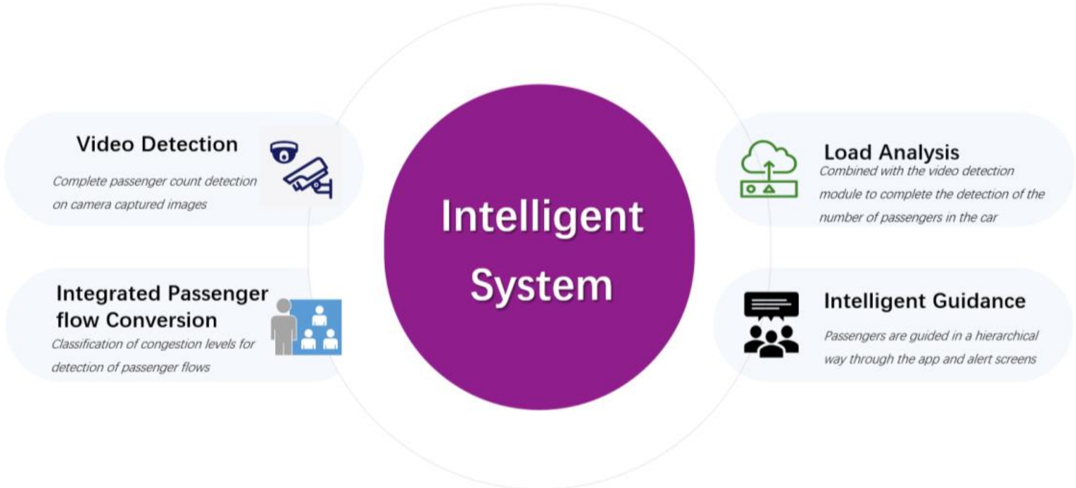

Figure 1. System composition

2.2. Data Acquisition and Processing

Figure 2 shows data acquisition and processing roadmap. In consideration of the small effective waiting area on both sides of the train and the elevator area, and in order to make the data results more practical, we use the passenger density value obtained from the ratio of passenger quantity to the corresponding area to replace the single variable of passenger quantity. This effectively avoids the errors caused by the influence of the platform level structure on the waiting area outside the compartments, accurately reflects the congestion level of the area, and finally processes the passenger density into a compartment recommendation index through a certain formula to efficiently guide passengers.

For the compartments, a combination of "air springs + cameras" is adopted, and the passenger density is calculated by processing with the on-board PIS system. The TCMS system establishes communication with this air suspension system to continuously measure and collect the pressure values inside the air springs of the subway air suspension system. The air suspension system then transmits the dynamically collected dynamic load values to the TCMS system through vehicle MVB. The TCMS system stores the dynamic load values on the vehicle MVB and sends them to the on-board PIS through the vehicle PIS interface. The on-board PIS converts the actual passenger count by using the formula: actual passenger count = occupancy rate * overcrowded passenger count * model coefficient (occupancy rate = (actual load - empty load) / (overcrowded load - empty load) * 100%; model coefficient is related to the specific compartment model and needs to be obtained in combination with the actual model).

Meanwhile, we use the YOLOv5 target detection algorithm to process images captured by cameras, detect the number of passengers in the compartments, and upload them to the on-board PIS. Finally, in the PIS, we perform weighted processing on the detected passenger counts from both methods to obtain compartment passenger density = (a * actual passenger count + b * passenger count in compartment) / effective standing and sitting area in compartment (where a and b are weighting parameters for the detection results of both methods, which are obtained according to the actual detection results).

