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# Visual Exploration of Spatial-Temporal Traffic Congestion Patterns Using Floating Car Data

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# Abstract

Nowadays, traffic congestion becomes a big concern in transportation management. There are many negative effects caused by traffic congestion, such as the increasing of travel time, air pollution and carbon dioxide (CO2) emissions. Therefore, this problem need to be solved so that efficiency in the road management could be achieved. As mostly traffic congestions are recurrent events which happened in particular road section during particular time of the day where the demand of road space exceeds supply, find traffic congestion pattern by answering questions on when, where and how long the traffic congestion usually occur could be one of the effective solutions.

The main objective of the study is to do visual exploration of spatial-temporal traffic congestion based on Floating Car Data. Floating Car Data is chosen because this data acquisition method provides accurate data and is less cost than the other methods. Visual analytics methods are used to utilize spatio-temporal visualization of traffic data derived from FCD, to find traffic congestion patterns to answer questions about the conditions of traffic congestion, when, where and how long the traffic congestion is.

The visualization method that has been chosen are density mapping, visualization on the road network and three dimentional spatio-temporal data visualization. Density mapping can easily illustrate density and expose large patterns and fine features from a combined density fields using different radius. Visualizing traffic congestion based on the road network will bring a betterand intuitive understanding about the spatial dimension of the traffic congestion. Three dimentional spatio-temporal data visualization, integrating animation technique is useful to visualize data which represent changes in both temporal and spatial dimensions.

This study result reveals the spatio-temporal distribution of traffic congestion in Shanghai and could be used as a basis for traffic monitoring and estimation. The result shows that the peak of traffic congestion in Shanghai are from 07:00 AM to 09:00 AM in the morning and from 17:00 PM to 18:00 PM in the evening. And most traffic congestions last for about 15 minutes until 25 minutes. The most congested road sections are the expressway/elevated road and the main arterial roads heading to the city center area.

**Keywords**: Visual Analytics, Traffic Congestion, Pattern, FCD, Shanghai

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# List of Abbreviations

| | |
|---|---|
| 3D | Three Dimention |
| ANPR | Automated Number Plate Recognition |
| CCTV | Close Circuit Television |
| CEBR | Centre for Economics and Business Research |
| $CO^2$ | Carbon Dioxide |
| ECMT | European Conference of Ministers of Transport |
| FCD | Floating Car Data |
| FCE | Floating Car Evaluator |
| FCMS | Freeway Congestion Monitoring System |
| FHWA | Federal High Way Administration |
| GPS | Global Positioning System |
| GRA | Grande Raccordo Anulare |
| HCM | Highway Capacity Manual |
| ITS | Intelligent Transportation Systems |
| KDD | Knowledge Discovery and Data Mining |
| KDE | Kernel density estimation |
| LOS | Level of Service |
| OECD | Organisation for Economic Co-operation and Development |
| TIME | Transport Information Monitoring Environment |
| veh | Vehicle per hour |
| WFRC | Wasatch Front Regional Council |

# 1. INTRODUCTION

Rapid urbanization and economic growth caused by rapid growth of population in big cities in developing or even developed country actuates rapid traffic movement of people and goods from one place to another in a certain time. This development brings up a problem for the transportation system as the number of vehicles in the city is increasing annually which then cause traffic congestion in the city area. But the high volume of vehicles is not the only cause of the traffic congestion. Inadequate infrastructure, the imbalance distribution of developing area and irregularity of traffic management are also the main causes of the traffic congestion.

Traffic congestion has many effects. It increases travel time, air pollution, carbon dioxide (CO2) emissions and fuel. In 2013, INRIX collaborated with the Centre for Economics and Business Research (CEBR) delivered a report of the environmental and economic impact of congestion [1]. The result was a shocking, as traffic congestion cost the US economy $124 billion. And if there are no changes to a better traffic management this cost is expected to increase 50 percent to $186 billion by 2030. Air pollution and stressed out for stuck in traffic jam for a long time also could make a health problem for the drivers. The carbon particles from the smoke not only could cause a heart disease, cancer and respiratory ailments, but also may injure brain cells. TomTom in 2014 released a report that drivers in China lose nine working days per year due to traffic [2].

With so many negative effects that caused by traffic congestion**,** this problem needs to be solved so that efficiency in the road management could be achieve. Some people might think that building new road segments as the solution, but it is not absolutely the right answer for this problem. One of the effective solution that can be used is by finding traffic congestion patterns which will answer the question about when, where and how long the traffic congestion usually occur as mostly traffic congestions are recurrent events which happened in particular road sections during particular time of the day where the demand of road space exceeds supply. This solution will also help traffic management to find an effective solution to reduce traffic congestion in certain roads and also for monitoring and estimating traffic congestion.

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[1] *http://www.inrix.com/economic-environment-cost-congestion/*
[2] *http://www.tomtom.com/en_gb/trafficindex/*

However, for the analysis of traffic congestion patterns, accurate traffic data are needed. In recent years, the Intelligent Transportation Systems (ITS) term has become a big issues in the transportation management, especially in term of traffic monitoring systems by using traffic information data which derived from the traffic sensors . ITS is built with hope to bring innovation to improve transportation systems so that transportation problem such as traffic congestion could be solved. It deals with data information and communication technology in vehicles, between vehicles (e.g. car-to-car), and between vehicles and fixed location (e.g. car-to-infrastructure) that could be used to provide road information to guide transportation systems users and traffic monitoring. There are many technologies that have been developed to provide traffic data in ITS. The conventional and most common method is by using sensors, such as inductive loops. An inductive-loop detector senses the presence of a conductive metal object by inducing currents in the object, which reduces the loop inductance. Inductive-loop detectors are installed in the roadway surface. This sensor gathers traffic information from vehicles which pass the sensor. Therefore this information has a big limitation as it could only provide information traffic estimation in a certain road segment which could not be an accurate representation for all road segments. Another limitations is that these sensors are quite expensive and need to be placed on the road which prone to be broken because of heavy vehicles, short lifetime. In addition, for a long road segment, the sensors need to be place in several places in a certain interval to maintain an accurate measurement (Jain, Sharma and Subramanian, 2012).

Another method that can be used to gather traffic information is by using CCTV camera. This method used to monitor real-time-traffic by utilizing CCTV camera images for measuring density of the vehicles. The advantage of using this method is the installation of cameras does not involve breaking up pavement, which is a necessity for installing ground sensors. However this method also has some disadvantages, such as low camera resolution resulting in highly noisy images, traffic camera's limited field of view and light illumination from multiple reflecting sources distorting vehicle classification capabilities.

With the development of the Global Positioning System (GPS) technology, a novel technology was developed which called Floating Car Data (FCD). FCD is a method to gather road information based on the exchange of information between a fleet of floating cars traveling on a road network and a central data system (Fabritiis, Ragona and Valenti, 2008). Cars which equipped with GPS receiver act as agents to gather information about traffic condition. This method provides a network-wide, accurate and real time information, which is less cost and constantly accessible which make this method gain popularity to provide data for traffic management system.

The data provided by different sensors are spatio–temporal data which contain both the spatial locations of the vehicles and the time recorded. By collecting and processing this kind of data, traffic information, in this case traffic congestion, could be analyzed in different period of time. Therefore identification of traffic congestion for different time intervals could be done and the patterns of the traffic congestion could be explore by comparing the traffic congestion events for each period of time to answer and help solving the traffic congestion problems.

## 1.1 Related Works

Several research works have been investigated related to the identification of traffic congestion. Wang, et al (2002) proposed an approach by using a measurements from single-loop detectors produces traffic congestion information based on estimated speeds for Freeway. This procedure is divided into three steps: loop data pre-processing, traffic speed estimation and congestion detection. They also built an automate procedure called Freeway Congestion Monitoring System (FCMS) which performed well under both congested and un-congested conditions. The results from this study are this approach could calculate congestion onset, dissipation and duration which are quite accurate.

