Virtual Geographic Environment Based Coach Passenger Flow Forecasting

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Abstract—There are lacks of integrated analysis and visual display of multiple real-time dynamic traffic information. This research proposed a deep research and application examples on this basis which is conducted in virtual geographic environment. Currently, there are many kinds of traffic passenger flow forecasting models, and the common models include regression forecasting model and time series prediction model. The coach passenger flow shows strong regularity and stability without long-term change trend, so this research adopts regression forecasting model to forecast the coach passenger flow.

Keywords—WebVRGIS; Passenger Flow Forecasting; Virtual Geographical Environment; HCI

I. INTRODUCTION

That long-distance passenger flow refers to the passenger flow by long-distance coach. Long-distance passenger flow is the meaning of space areas, refers to the passenger flow of long distance travel, and the specific distance boundary is uncertain, which is just the agreed within the boundary. For the transport sectors located in major cities, those of 10km above are called long distance; and for those located in small towns or rural areas, 30-50km above is also known as long distance.

As an important part of urban transportation system, the urban passenger terminal is an important joint-point for urban internal traffic and external traffic (42). It integrates transportation routes including many highways and urban roads, multiple means of transportation, has necessary service function and control equipments, and also has the comprehensive infrastructure which provides places for urban internal and external traffic transition and integrates with traffic, commerce, and leisure. The urban passenger terminal often gives a comprehensive consideration on urban external highway passenger transportation and urban public traffic (track, bus, and taxi, etc.), private transportation, as well as railway, aviation, and other external passenger transportation to establish an organic passenger transportation and bring important benefits to urban development (28).

With evolution and outward extension of urban spatial structure, the lines of public transportation are continuously expanded and extended; meanwhile, the means of transportation also develop in a diversified way. The reasonable planning and design and efficient management on urban passenger terminal are the important link to improve urban public transportation system, solve residents transfer, and improve the service quality and operation benefits of public transportation (8).

Nowadays, there is an increasing interest in creating Virtual Reality Geographical Information System (VRGIS), which can obtain the landscape geospatial data dynamically, as well as perform rich visual 3D analysis, calculations, managements based on Geographical Information System (GIS) data. Accordingly, ‘3-D modes’ has been proved as a faster decision making tool with fewer errors (29). A parallel trend, the utilize of bigdata is becoming a hot research topic rapidly recently (1). GIS data has several characteristics, such as large scale, diverse predictable and real-time, which falls in the range of definition of Big Data (3). Besides, to improve the accuracy of modeling, the city planning has an increasingly high demand for the realistic display of VR system, however this will inevitably lead to the growth of the volume of data. Virtual scene from a single building to the city scale is also resulting in the increased amount of data. Beside spatial data integration, new user interfaces for geo-databases is also expected (2). Therefore, the management and development of city big data using virtual reality technology is a promising and inspiring approach.

II. SYSTEM

Currently, there are lacks of integrated analysis and visual display of multiple real-time dynamic traffic information, and also lacks of deep research and application examples on this basis. This research takes Shenzhen Futian comprehensive transportation junction as the case, and makes use of continuous multiple real-time dynamic traffic information (including taxi and floating car data, card swiping data of public transport, and long-distance passenger traffic information, etc.) to carry out monitoring and analysis on spatial and temporal distribution of passenger flow under different means of transportation and service capacity of junction from multi-dimensional space-time perspectives such as different period and special period.

In this work, we utilize 3D Shenzhen as a convincing case to present WebVRGIS (24), which is based on WebVR render engine (27). Shenzhen is a thirty-years new city, however, it has the highest population density in China, which reaches 7785 people per square kilometer (2013). It causes some embarrassments to the city information management (16). While virtual environments have proven to significantly improve public understanding of 3D planning data (6). To share
of information resources of all departments and the dynamic tracking for the geospatial information of population and companies, by construction an integrated information platform of social services. The use of virtual reality as visual means changed the traditional image of the city [7].

The geographic statistical analysis is to assist management decision-making and conduct data analysis. The 2D statistical analysis visualization is overlapped with a white background on 3D virtual reality environment, since it’s more intuitive and a cognitively less demanding display system, which lessens the cognitive workload of the user [29]. The innovation points of this work include, real-time dynamic comprehensive transportation data mining, three-dimensional GIS analysis and release as for transportation junction; Carry out comprehensive assessment on service scope of junction through analyzing long-term dynamic traffic data; Carry out comprehensive analysis on actual travel time and then comprehensive assessment on service capacity of public transportation (accessibility and reliability).