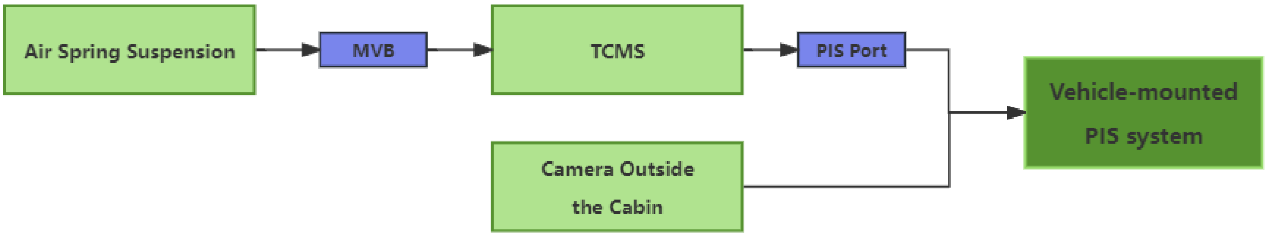

Figure 2. Data Acquisition and Processing Roadmap

For the compartments outside, considering the configuration cost and the relatively low requirements for cameras on the platform area height, we adopt a configuration of one camera for each corresponding platform door (5 doors for A-type compartments),as shown in Figure 3. The camera is placed parallel to the tracks, with its field of view covering the area in front of the 5 platform doors. After dividing the area, we use the YOLOv5 target detection algorithm to separately obtain the number of waiting passengers for each compartment outside. The passenger density outside the compartments is calculated as the number of waiting passengers outside each compartment / the corresponding platform waiting area (the corresponding platform waiting area depends on the compartment location and the design planning of the platform level at that station). We allocate weights based on the proportion of effective areas outside each compartment to the total effective area, and calculate the ideal passenger density outside each compartment by multiplying the sum by the weight.

Figure 3. Target Detection Examples on the Platform Level and Inside the Compartments

To better guide passengers by combining data from inside and outside the compartments, we introduce a variable called the compartment recommendation index and implement relevant calculations using PIS. The compartment recommendation index = (ideal passenger density outside the compartments + ideal passenger density inside the compartments) / (passenger density outside the compartments + passenger density inside the compartments). This index has a value of 1 as an ideal value. The larger the deviation from 1, the lower the evenness of passenger distribution. When the index is less than 1, we expect higher passenger volume; when it is greater than 1, we expect lower passenger volume. Therefore, we recommend that passengers wait at the corresponding platform door in front of the car with a higher index value.

Based on the above results, we can obtain real-time actual total passenger numbers in each compartment and use them to count the total number of passengers on board when trains leave stations at different times on the same day. We then generate an approximate table showing total passenger numbers for each station-time-compartment combination. By collecting a sufficient number of sampling data, we can analyze changes in passenger numbers on a daily, weekly, or other specific timeframes. According to relevant literature, there is a periodically changing trend, and we collect relevant data to create charts.

2.3. Intelligent Guidance

In terms of guidance, we designed the system based on the passengers' route to the train. Firstly, we connected the ticket machines' display screens to the on-board PIS system. Whenever a passenger swipes their ticket to enter the station, the display screen shows the car number with the highest compartment recommendation index. At the same time, we utilize the hanging intelligent on-platform screens and display the certain range of the compartment recommendation index through the on/off status of the indicator lights on the screens. By using multiple screens, we can achieve real-time information sharing. Secondly, we developed a related mini-program to integrate and provide information feedback to the WeChat mini-program for passenger guidance. This allows passengers to understand real-time conditions on the train and platform throughout their entire journey through the WeChat mini-program. They can also use the predictive reference in the mini-program to better plan their travel routes.

3. Results

3.1. Data analysis

We selected two weekday operating conditions of Shanghai Metro Line 5 as analysis objects and collected and calculated the arrival time differences for the same train and the total number of passengers in each car as reported by the corresponding railway bureau, as shown in Table 1 and 2. We then created tables to analyze and list the corresponding data. Based on the table data, we identified trends in actual arrival times compared to standard arrival times and selected each station as the horizontal axis and the calculated time difference as the vertical axis to create a curve for both weekdays. Similarly, we used station names as the horizontal axis and total passengers at each station as the vertical axis to create another curve for both weekdays, as shown in Figure 3 and Figure 4. From the curve's inflection points and trends, it can be seen that there is not a significant difference between the actual arrival time of the subway and the standard time for the same train on both weekdays. Additionally, there are similar patterns in the total number of passengers, including increasing trends and changes at key stations. Therefore, we can use arrival time as a sampling node to collect historical information on passenger load in each car and analyze its changing patterns to provide predictive information that can help passengers plan their travel in advance.