Bacon, et al (2008) developed a project called TIME (Transport Information Monitoring Environment) project to investigate real-time road traffic data for congestion evaluation. They were using many sensors to gather information to determine the state of the road network such as static sensors (inductive loops at junctions, infra-red counting) and mobile sensors (bus probe). They believe that combining many data from different sensors will give a whole and better picture of traffic situation. They estimated the congestion by calculating the travel time of the buses from one station to another station which will be different depending on the situation. Travel time on school days take longer than travel time on non-school days, and when an accident happens on the road, the travel will also take a longer time. They also concluded that public transport data in this case buses probe is a really a great source of data because its minimum cost and vast coverage in terms of space and time.

Hong-Li Zeng, et al (2009) studied congestion patterns of traffic in Nanjing city by using dual graph to represent the Nanjing city map on which they implement and stimulate the traffic model with two important features: navigation and queuing. The model adopted the idea of the traffic of information on the Internet, where information travel to a specified address being navigated and are queuing at nodes along their paths. The dual graph was chosen because it highlights certain topological feature of the city road structure and their contribution in the spatio-temporal congestion patterns. Then they analyze the load on nodes and edges to reveal the congestion patterns and map it back to the geographical space. The traffic patterns could also be obtained by analyzing the eigenvalue spectrum of the network.

Wei Zhang, et al (2012) presented a model and algorithms for traffic congestion evaluation and optimal traffic light control based on wireless sensor networks. They introduced the congestion factor based on traffic data and the principle of traffic congestion parameter to evaluate the degree of traffic congestion along the road segments and to predict the subcritical state of traffic jams. Traffic congestion model named Jamitons and LWR model were used to gather information about traffic flow density and speed to evaluate traffic congestion. They were using *Mobile Century* dataset and working on VISSIM platform. The result of this study are algorithms to calculate congestion and its influence on future traffic flow, in this case in the intersection road, to help traffic control system so that average delay and maximum queue length at the intersection could be reduced.

Fusco and Colombaroni (2013) presented an integrated method for the short-term prediction of road traffic conditions. They were using fusion data from inductive loop monitoring and RFID detectors in 223 km long stretch motorway in Italy which then are processed by using some methods such as Artificial Neural Network, automatic incident detection and road traffic network model. As the results, time-series models provide quick and sufficiently accurate short-term predictions when variation of traffic is mainly caused by random disturbance. While traffic simulation is necessary for accidents or other anomalous traffic pattern.

## 1.2. Research Goals

This goals of this study is to do a spatio-temporal visual exploration of traffic congestion patterns which is derived from Floating Car Data (FCD) in some part of Shanghai city. This study wants to try to answer the questions about traffic congestion pattern from the analysis, such as how the traffic congestion level in Shanghai city based on the Floating Car Data (FCD), in which part of the city that the traffic congestion is most likely occur in which time period and how long the traffic congestion is in the bottleneck area or in the congested road segment.

# 2. METHODOLOGICAL FRAMEWORK AND STATE OF THE ART OF TRAFFIC CONGESTION ANALYSIS BASED ON FLOATING CAR DATA

This chapter reviews some basic concepts that will be used as basic knowledge for further analysis in the next chapters. This chapter is divided into four sections, the first section explains about the basic concept of traffic congestion including some formulas to describe how traffic congestion could be classified. The second section is about the basic concept of Floating Car Data (FCD) and how it can be used as a data source for traffic monitoring. Third section is about the basic theories about visual analytics that could be used for spatio-temporal data analysis. The fourth section will discuss some literature review about traffic congestion monitoring and analysis of FCD data.

## 2.1. Concept of Traffic Congestion

Traffic congestion actually does not have an exact and broadly accepted definition because traffic congestion is a physical phenomenon relating to the manner in which vehicles impede each other's progression as demand for limited road space approaches full capacity and also a relative phenomenon relating to user expectation *vis-à-vis* road system performance (OECD/ECMT, 2004). Basically traffic congestion could be define as a situation in which demand for road space exceeds supply or traffic volume exceeds road capacity. By the type, traffic congestion could be classified as recurrent traffic congestion which happened in particular road section during particular time of the day where the demand of road space exceeds supply and non-recurrent traffic congestion which happened because of special or random occasions such as road construction or accidents that makes a temporary increase of demand or reduce the road capacity.

Based on Federal Highway Administration (2005), there are seven causes of traffic congestion, which are physical bottlenecks, traffic incidents, work zone, bad weather, poor signal timing, special events and fluctuations in normal traffic. From the percentage of the causes of traffic congestions, physical bottlenecks, traffic incidents and bad weather are the main causes of traffic congestions. Every cause has a different level of frequency, therefore traffic congestion pattern or type could change or develop from time to time.

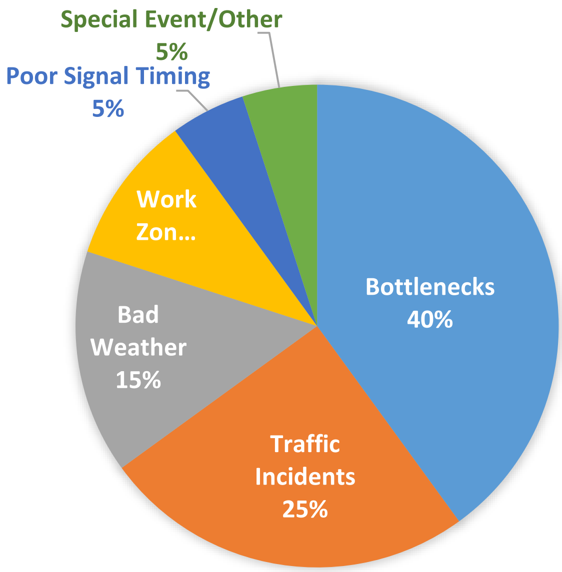


**Figure 2.1.** Percentage of Traffic Congestion Causes
Source: Federal Highway Administration (2005)

An understanding in traffic flow theory is a necessity to understand and analyze traffic congestion. Based on traffic flow parameters such as time headway, flow, time-space projectory, speed, distance headway and density, there are two types of traffic models:

- Microscopic flow model, where vehicles are treated as individual units and will be given a simple rule to follow to see what kind of behavior will emerge from that. This model could only be used when the number of vehicles that passing through the system are relatively small and there is a need to study the behavior of individual units in the system.
- Macroscopic flow model, where mathematical equations between flow, speed and density to represent the flow of traffic entirely based on the assumption that traffic streams as a whole are comparable to fluid stream. This model can be used for higher density, larger scale system in which a study of behavior of groups of units is sufficient.

In the macroscopic flow model, vehicles are not seen as an individual entity therefore this model would be more suited to visualize the dynamic of traffic or traffic condition. Immers LH and Loghe S (2002) stated that macroscopic variables can translate the discrete nature of traffic into continuous variables. The fundamental characteristics of traffic flow in macroscopic flow model are flow, speed and density.

These three fundamental characteristics are not independent, there is a fundamental relationship which connect them that shown in equation.

$$q = \rho . v \qquad \text{.......................................................} \ (1)$$

- $q\ (x, t)$ is the flow rate or volume at location *x* and time *t*, which is defined as the number of vehicles passing through the location in a unit of time.
- $\rho\ (x, t)$ is the density at location *x* and time *t*, which is defined as the number of vehicles in a distance.
- $v\ (x, t)$ is the speed of the vehicles at location *x* and time *t*.

These three basic parameters can be used to describe traffic on any roadway. Volume or flow rate are variables that quantify demand, that is, the number of vehicles who desire to use the road during the specific time period. Congestion can influence demand, and observed volumes sometimes reflect capacity constraints rather than true demand. Volume and flow rate have a different definition, as volume is the number of vehicles observed or predicted to pass a point during a time interval while flow rate is the number of vehicles passing a point during a time interval less than one hour, but expressed as an equivalent hourly rate. For example, the number of vehicles observed for four consecutive 15 minutes period are 1,000, 1,200, 1,100 and 1,000. These are flow rate, and the volume is the sum of these numbers or 4,300 vehicles. The peak flow rates is important in capacity analysis, because sometimes the peak flow rates exceed the capacity number even though the volume is less than capacity during the full hour which could trigger a congestion in the road segment. The flow rate as a variable describing traffic quantities inside a map representation may deliver meaningful illustrations in the background of detecting traffic congestions (Keller, 2013).