III. COACH PASSENGER FLOW FORECASTING

Shenzhen Futian comprehensive transfer junction is the first comprehensive transportation junction with car harbor function in Shenzhen City; the usable areas for long-distance passenger transportation, public transportation, and taxis are 50,000m², 29,000m², and 2,310m² respectively. It is planned that the daily transfer volume of bus and metro is 250,000 person-times; the number of urban bus lines is 30; the departure volume is 70,000 person-times, and the peak is 100,000 person-times; the number of urban bus lines is 30; the average daily passenger transfer capacity is 350,000 person-times.

Futian Transportation Hub Station is the integrated hub of the provincial and inter-provincial long-distance passenger transportation and the transit passenger distribution for Luohu Huanggang two major ports. The departure long-distance lines has covered 13 provinces as Guangdong, Fujian, Zhejiang, Shanghai, Jiangxi, Jiangsu, Hainan, Shandong, Hong Kong SAR and 21 cities and counties within the province such as Guangzhou, Zhongshan, Zuhai, Meizhou, Shanwei and others, with the average daily numbers of run about 720. The following two figures show the inter-city and inter-province service range of Futian Transportation Hub long-distance passenger station; it undertakes the long-distance passenger task of Shenzhen to most areas inside and outside the province, and the service capabilities can basically meet the long distance travel needs of the people of Shenzhen.

There are many kinds of traffic passenger flow forecasting models, and the common models include regression forecasting model and time series prediction model [14, 17]. In the observation period of this research, the coach passenger flow shows strong regularity and stability without long-term change trend; therefore, this research adopts regression forecasting model to forecast the coach passenger flow. While we forecast the passenger flow, there may be many independent variables which have influence on the result of dependent variable (passenger flow), but the actual situation is that it is only allowed to find out several independent variables which have important influence on the dependent variable and ignore other independent variables. In specific application, it is required to screen out some main independent variables which cause influence on the result of dependent variable for research and analysis, and the analysis of variance theory is applied in this screen-out process.

The analysis of variance is a kind of statistical analysis method in which the analysis and processing is made for significance of difference in mean values of some sets of experimental data. The passenger flow samples are different in different periods in each day; therefore, it is able to know that the date and period are 2 variables which influence passenger flow; through dual-factor analysis of variance, it is able to determine whether these two factors are important factors which influence passenger flow and then regard them as input variables in later forecasting analysis if so.

Due to difference in inbound and outbound coach passenger flow, this research carries out forecasting modeling and model validation on inbound and outbound passenger flow respectively.

We have got the numbers of long-distance passenger run of Futian long-distance passenger station from July to October; the data information includes long-distance coach license plate number, starting location and time of departure, terminal, distance, fare, long-distance type, number of passengers, rated number of passengers and other information, we figured out the number of different types of long-distance passenger every day.

Through the statistics for four months of long-distance passenger flow in the long-distance passenger station, it was found that the long-distance passenger flow was generally showing a periodic law, namely the passenger flow trough appears from Monday to Thursday, and passenger flow peak appears on Friday and Saturday, suggesting Futian transportation hub station serves mainly for local people travel; and it has been proved in the later mid-Autumn Festival and National Day Golden week holiday, and the holiday passenger flow peak appeared on the day before holiday, while no passenger flow peak appeared in end of holiday, indicating Futian transportation hub station mainly undertakes local people travel, rather than nonlocal passenger flow, business passenger travel.

Through the passenger whereabouts statistics, it was found the passenger whereabouts of Futian long-distance passenger station is mainly the cities inside Guangdong province, and meanwhile there is a basic feature for every day long-distance flow: From Monday to Thursday, two peaks appeared every day, respectively from 9:00 -10:00am and 5:00 -6:00pm, and the number of morning peak is larger than the evening peak;
the same two peaks appeared on Friday to Sunday, but the number of evening peak is larger than morning peak, indicating that the major travel purpose of passenger crowd in Futian long-distance passenger station is relatives-visiting flow and business trip flow within the province.

The shift of long-distance transportation is fixed, so its passenger flow has great relevance to people activity pattern; due to the people activity pattern is a weekly cycle, the passengers for tourism and relatives-visiting of long-distance travel mostly select weekends, and for business travel, they select weekdays; so long-distance all day passenger flow with different lines indicates regular changes within a week. So we chose a weekly cycle to conduct analysis of the changes in long-distance passenger flow, and predict the long-distance passenger flow within a week.