Table 1. Shanghai Metro Line 5 (Downstream) Station-Time-Total Passenger Count Information Table (Weekday 1)

Station	Standard Time	Actual Time	Subtraction/s	Total number of compartments
Minhang Development Zone	7: 36	7: 36: 23	23	89
Wenjing Road	7: 38	7: 38: 22	22	117
Hua Ning Road	7: 40	7: 40: 25	25	316
Jinping Road	7: 43	7: 43: 26	26	570
Dongchuan Road	7: 45	7: 45: 49	49	811
Jianchuan Road	7: 47	7: 47: 51	51	940
North Bridge	7: 49	7: 49: 50	50	1071
Zhuan Bridge	7: 53	7: 53: 46	46	1126
Yindu Road	7: 57	7: 57: 58	58	1250
Chunshen Road	8: 00	8: 00: 51	51	1298
Xinzhuang	8: 03	8: 03: 43	43	1298

Table 2. Shanghai Metro Line 5 (Downstream) Station-Time-Total Passenger Count Information Table (Weekday 2)

Station	Standard Time	Actual Time	Subtraction/s	Total number of compartments
Minhang Development Zone	7: 36	7: 36: 45	18	61
Wenjing Road	7: 38	7: 38: 16	16	90
Hua Ning Road	7: 40	7: 40: 20	20	280
Jinping Road	7: 43	7: 43: 24	24	600
Dongchuan Road	7: 45	7: 45: 45	45	760
Jianchuan Road	7: 47	7: 47: 49	49	880
North Bridge	7: 49	7: 49: 50	50	990
Zhuan Bridge	7: 53	7: 53: 43	43	1038
Yindu Road	7: 57	7: 57: 56	56	1360
Chunshen Road	8: 00	8: 00: 57	57	1388
Xinzhuang	8: 03	8: 03: 40	40	1376

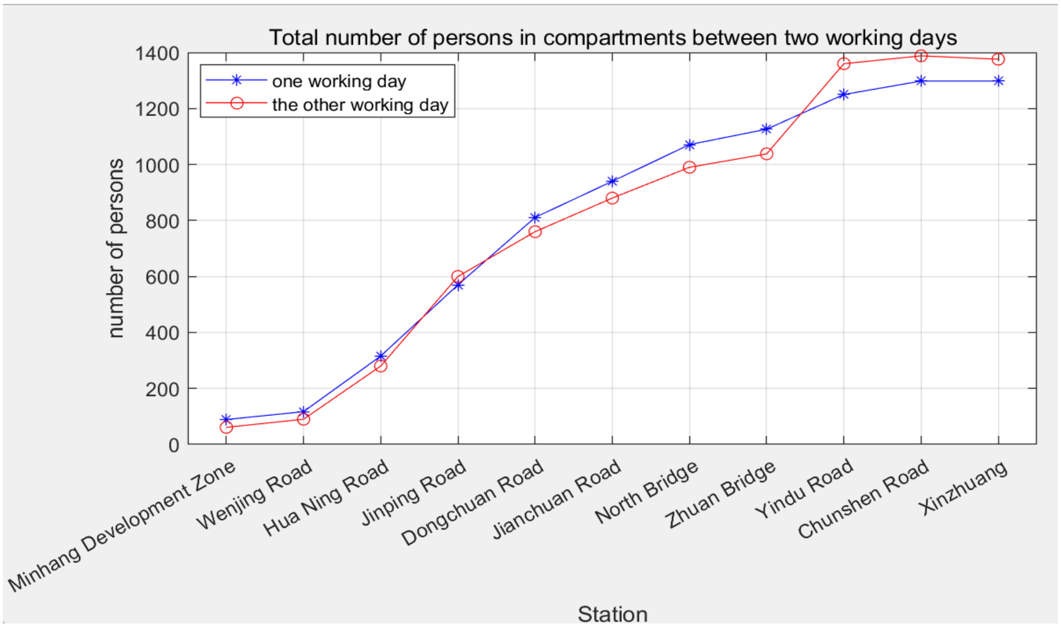

Figure 3. Change curve of the difference between the arrival time of Shanghai Metro Line 5 (downward) and the standard time on two working days.