Speed is defined as a rate of motion expressed as distance per unit of time, generally as kilometer per hour (km/h). It is an important measure of the quality (effectiveness defining levels) of the traffic service. In most cases, space mean speed is used as the speed measure because it easily computed from observations of individual vehicles within the traffic stream and is the most statistically relevant measure in relationships with other valuable. It is computed by dividing the length of road section by the average travel time of the vehicles traversing it.

Density is the number of vehicles occupying a given length of lane or roadway at a particular instant, which usually expressed as vehicles per kilometer (veh/km).

Unlike flow rate and speed, density could not be measure directly in the field, however density can be computed from the average speed and flow rate data. Density is a critical parameter to characterize the quality of traffic operation because it describes the proximity of vehicles to one another and reflects the freedom to maneuver within the traffic stream.

From the study of the relation between these parameters, it shows that a zero flow rate occurs under two different conditions, when there are no vehicles on the facility (density is zero) and when density becomes so high that all vehicles must stop so there are no movement or congestion occurs. It also show that flow rate and density are linked in interesting way, because normally flow rate increase as density increase. However, when density reaches a so called 'critical density', the flow rate begins to decrease and congestion occurs (He Shulin, 2012).

According to Highway Capacity Manual, traffic could be classified based on Level of Service (LOS). LOS is a qualitative classification by measuring the quality of operational situation of traffic flow, such as speed and travel time, density, traffic interruptions, comfort and convenience. The classification is represented by letters from A to F to describe traffic conditions. LOS A and B means no congestion, C and D means minimal to moderate congestion and E and F means severe to extreme congestion. For further detail, it could be seen in tables 2.1. and 2.2.

**Table 2.1.** LOS for Urban Roads Depend on Road Class and Travel Speed (HCM, 2005)

| Urban Street Class | I | II | III | IV |
|---|---|---|---|---|
| Range of free-flow speed (FFS) | 90 to 70 km/h | 70 to 55 km/h | 55 to 50 km/h | 55 to 40 km/h |
| Typical FFS | 80 km/h | 65 km/h | 55 km/h | 45 km/h |
| LOS | Average Travel Speed (km/h) | | | |
| A | > 72 | > 59 | > 50 | > 41 |
| B | > 56 – 72 | > 46 - 59 | > 39 – 50 | >32 -41 |
| C | > 40 – 56 | > 33 - 46 | > 28 – 39 | > 23 – 32 |
| D | > 32 - 40 | > 26 - 33 | > 22 – 28 | > 18 – 32 |
| E | > 26 – 32 | > 21 - 26 | > 17 – 22 | > 14 - 18 |
| F | ≤ 26 | ≤ 21 | ≤ 17 | ≤ 214 |

**Table 2.2.** LOS for Signalized Intersections Depending on Delay (HCM, 2005)

| LOS | Control Delay per Vehicle (s/veh) |
|---|---|
| A | ≤ 10 |
| B | > 10 -20 |
| C | > 20 -35 |
| D | > 35 – 55 |
| E | > 55 – 80 |
| F | > 80 |

Duan, Liu and Sun (2009) have researched about traffic congestion in Shanghai based on FCD. They were using data collection from 6,000 taxis for a month. Based on the percentile of average speed for each class of the road, they set a threshold and define traffic congestion in 5 states (seen in table 2.3).

**Table 2.3.** Classification of traffic congestion (km/h) (Duan, Liu and Sun, 2009)

| Road type | State 1 | State 2 | State 3 | State 4 | State 5 |
|---|---|---|---|---|---|
| Elevated road | < 20 | 20 - 35 | 35 - 55 | 55 – 75 | > 75 |
| Expressway | < 20 | 20 - 30 | 30 - 40 | 40 – 75 | > 75 |
| Main arterial road | < 15 | 15 - 20 | 20 - 25 | 25 - 40 | > 40 |
| Arterial road | < 15 | 15 - 20 | 20 - 25 | 25 - 40 | > 40 |
| Collector road | < 13 | 13 - 18 | 18 - 23 | 23 - 33 | > 33 |
| Branch road | < 13 | 13 - 18 | 18 - 23 | 23 - 33 | > 33 |

## 2.2. Floating Car Data

Floating Car Data is one of a method to gather information about traffic by collecting real-time traffic data from vehicles via mobile phones or GPS over the entire road network. The data will be sent to a central processing center to be processed to extract information about the traffic condition. The floating car data technology is a new approach to gather traffic information for ITS. This method is quite useful because it could represent a full coverage of monitored areas automatically in real time with minimum cost and still generate a high quality of data. Basically, there are two types of FCD, GPS and cellular-based systems. GPS system utilizes the GPS receiver system which is already attached on the car, for example fleet vehicles such as taxis or courier services, to gather information about the vehicles. Then the data will be sent to the data center through the regular on-board radio unit or via cellular network data. The precision of the vehicle location is relatively high. In case of urban traffic, taxi fleets are particularly useful due to their high number and their on-board communication system already in place (Leduc, G., 2008).

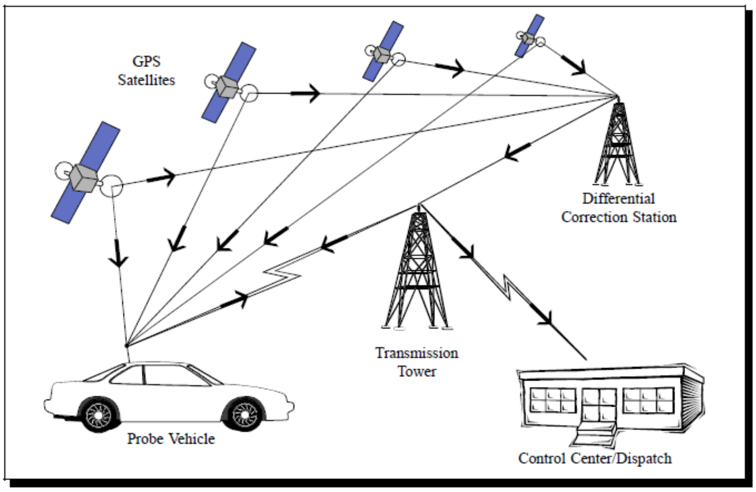


**Figure 2.2.** Communication from GPS (FHWA, 1998)

In FCD based on cellular phones, the mobile phone positioning is regularly transmitted to the network usually by means of triangulation or by other techniques and then travel time and further data can be estimated over a series of road segments before being converted into useful information by traffic center. There are no special device or hardware or specific infrastructure need to be built along the road for this method, however more complicated algorithms are required to extract the information.

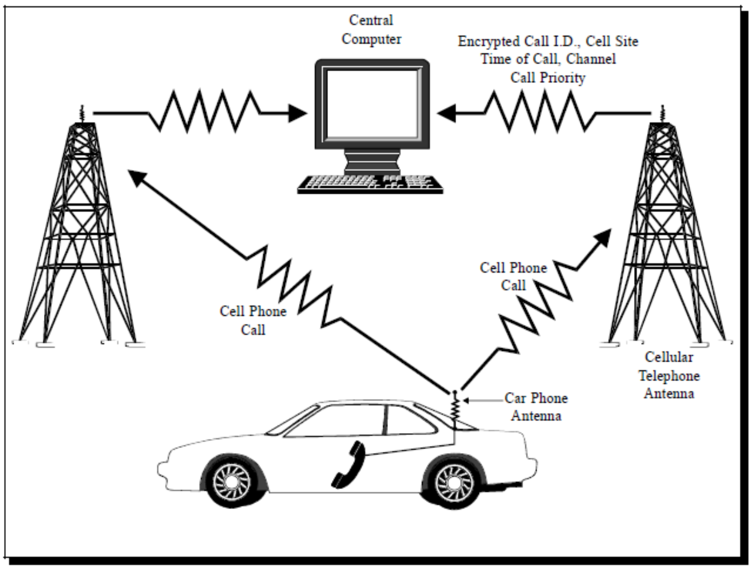


**Figure 2.3.** Communication from cellular phone (FHWA, 1998)

There are many benefit that can be obtained from the FCD data as FCD provides a network-wide, accurate and real time information, which is less cost and constantly accessible. FCD data also has some disadvantages such as complex data processing, massive volume of data storage, no direct information on traffic flow or density, and privacy issues. However there are many applications that could be benefit from the improvement of FCD, especially in the transportation field. Congestion monitoring, bottleneck analysis, traffic growth and route choice analysis for traffic simulation could be examples of the potential application for FCD.