We used regression prediction method to predict the long-distance passenger flow changes of Futian transportation hub. We have now mastered the passenger flow data of Futian transportation hub long-distance station in July, August, September and October, but due to the impact of Universiade in August, Mid-Autumn Festival in September, National Day holiday in October, we chose the complete data of July as training sample to predict the passenger flow in August.

For outbound traffic, predictive modeling and model validation contain the following steps:

1. Outbound traffics of four weeks with normal data at each time period in July are selected as modeling samples.

2. All modeling samples are of repeatable double factor variance analysis in terms of day of week and time period, and results are as follows:

   According to Table I, the sample group has  $p - value = 3.62E-25 > 0.05$, and thus its traffics have significant difference, i.e. outbound traffics at different time periods from Monday to Sunday have significant difference; traffic of each time period within the group $p - value > 0.05$, and so there is also significant difference among outbound traffics at all time periods within the group. Thus, both day of week and time period can be considered as influencing factors of outbound traffic.

3. To further test differences in traffic changes within a week, this study carries out repeatedly combined double factor variance analysis and finds: significant difference in outbound traffics at time period from Monday to Sunday.

4. Based on the above analysis, regression models are established with respect to outbound traffics at different time periods from Monday to Sunday. This study divides time period into 16 parts, and makes time period variable become a categorical independent variable with 16 types, and thus 15 dependent variables are generated. These four regression models are expressed as follows:

   (1) Outbound traffics on Monday: $Flow_{Mon} = a_1t_1 + a_2t_2 + a_3t_3 + a_4t_4 + a_5t_5 + a_6t_6 + a_7t_7 + a_8$

   (2) Outbound traffics on Tuesday: $Flow_{Tue} = b_1t_1 + b_2t_2 + b_3t_3 + b_4t_4 + b_5t_5 + b_6t_6 + b_7t_7 + b_8$

   (3) Outbound traffics on Wednesday: $Flow_{Wed} = c_1t_1 + c_2t_2 + c_3t_3 + c_4t_4 + c_5t_5 + c_6t_6 + c_7t_7 + c_8$

   (4) Outbound traffics on Thursday: $Flow_{Thu} = d_1t_1 + d_2t_2 + d_3t_3 + d_4t_4 + d_5t_5 + d_6t_6 + d_7t_7 + d_8$

   (2) Outbound traffics on Friday: $Flow_{Fri} = e_1t_1 + e_2t_2 + e_3t_3 + e_4t_4 + e_5t_5 + e_6t_6 + e_7t_7 + e_8$

   (2) Outbound traffics on Saturday: $Flow_{Sat} = f_1t_1 + f_2t_2 + f_3t_3 + f_4t_4 + f_5t_5 + f_6t_6 + f_7t_7 + f_8$

   (2) Outbound traffics on Sunday: $Flow_{Sun} = g_1t_1 + g_2t_2 + g_3t_3 + g_4t_4 + g_5t_5 + g_6t_6 + g_7t_7 + g_8$

   Where, $t_1, t_2, ... t_{15}$ are dependent variables of 16 time periods. When $t_1 = t_2 = t_3 = ... = t_{15} = 0$, dependent variables denote outbound traffics of the first time period; when $t_2 = t_1 = t_3 = ... = t_{15} = 0$, dependent variables denote outbound traffics of the second time period; reason by analogy; when $t_1 = t_2 = t_3 = ... = t_{15} = 0$, dependent variables denote outbound traffics of the eighth time period. $a_i, b_i, c_i, d_i, e_i, f_i, g_i$ are independent variable parameters and constant terms of these seven models respectively.

5. By modeling with sample data in Table II results of predictive modeling of outbound traffics at time period from Monday to Thursday are as follows:

   According to Table III predictive model of outbound traffics on Monday has Adjusted R Square=72.35%, i.e. this model can explain 72.35% of sample data; the entire model has statistical significance at level $\alpha = 0.05$; all parameters of the model have p-value smaller than 0.05, which means that all of these parameters have statistical significance at level $\alpha = 0.05$.