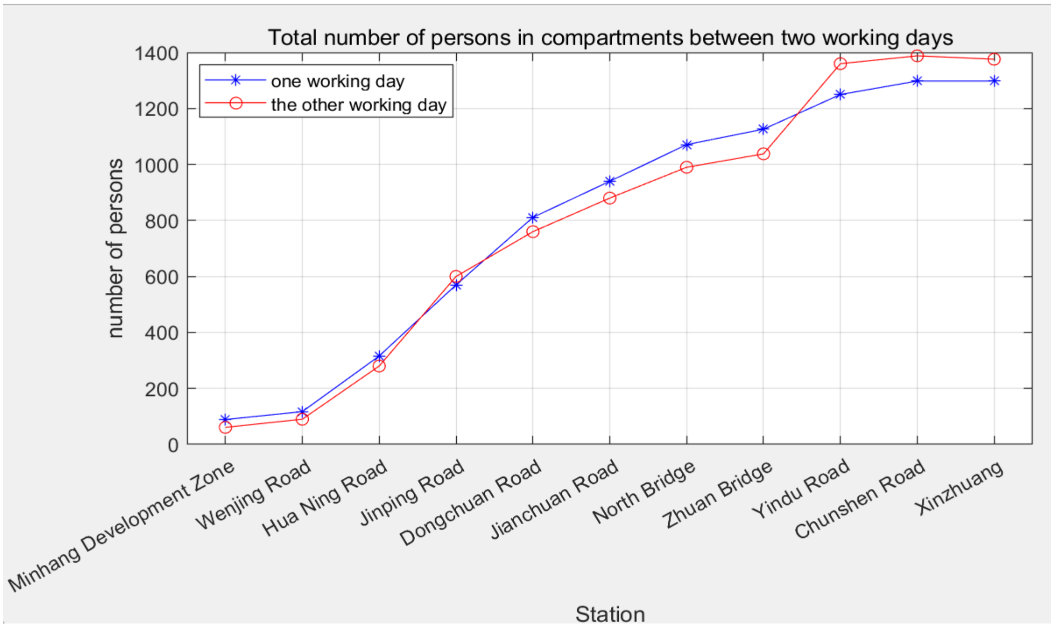

Figure 4. Change curve of the total number of people in the cars of Shanghai Metro Line 5 (downward) on two working days.

3.2. Intelligent Guidance

In terms of guidance, we designed the system based on the passengers' route to the train. The overall process is illustrated in Figure 5. Firstly, we connected the ticket machines' display screens to the on-board PIS system. Whenever a passenger swipes their ticket to enter the station, the display screen shows the car number with the highest compartment recommendation index. At the same time, we utilized the hanging intelligent on-platform screens, as shown in Figure 6, to display the different levels of congestion in each car using a varying number of human icons and color shading. We also displayed the recommended car index range through the on/off status of the indicator lights on the screens, allowing real-time information sharing through multiple screens.

Secondly, we developed a related mini-program to integrate and provide information feedback to the WeChat mini-program for passenger guidance, as shown in Figure 7. The program allows passengers to input their departure and destination stations, and the system determines the optimal travel route based on the congestion levels along the subway lines. Passengers can also view recommended entry directions, estimated arrival times, and predicted congestion levels on the app's interface to better plan their travel routes.

To visualize the congestion levels on the platform level and in each car, we used a graphical representation to show their two-dimensional bird's-eye view, with color shading indicating different levels of congestion. This allows passengers to easily visualize and understand the real-time conditions on the train and platform throughout their entire journey through the WeChat mini-program. They can also use the predictive reference in the mini-program to better plan their travel routes.