**Table 2.4.** Potential applications derived from the FCD Technology

| Actors | Applications |
|---|---|
| Government/public authorities | Congestion monitoring; local transport plans; journey time studies; planning studies; air pollution studies; OD matrices |
| Logistic and fleet operators | Vehicle fleet planning |
| Location based service providers | Predictive routing |
| Consultants | Congestion monitoring; journey time studies; planning studies; air pollution studies; transport studies |
| Map providers | Predictive journey times |
| Marketing | Optimized Traffic Systems - Static mobile sites; campaign planning; site planning |
| Automotive manufacturers | RDS-TMC live data for mobility portal; NavTrack GPS tracking solutions |
| Telecommunications | Real-time traffic information; short dial telephone traffic service |

Source: ITIS Holdings in Leduc, G (2008)

There has been many projects related to FCD applications. Reinthaler, et al (2007) proposed a project called Dmotion which aims to provide an effective traffic management strategy for regional and local authorities. This project tries to provide an efficient way for estimating speeds and traffic state based on FCD data from taxi fleets and public transport. The data is provided by 1,200 taxis, then a multi-stage algorithm (Floating Car Evaluator, FCE) is employed to calculate the speed per road link. Data from public transport are used to complete missing data from FCD. As a result, the estimated path speed based on FCD follow the trend of the average path speed measured by ANPR (Automated Number Plate Recognition) but the level of estimated speeds is lower than average path speeds. However this result shows that temporal trends of average speeds during a day could be captured by FCD data and this data prove to be a reliable and cheap additional data source for urban traffic state estimation.

Another application is proposed by Tang, et al (2012) which tries to utilize FCD data to detect and update changes in the road network. They choose taxi fleets data because taxis travel all over the city every day. The road network change detection and update follows these steps: data preprocessing, map matching, incremental detection, new data sampling, road network update and new road network detection. The most crucial part in this study is the map matching process as this step will detect whether the position of GPS point data match with the existing road network or not which means that an addition to the road network is needed.

In Europe, there were many FCD projects that has been conducted throughout last decade. OPTIS in Sweden is using FCD to collect data of traffic condition to provide traffic information for travelers. From the trials, FCD is proven to be a cost-effective method to provide accurate real-time traffic information for the user. Mediamobile in France is using FCD data which are gathered from 1,700 taxis operating in Paris to provide live traffic information on motorway congestion and traffic congestion for Paris.

## 2.3. Visual Analytics

Visual analytics is the science of analytical reasoning supported by interactive visual interfaces (Thomas,J., Cook, K., 2005). A more specific definition would be: "Visual analytics combines automated analysis techniques with interactive visualisations for an effective understanding, reasoning and decision making on the basis of very large and complex datasets" [3]. It is an integral approach combining visualization, human factors, and data analysis, which allow users to combine their knowledge with the automation data processing and analysis which done by computer to explore and gain more information from the data.

The Visual Analytics Process combines automatic and visual analysis methods with a tight coupling through human interaction in order to gain knowledge from data. Different data sources need to be integrated first in the preprocessing steps (e.g. data cleanning, normalization, etc) before the analytics step could be executed. Then the analyst could apply automatic analysis methods using data mining techniques to generate models of the original data which then could be combined with visualization methods where the analyst interacts with visualization of data model to define which data model could generate a better result based on certain parameters. The analyst could also do the visual analysis first to reveal an insightful of information which then could be used as a base to build the model to do the automatic analysis. Figure 2.4. shows the overview of visual analytics process.

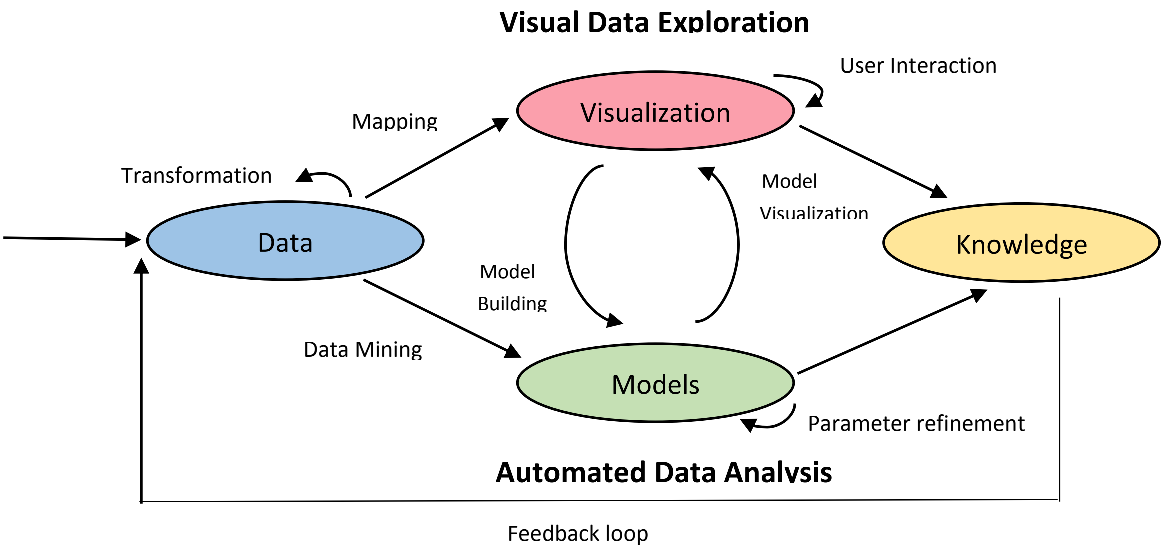


**Figure 2.4.** Visual Analytics Process
**Source :** http://www.visual-analytics.eu/faq/

### 2.3.1. Data Mining

Computer utilization becomes a key role in improving data acquisition and processing to extract relevant information from data sources. Knowledge discovery and data mining (KDD) is the computational process of discovering patterns in large data

[3] http://www.vismaster.eu/book/chapter-2-visual-analytics/

set involving methods at the intersection of artificial intelligence, machine learning, statistics, and database systems. KDD methods are mostly suitable for evaluating the quality of the proposed solutions of the problem. Therefore this methods do not take analysist knowledge into account to provide a solution for a problem.

The main idea of KDD is to extract information from large datasets. In KDD, there are some stages of process to transform data into various model or representation to obtain the pattern that represent the implicit information within the data. The KDD process consists of data selection, data pre-processing, data transformation, data mining and interpretation or evaluation. In pre-processing stage, the dataset will be cleaned from the noises and missing data and formatted to suit the data mining algorithms. This stage is an essential process as the data could be heterogeneous (e.g. textual data, data stored in database, satellite imagery, etc) therefore it requires effective methods for data cleaning and integration. The output of this stage then will be transformed into a form that can be understood by the analyst.

Data mining tasks can be divided into predictive task and descriptive tasks. In predictive tasks, such as classification and regression, data are analysed to build a global model to be able to predict the value of target attributes based on the observed values of the explanatory attributes. In descriptive tasks, such as clustering and pattern mining, the data will be summarised by using local patterns which describes the implicit relationship and characteristics of the data itself. The last stage is to verify the patterns produced by the data mining process to meet the desired standard because some patterns found by the data mining algorithms are not necessarily valid. When the results are in accordance with the standards, the results then can be interpreted to gain knowledge about the information.

The current KDD methods are not directly applicable in visual analytics scenarios and only support limited user interaction. The models and patterns extracted by traditional KDD from a larger dataset could also be difficult to interpret in which the information within the dataset might still hidden in the large number of data. Hence for data mining method to be useful in visual analytics it should be (Keim et al, 2010):

- Fast enough – sub-second response is needed for efficient interaction

- Parameters of the method should be representable and understandable using visualizations
- Parameters shoul be adjustable by visual controls.