   Similarly, modeling results of outbound traffics at time periods from Tuesday to Sunday are as follows: predictive model of outbound traffics on Tuesday has Adjusted R Square=81.7% and statistical significance at level $\alpha = 0.05$, and all of its
parameters except $p-value - b_1 = 0.18$ have $p$-value smaller than 0.05;

predictive model of outbound traffic on Wednesday has Adjusted R Square $= 77.3\%$ and statistical significance at level $\alpha = 0.05$, and all of its parameters except $p-value - c_1 = 0.08$ have $p$-value smaller than 0.05;

predictive model of outbound traffic on Thursday has Adjusted R Square $= 74.2\%$ and statistical significance at level $\alpha = 0.05$, and all of its parameters except $p-value - d_1 = 0.21$ have $p$-value smaller than 0.05;

predictive model of outbound traffic on Friday has Adjusted R Square $= 77.6\%$ and statistical significance at level $\alpha = 0.05$, and all of its parameters except $p-value - e_1 = 0.056$ have $p$-value smaller than 0.05;

predictive model of outbound traffic on Saturday has Adjusted R Square $= 71.1\%$ and statistical significance at level $\alpha = 0.05$, and all of its parameters except $p-value - f_1 = 0.38$ and $p-value - f_1 = 0.09$ have $p$-value smaller than 0.05;

predictive model of outbound traffic on Sunday has Adjusted R Square $= 54.5\%$ and statistical significance at level $\alpha = 0.05$, and all of its parameters except $p-value - g_1 = 0.61$ and $p-value - g_1 = 0.18$ have $p$-value smaller than 0.05;

To sum up, predictive models of outbound traffic at four time periods from Monday to Sunday have good imitative effects of sample data and are expressed as follows:

(1) Outbound traffic on Monday: $Flow_{-}Out_{-}Mon = -8.25t_1 + 270.58t_2 + 544.33t_3 + 607.00t_4 + 425.00t_5 + 284.83t_6 + 295.42t_7 + 336.50t_8 + 305.42t_9 + 326.42t_{10} + 336.92t_{11} + 309.08t_{12} + 243.08t_{13} + 145.58t_{14} + 90.42t_{15} + 66.50$

(2) Outbound traffic on Tuesday: $Flow_{-}Out_{-}Tue = -38.25t_1 + 188.50t_2 + 450.83t_3 + 499.75t_4 + 343.55t_5 + 245.67t_6 + 269.92t_7 + 280.17t_8 + 304.33t_9 + 273.25t_{10} + 355.50t_{11} + 286.17t_{12} + 258.33t_{13} + 119.42t_{14} + 96.67t_{15} + 70.83$

(3) Outbound traffic on Wednesday: $Flow_{-}Out_{-}Wed = -58.83t_1 + 177.67t_2 + 428.17t_3 + 524.92t_4 + 350.75t_5 + 261.67t_6 + 251.33t_7 + 286.83t_8 + 298.08t_9 + 301.92t_{10} + 363.33t_{11} + 308.33t_{12} + 281.51t_{13} + 148.42t_{14} + 93.92t_{15} + 87.08$

(4) Outbound traffic on Thursday: $Flow_{-}Out_{-}Thu = -43.92t_1 + 198.33t_2 + 451.92t_3 + 479.83t_4 + 352.67t_5 + 235.50t_6 + 248.75t_7 + 305.17t_8 + 305.83t_9 + 284.00t_{10} + 254.08t_{11} + 247.25t_{12} + 111.75t_{13} + 106.58t_{14} + 67.42t_{15} + 71.33$

(5) Outbound traffic on Friday: $Flow_{-}Out_{-}Fri = -67.42t_1 + 145.67t_2 + 408.50t_3 + 444.67t_4 + 339.50t_5 + 227.42t_6 + 262.42t_7 + 326.25t_8 + 348.08t_9 + 380.92t_{10} + 441.25t_{11} + 423.33t_{12} + 469.08t_{13} + 340.67t_{14} + 187.08t_{15} + 101.67$

(6) Outbound traffic on Saturday: $Flow_{-}Out_{-}Sat = -42.00t_1 + 228.42t_2 + 570.50t_3 + 593.33t_4 + 416.92t_5 + 321.17t_6 + 287.33t_7 + 382.08t_8 + 397.33t_9 + 398.42t_{10} + 415.83t_{11} + 349.00t_{12} + 307.58t_{13} + 143.42t_{14} + 80.00t_{15} + 70.33$

(7) Outbound traffic on Sunday: $Flow_{-}Out_{-}Sun = -34.75 + 220.92t_2 + 552.83t_3 + 530.00t_4 + 383.50t_5 + 270.50t_6 + 280.58t_7 + 347.00t_8 + 382.17t_9 + 459.75t_{10} + 546.83t_{11} + 4522.25t_{12} + 457.17t_{13} + 281.83t_{14} + 159.08t_{15} + 63.25$

Outbound traffic at time periods with normal data within a week of August are selected as model validation samples, and such data includes:

Validate prediction formula with validation samples and calculate the accuracy of each independent predicted value with absolute percentage error (APE): $APE = 100\times \frac{|predicted value - actual value|}{actual value}$. Validation results are as Table V.