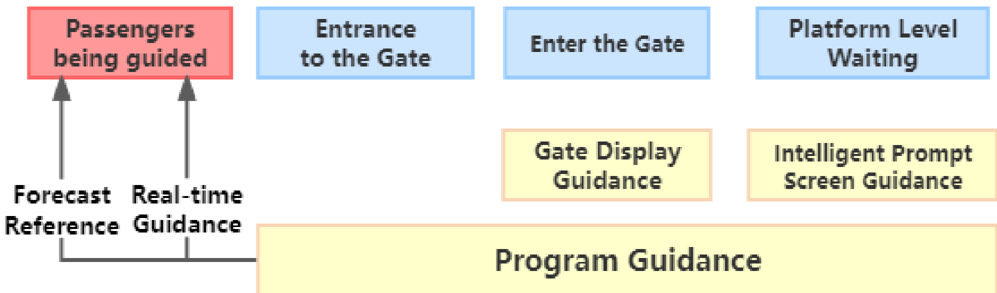

Figure 5. Smart Guidance Diagram

Figure 6. Intelligent Subway Information Screen

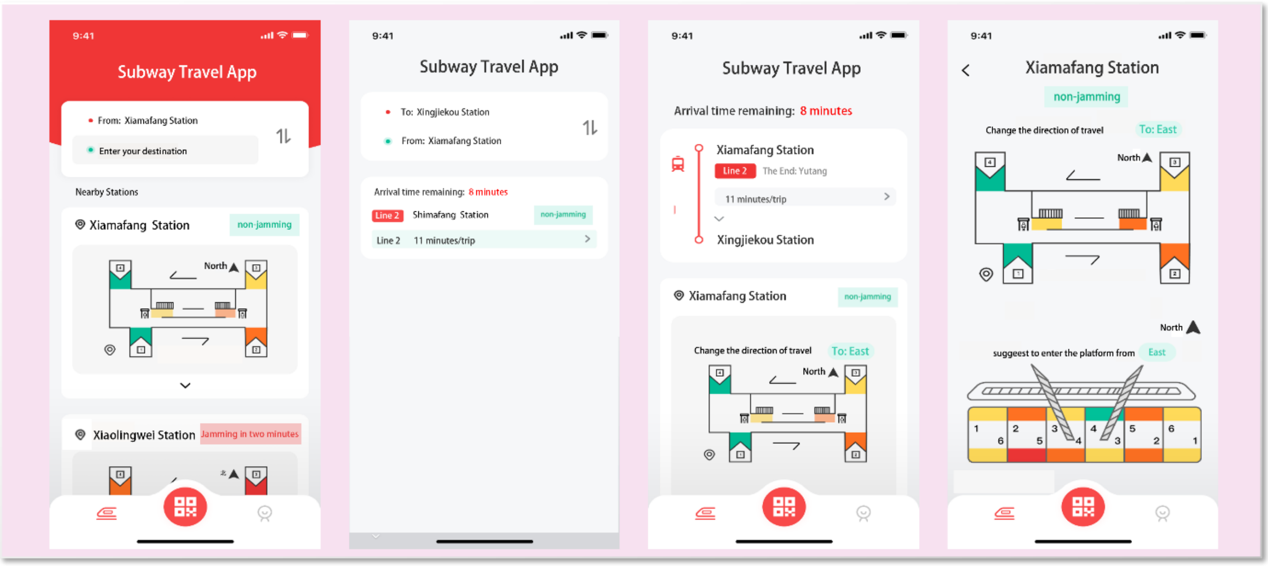

Figure 7. Subway Passenger Flow Guidance System Mini-Program

3.3. Innovation Analysis

Compared with previous passenger flow detection methods, the detection mode of "outside the train + inside the train" with multi-terminal input has higher reliability through data processing and fusion of the suspension system and camera, while utilizing the equipment of the subway itself, resulting in lower system costs.

By using the collected data as samples, the system can combine statistical methods and relevant algorithm models to achieve passenger flow prediction, providing effective data support for people's travel planning and the management of urban rail transit systems.

Using the relevant data processing results of the system, passengers are guided in real-time through the mini-program and travel routes. This guidance is more advantageous compared to other similar systems at home and abroad in terms of guiding effectiveness.

By combining the relevant data of the system with the original subway information system, data interconnection is formed, laying a foundation for the development of a more comprehensive next-generation subway information system and the construction of the future subway Internet of Things.

4. Conclusion

This research aims to analyze the passenger flow situation in the subway and guide passengers to improve their ride comfort. With the rapid development of the subway, more and more people choose the subway as their mode of transportation. Therefore, managing subway passenger flow is an important task. This work combines computer vision, train control and management systems, enabling urban subway operation systems to achieve digital and intelligent management. It optimizes the utilization of subway car space and implements efficient management of large passenger flow and precise guidance for passengers. It is of great significance in terms of subway passenger flow management and subway operation safety management.

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