An example of data mining is spatial data mining. Spatial data mining could be interpreted as a process of discovering interesting and previously unknown, but potentially useful patterns from spatial databases (Sumathi, et al., 2008). Spatial databases contain spatial and non-spatial attributes of the areas under the study, in which spatial data mining could be done to find implicit rules or patterns hidden in spatial databases that could be helpful for some fields such as geo-marketing or traffic control. The basic tasks of spatial data mining are classification, association rules, characteristic rules, discriminate rules, clustering and trend detection.

There are many techniques that could be used in this method, such as clustering, association and co-location and trend detection. Spatial clustering is a process of grouping a set of spatial objects which have a high degree of similarity into one cluster group. In general, clustering could be classified into four categories: partitioning method, hierarchical method, density based method and grid based method. In partitioning method, the data is considered as one big cluster which then will be classified into certain predefined numbers of group (*k*). For each cluster, we then find the *k*-cluster centers and assign objects to the nearest cluster center. In hierarchical method, the dataset is hierarchically decompossed based on the idea that nearby objects has more similarity than far away obejcts which means that the distance between objects is used to describe each cluster. In density based method, clusters are defined by the density of objects on the area which separate the areas of high density and of low density. In grid based methods, a finite number of cells of grid structure needs to be built firstly in the area. The cells which contain more than a certain points or objects are treated as dense area.

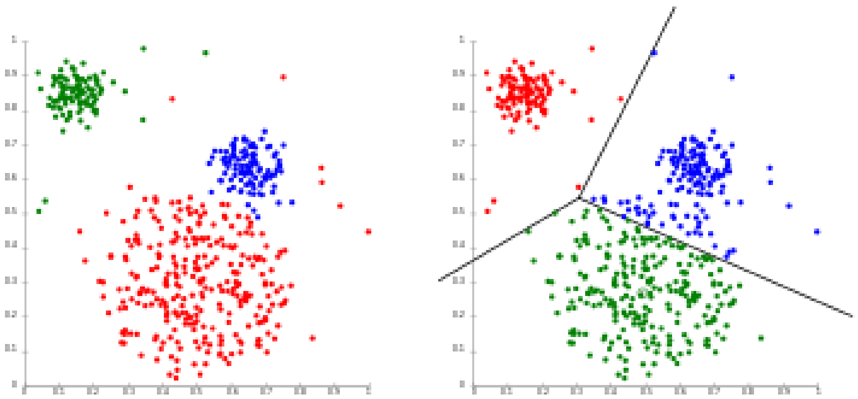

**Figure 2.5.** Spatial clustering by using density method (left) and partitioning or k-means method (right) (Chire, 2011)

**Source:** http://en.wikipedia.org/wiki/Cluster_analysis

Association and co-location are a data mining function that discovers the probability of the co-occurrence of items in a collection [4]. This function is sometimes referred to as market basket analysis. In this function, association rules between objects are used to define the relations between data. Association rules are created by analyzing data for frequent if/then patterns and using the criteria *support* and *confidence* to identify the most important relationship [5]. Support indicates the frequency the items appear in the database, while confidence indicates how many times the statement is true.

Trend detection or frequent pattern mining is a technique to find existing patterns in data which then could be used to predict trends of the attribute changes with respect to the neighborhood of some spatial objects. This function is the most basic function in data mining. Frequent patterns are those patterns that occur frequently in the database. Those patterns could be used to find predictive trends of the data. For example, when people go to their offices they have frequent routes that they choose. Based on those patterns we can predict the trends of the routes and the road segments which are mostly passed on.

As above mentioned, KDD methods are useful but still limited. Therefore an integration with data visualization methods is needed to support this method, especially for pattern identification for spatial dataset.

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[4] *http://docs.oracle.com/cd/B28359_01/datamine.111/b28129/market_basket.htm#DMCON009*
[5] *http://searchbusinessanalytics.techtarget.com/definition/association-rules-in-data-mining*

### 2.3.2. Spatial and Temporal Data Visualization

The decision making process for a problem depends on where and when the problem occurs. Therefore, traditionally maps were used as representative models of the real world to help people orient the problem in spatial scope to gain more knowledge about the problem and its evolution in time to find a better solution to solve these problems. However, with the revolution of information technology which brings larger datasets and more complex systems, simple maps are no longer sufficient. Sophisticated maps and advanced computational techniques which are interdependent and synergetic, accessible and usable, and support decision making process are needed to overcome this problem. These maps allow people to compare possible options and strategies and make decisions by visualy analyzing it. As spatio-temporal analysts, they must be enabled to gain information from the data effectively and efficiently and then record, report and share the information.

Spatial and temporal data have different properties from other types of data. The processing, integration and analysis of spatio-temporal data are constrained and underpinned by the fundamental concept of spatio and temporal dependences, in which in spatial domain it is often referred as “Tobler’s first law”: “everything is related to everything else, but near things are more related than distant things” (Keim,et al, 2010). This concept also applies for temporal dependence. These dependencies could also be used to give more values to the information in data processing and analysis by doing interpolation and extrapolation to fill the gaps for incomplete data, integration of different type of data using common locations as references, and many other operations. Spatio-temporal data also have uncertainty, therefore uncertainty needs to be considered to generate an effective analysis of spatio-temporal data.

Spatio-temporal events and processes exist and operate at different spatial and temporal extents. The dimension of time can include a single or multiple levels of scale, hence temporal primitives could be aggregated or disagregated into larger or smaller conceptual units. The scale of spatial analysis is reflected in the size of the units in which events are measured and the size of the units in which the measurements are aggregated, which may significantly affects the results. Identifying the correct scale of events is important to accurately observe the events. The scale of analysis should also be chosen according to the goals of analysis. An example could be seen in Figure 2.6.

where individual trajectories visualized in different spatial scales and levels of aggregation. The appropriate scale depends on the need of analyst, whether they need to investigate movements in particular road section or to investigate movements in larger areas.

**Figure 2.6.** Different scales are using to show different paterns for visual analytics results (Andrienko, N and Andrienko, G., 2006)

From the example, the use of map as a representation of real world in space dimension is one key point of spatio-temporal data visualization. Maps have the ability to present and simplify the complexity in real world into two dimensional plane which makes the analysis process much easier. Cartography discipline also developed guidelines to help to improve the design of maps to produce maps which offers insight in spatial patterns and realtion in particular contexts. Cartographic generalisation is used to filter unnecessary information and preserve the important and relevant information which are different based on the scale. Because all of these advantages, maps are very suitable for visual analysis. Maps offer interaction with the data spatially and encourage deeper exploration about geospatial patterns, relationships and trends.

While spatial data could be easily visualized by using maps, temporal data visualization is a big challenge to all disciplines of data visualization and analysis. The existing approaches in general proposed visualize time and temporal data by creating a spatial arrangement of the time axis on the display or utilizing real world time so that an animation shows visual representation of different time steps in quick succesion. Visualization methods of temporal data also depend on wheteher temporal attributes are conceptually modelled as time points or time intervals. Integrating appropriate interaction methods for temporal data in visual analytics for spatio-temporal data need to be done in order to allow analyst to adapt to the visualization and do a variety of tasks to analyze and explore the data.

An interactive method to combine the visualization for spatio-temporal data is by using animated maps. Animated maps portray time-dependent data and dynamic event by mapping the temporal dimension of the data to physical time. It implements the idea that space and time are inseparable and suggestd a three-dimensional visual representation where two dimensions encode spatial aspects of data and the third dimension represents time. The analysis of the data is done in a single display with the maps are displayed simultaneously by the sequence of the events. In Figure 2.7., an interactive map is used to display changes in some areas in different time periods.