As can be known from Table V, the mean error of predictive model of subway outbound traffic at different time periods is 7.88%, and thus this model has good validation effects.

IV. GRAPHIC USER INTERFACE

Geographic human-computer interaction (GeoHCI) is becoming a hot-topic in CHI community [11]. The research of urban interaction on ubiquitous context [10] [30] [33] [32] have inspired our work. With a 3D earth model as the browser, this system is loaded with all 3D model data and the 3D visualization analysis result. By selecting the house inquiry, it is possible to find out the information of the address and owner, and to locate the house in the 3D scene. 3D roaming function can not only conduct soaring top view observation above the virtual community [19] [49], but can also observe the detailed layout near the street, and further enter the building to observe the internal building structure. The system also support ocean data visualization [31] [23] [26], which has potential to extend to ocean traffic forecasting system. Some novel interaction approaches are considered to integrate in our future work [18] [22] [21]. The separated core technology of our system also has potential to be applied into other fields, such as climate [44], biology [54], clinical assist [20]. Some
novel interaction approaches are considered to be integrated in our future work [18] [22] [21]. The new network data management algorithm [35] [37] [13], spatiotemporal database model [41], smart grid system [8] [4], neural network [12], data classification method [9], pedestrian detector technology [38] and stereoscopic 3D visualization approach [40] will be also considered.

V. Conclusion

This research takes Futian transportation junction as research objective, and finds the spatial and temporal distribution rules of passenger flow and service scope of junction of all means of transportation via carrying out statistical analysis on long-term daily passenger flow and daily time-phased passenger flow of metro, urban bus, taxi, and long-distance passenger transportation in Futian transportation junction according to the data such as Shenzhen TransCard data, taxi and floating car data, and long-distance passenger transportation data, as well as carries out a short-term forecasting on various kinds of passenger flow. Furthermore, the key analysis is made on abnormal traffic condition in the period of Universiade and National Day holidays. It is found via research that Futian transportation junction currently has good operation condition, and the passenger flow of various means of transportation doesn’t reach the designed upper limit of passenger flow even in peak of passenger flow in holidays, without obvious transfer and congestion. Within short term, various means of transportation have stable passenger flow, and the time-phased passenger prediction model is reliable. The main service group of junction is distributed in west of Nanshan District and Futian District, as well as west of Luohu District and the scope which radiates about 9km based on the junction.

Then, the travel time is used as index to carry out a series of research and analysis on accessibility of public transportation and taxis of Futian transportation junction. It is found via research that the junction based on metro and taxis has good accessibility, and the junction based on urban bus has poor accessibility at the peak in morning and evening, and they can supplement each other to certain degree. Then, the actual fluctuation of travel time is taken as index to carry out analysis on reliability of junction network based on metro and taxis respectively. It is found that the overall reliability of metro is high, and there is only poor reliability at the peak travel time at Huqiang North station and Baoan center station; the reliability based on taxis declines with distance; as for some business centers and hot working area, there is poor reliability at the peak travel time; as for places with strong entertainment such as Overseas Chinese Town and Honey Lake, there is a poor reliability at travel time in holidays.

The 3D Shenzhen case proves 3D city visualization and analysis platform is a useful tool for the social service agencies and citizens for browsing and analyzing city big data directly, and is agreed upon as being both immediately useful and generally extensible for future applications [23] [15].

VI. Future Work

Through long-term monitoring and analysis, the long-term transportation junction demand model, and long-term passenger flow forecasting and early-warning model are established under the condition of combing with economic development and urban planning. The analysis is made on population travel behavior, taxi route, degree of influence on public bus, and road travelling speed under special weather conditions (such as rainstorm, typhoon, and heavy fog, etc.) The deeper data mining is made, such as emergency evacuation aided decision support, monitoring and forecasting on large-scale group event, assisting crowd and vehicle evacuation under emergency.

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