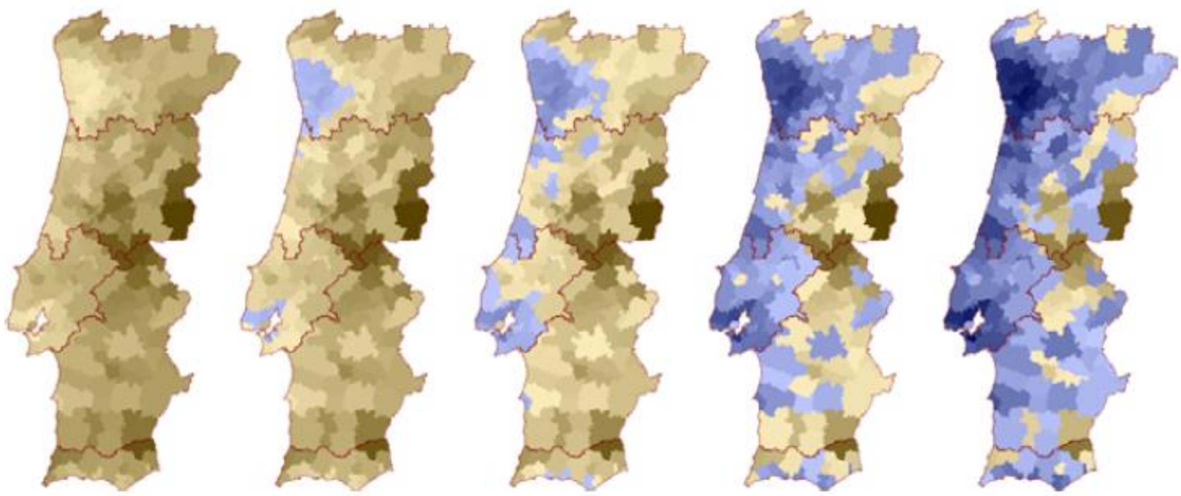


**Figure 2.7.** An interactive map display dynamic changes (different color shades) in some areas from different time period (Andrienko, N and Andrienko, G., 2006)

## 2.4. Traffic Congestion Monitoring and Analysis Based On Floating Car Data

In the recent years, FCD became one of the most essential part in transportation information system as a reliable and low cost source to gather traffic information for traffic monitoring. FCD also begun to show its potential as a source for real-time traffic information systems, which is already applied in some countries.

Sun, et al (2009) has done the research to improve metropolitan congestion performance measurement method based on floating car data. With this method, congestion performance measurement could be done at different types of road classes in real time including freeway, arterial road and even local streets. In this research, they measure traffic congestion based on 'five-dimensional' traffic congestion performance measure that could be seen in this Table 2.5.

| Characteristic Sort | Code | Index name |
|---|---|---|
| congestion intensity | K1 | Traffic congestion index |
| congestion spatial distribution | K2 | The kilometrage proportion on different congestion grade |
| congestion temporal distribution | K3 | Congestion grade duration by time of the day |
| traffic bottlenecks (congestion frequency) | K4 | The number and distribution of recurrent congested nodes and segments |
| Reliability | K5 | Road network reliability index |

**Table 2.5.** Traffic congestion performance measures

Travel time is used as a basic parameter to calculate the average speed for congestion performance measurement after map matching process has been done. Then congestion performance measurement could be done as these steps: aggregate the 5 minutes interval travel speed data from FCD to 15 minutes for each link, identify each link belong to which congestion grade according to the speed level criteria, sum up the kilometrage in each congestion grade for each road class separately then classified, select out the AM peak (PM peak) and average proportion values during the peak, establish a linear function between road network kilometrage proportion and the traffic congestion grade to transforms the road network kilometrage proportion to a no unit index to describe congestion grade, identify the recurrent links considering the AM peak and PM peak according to frequency of congestion occur. As the result, the road network in Beijing is at severe congested level between 7:45 AM and 8:45 AM, and between 17.15 PM and 18:45 PM on weekdays. And implementation of congestion performance measurement based on road network dynamic data could be used in traffic congestion characters and trends monitoring in actual and detail way.

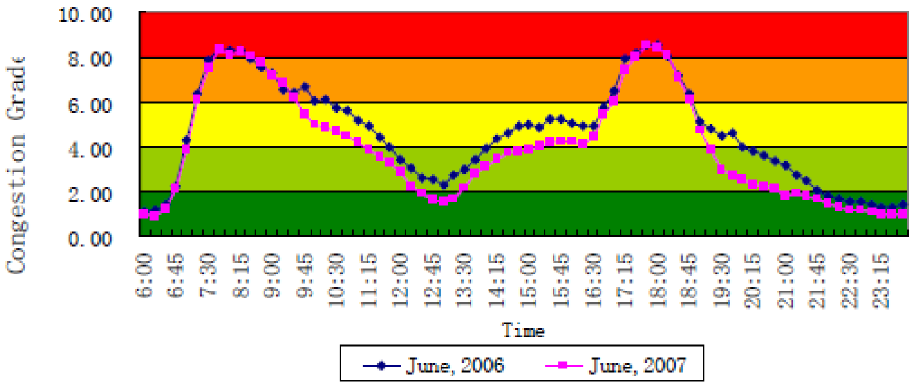



**Figure 2.8.** The congestion index by time of day on weekdays
(Beijing, June 2006 VS June 2007) (Sun, et al, 2009)

X. Liu, et al (2012) used FCD data from 6000 taxis in Changsha city to detect urban traffic conditions of road network. This study evaluates road condition through three levels that are respectively point, line and area, which is 'road joint_road section_zone' model. For road joint, the evaluation is based on the average stop frequency of traffic lights at intersection at a certain time period, which the bigger the value, the longer the time to wait and the more crowded or congested the crossroad. As for road section, driving speed is used to evaluate this index. Based on road grade and vehicle speed, road condition is classify into five grades: very smooth, unblocked, slight traffic congestion, moderate traffic congestion, and serious traffic congestion. As a result, from spatial distribution of road congestion, 12.7% roads are in heavy congestion degree which mainly concentrated in center zone (as Changsha is a single-center city). And from temporal distribution of road congestion, 8.00 – 8.15 is the morning peak hour with average speed of 19.3 km/h, and 17.45 – 18.00 is the evening peak hour with average speed of 16.3 km/h.

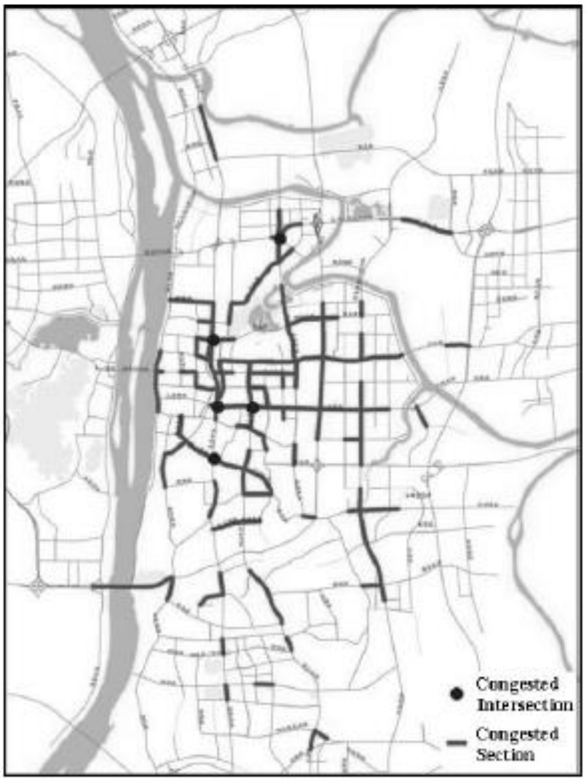



**Figure 2.9.** Congested section and heavily congested intersection distribution at rush hour main urban areas (X. Liu, et al, 2012)

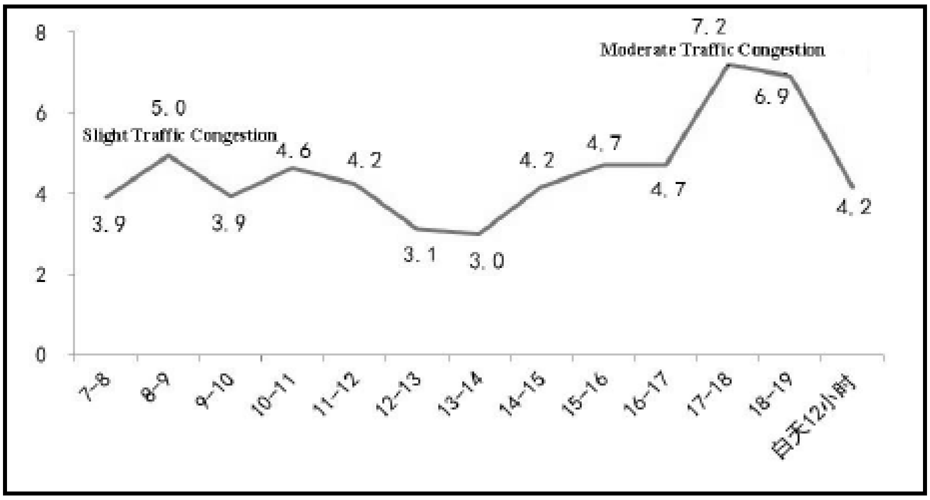



**Figure 2.10.** The distribution of road network congestion index during 12 hours in the main urban areas (X. Liu, et al, 2012)

Fabritiis, Ragona and Valenti (2008) presented an application based on FCD which is developed and operated by OCTOTelematics to deliver real-time traffic speed information throughout Italian motorway network. Unlike the others, this system is using data from privately owned cars. From the case study carried on a tool-free motorway that encircles Rome (GRA) which mostly have a heavy traffic and experienced traffic jams in some part, the travel speed of vehicles which travelled across GRA for five days has been calculated and grouped into 6 classes. By visualizing the data, the spatio-temporal patterns of occurrence, propagation and dissipation of traffic congestion can be easily observed.

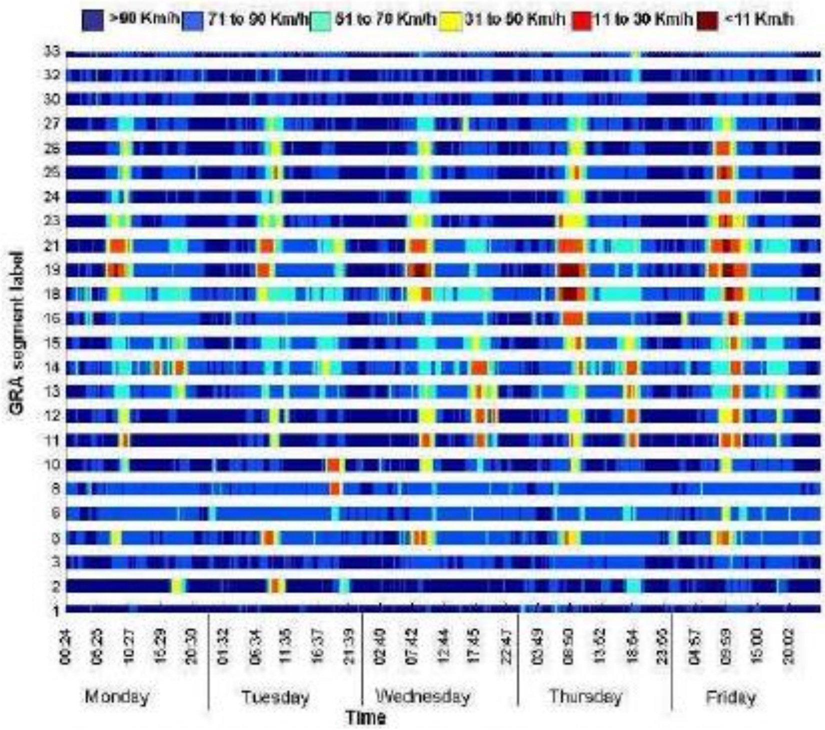



**Figure 2.11.** Spatio-temporal travel speed estimates of GRA (Fabritiis, Ragona and Valenti, 2008)

Wang, et al (2010) created a web-based real-time traffic congestion information system based on FCD data provided by a 500 taxis fleet. Traffic information is needed to improve traffic management system to maximize the capacity of existing road infrastructure and transportation network. A multi-stage algorithm is applied to calculate the average speed which is then used to define the traffic congestion state of the road links. Web-based map visualization is used to deploy the traffic information in real time.

Lin Xu, Yang Yue and Qingquan Li (2013) proposed a FCD analysis method for congestion exploration based on data cube. A historical FCD dataset from about 1,200 taxis for one week is used. Traffic congestion is identified based on spatio-temporal related relationship of slow-speed road segment, then it is aggregated by a cluster method to derive the traffic pattern. Congestion aggregation is done to identify recurrent congestion which appear around the same location and time but on different days. Aggregated location, time period and duration for recurrent congestion are used to represent the congestion pattern.

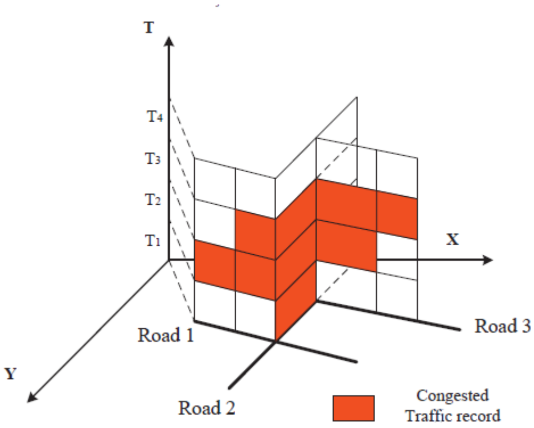
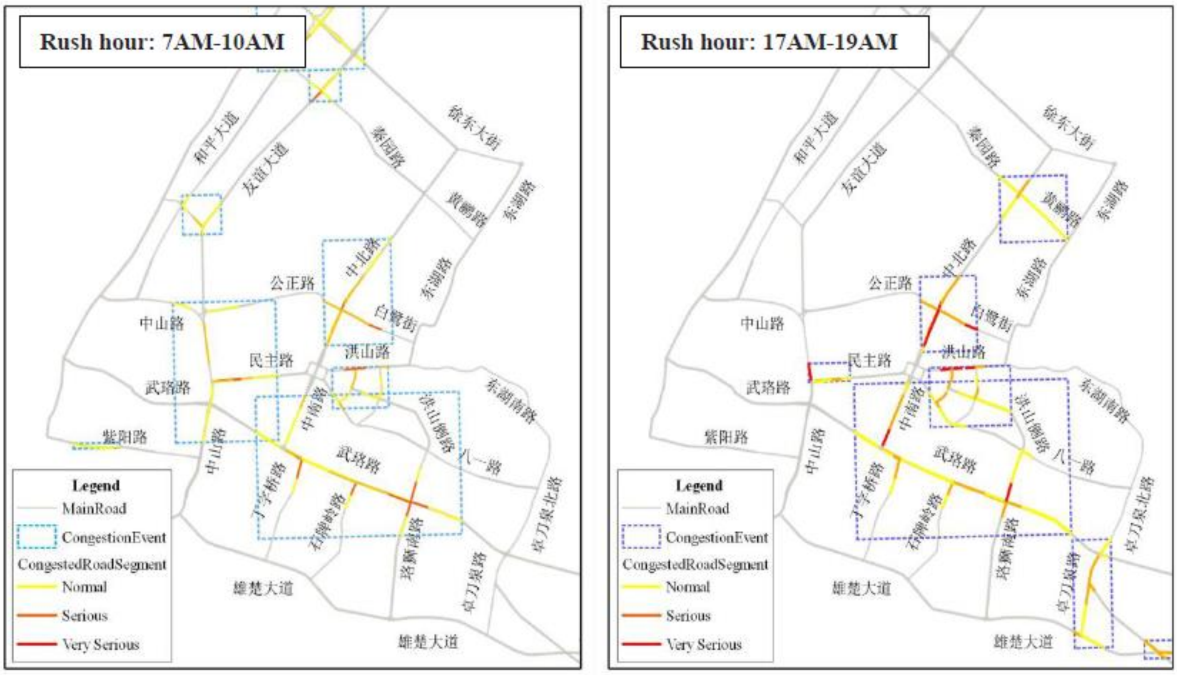



Figure 2. Spatial-temporal related record in congestion

**Figure 2.12.** Spatial-temporal related record in congestion

(Lin Xu, Yang Yue and Qingquan Li, 2013)




a. Rush hour at morning

b. Rush hour at evening

**Figure 2.13.** Recurrent traffic congestion event on the road network (Lin Xu, Yang Yue and Qingquan Li, 2013)

# 3. INITIAL TEST DATA PROPERTIES

## 3.1. Study Area Location and Characteristics

Shanghai has evolved into mainland China's largest city and commercial capital in recent years. Located in the Yangtze River Delta in East China, Shanghai sits on the south edge of the mouth of the Yangtze in the middle portion of the Chinese coast. Shanghai geographical coordinate is 31°12′N 121°30′E / 31.2°N 121.5°E. The municipality borders the provinces of Jiangsu and Zhejiang to the north, south and west, and is bounded to the east by the East China Sea. Shanghai is administratively equal to a province and is divided into 17 county-level divisions: 16 districts and one county. However, in this thesis we only take central part of Shanghai city as the study area, which is located in some part of Huangpu, Hongkou and Pudong district.

**Figure 3.1.** Study area location


### 3.1.1. Physical Characteristic

Shanghai lies on China's east coast roughly equidistant from Beijing and Guangzhou. Downtown Shanghai is bisected by the Huangpu River, a man-made tributary of the Yangtze. Shanghai is located on an alluvial plain which means that the vast majority of its 6,340.5 $km^2$ (2,448.1 square miles) land area is flat, with an average elevation of 4 m (13 feet). The city contains 53.1 km (33.0 miles) of rivers and streams and is known for its rich water resources as part of the Lake Tai drainage area. Shanghai has a humid subtropical climate and experiences four distinct seasons. Air pollution in Shanghai is low compared to other Chinese cities such as Beijing.

### 3.1.2. Socio-Economic Characteristic

Shanghai is an important economic, financial, trade and shipping center in China. Due to its excellent port, Shanghai has been a leading power of China's economic and trade development since ancient times. The great leap of Shanghai's economy benefited from the amazingly fast development of industry. The manufacture of automobiles, electronic and communication equipment, petrochemicals, steel products, equipment assemblies and biomedicine had once been promoted as the six pillar-industries of Shanghai.

Shanghai is China's most populous city, estimated about 23.9 million. It has a population density of 3,700 people per square kilometer. More than 39% of Shanghai's residents are long-term migrants, a number that has tripled in ten years. Migrants are primarily from Anhui (29%), Jiangsu (16.8%), Henan (8.7%) and Sichuan (7.0%), while almost 80% are from rural areas. Like most of China, the vast majority (98.8%) of Shanghai's residents are of Han Chinese ethnicity, with only 1.2% belonging to minority groups. Shanghai also has 150,000 officially registered foreigners, including 31,500 Japanese, 21,000 Americans and 20,700 Koreans. Of course, this is based on official figures, so the real number of foreign citizens in the city is probably much higher.

### 3.1.3. Transportation System

Shanghai has an expansive grade-separated highway and expressway network consisting of 14 city elevated and surface expressways, 9 provincial-level expressways, and 8 national-level expressways. Expressways from Nanjing (Shanghai-Nanjing Expressway) and Hangzhou (Shanghai-Hangzhou Expressway) terminate at Shanghai, allowing direct access to different directions of China. In the city center, there are numerous elevated expressways (skyways), which lessen the traffic pressure of normal roads. However, traffic in and around Shanghai is often heavy and traffic jams are commonplace during rush hour. Private car ownership in Shanghai has also been rapidly increasing in recent years. Based on Shanghai Statistics Bureau, Shanghai had a total vehicle population of 3.09 million units at the end of 2010 which an increase of 8.7% from a year earlier.

Shanghai also has an extensive public transport system, largely based on buses, trolley buses, taxis, and a rapidly expanding metro system. More than 1,100 bus lines in Shanghai run to every corner of the city proper. Taxis are the most convenient means of transportation in Shanghai. There are five main taxi companies in Shanghai, and different companies operate taxis of different colors.

## 3.2. Floating Car Data Properties

Floating Car Data sets with the description of attribute information is saved in the form of Comma-separated values (CSV). Each line in CSV is represented one record of the dataand the attribute in each colum is separated by comma. The FCD dataset is using latitide and longitude to record each position of the taxi so that each point could be visualized geographically by using WGS84 coordinate system.

In this thesis, the data was derived from the taxi-FCD system. In this system, the data of the taxis are sent to the taxi headquarter and then the data will be sent to the FCD-server of the institute. The cycle times of the positioning are limited by the bandwidth of the communication channel and vary between about 10 and 120 seconds, depending on the status of the individual taxi. The collected GPS positions are sent then with the cycle times of about 10 minutes to the server of the institute. The overview of the general structure of FCD data set is describe in the table 3.1.

| Fieldname | Field Value | Details |
|---|---|---|
| Date | 20100617 | 8-digits number |
| Time | 230717 | 6-digits number |
| Car ID | 11692 | The unique ID of the taxi, 5 digits |
| Company Code | QS | Initials of the taxi company |
| Driving Direction | 6 | Direction in 2 digits |
| Longitude | 12.161.365 | in degree; accurate to the 6th decimal place |
| Latitude | 31.201.005 | in degree; accurate to the 6th decimal place |
| Instaneous Velocity | 34.9 | accurate to 0.1 km/h |
| Instaneous Altitude | 255 | accurate to 1 m |
| Car Status | 0 | 0 for empty; 1 otherwise |
| GPS Effectiveness | 0 | 1 for effective; 0 otherwise |
| Record Time Stamp | 17-06-2010 23:07:17 | In form of YYYY-MM-DD hh:mm:ss |

**Table 3.1.** Description of the data format of Shanghai FCD

From the table, the most important information are the longitude and latitude position of the taxi, the vehicle ID and velocity. The position of the vehicles could be used to calculate the flow rate or volume for each road section, and the vehicle ID is needed to distinguish the vehicles. Velocity is important factor to determine traffic congestion as traffic congestion is mostly occur when the velocity is low. From the calculation of flow rate and average speed from velocity data, then density information could also be calculated. Another important information is the time stamp of each data, which is really necessary when the detail information about when an event such as traffic congestion exactly occurs are needed.

# 4. VISUALIZATION METHODS

Data visualization is a method to convert data into a visual representation. Because a picture worth a thousand words, it will be easier for users to understand a huge amount of data from just a visual data representation such a graph, map or even a table. The main goal of data visualization is to communicate information clearly and effectively (Friedman, 2008). Therefore effective visualization methods are needed to convey the information to the user which not only consider about the functionality aspects but also aesthetic aspects. A nice data visualization could help enhance the analysis performance which result in better decision making.

Visualization is one of the most important parts in cartography, as a map is also one of visualized products. Cartographic visualization is mainly concerned with visual representation of spatial data. It not only deals with data presentation but also exploration of data. Exploration means to discover unknown information from the data or analytical process of data. From exploration processes, not only spatial information about the data could be obtain but also the relationships and patterns inside of the data.

In this thesis, traffic data will be visualized as a map so that trends and patterns inside the data could be detected. Traffic data is basically movement data, which are often regarded as points. In order that its spatial distribution in a period of time could be represented in effective way, map is a natural choice. Andrienko N. & Andrienko G (2007) stated that because movement data are very numerous therefore their positions have to be presented in an aggregated way. Aggregation is needed to handle large amount of data, in particular aggregation enables an overall view of the spatial and temporal distribution of movement data.

## 4.1. Density Mapping

The most common method to display FCD data pattern is dot mapping. Each point of data represents a taxi position with many attributes that can be chosen to show different kinds of information such as velocity or taxi status. This method is quite simple and accurate to represent the spatial distribution of data however the interpretation of spatial patterns and hot spots could be very difficult due to the clutter effect especially with the large amount of data.

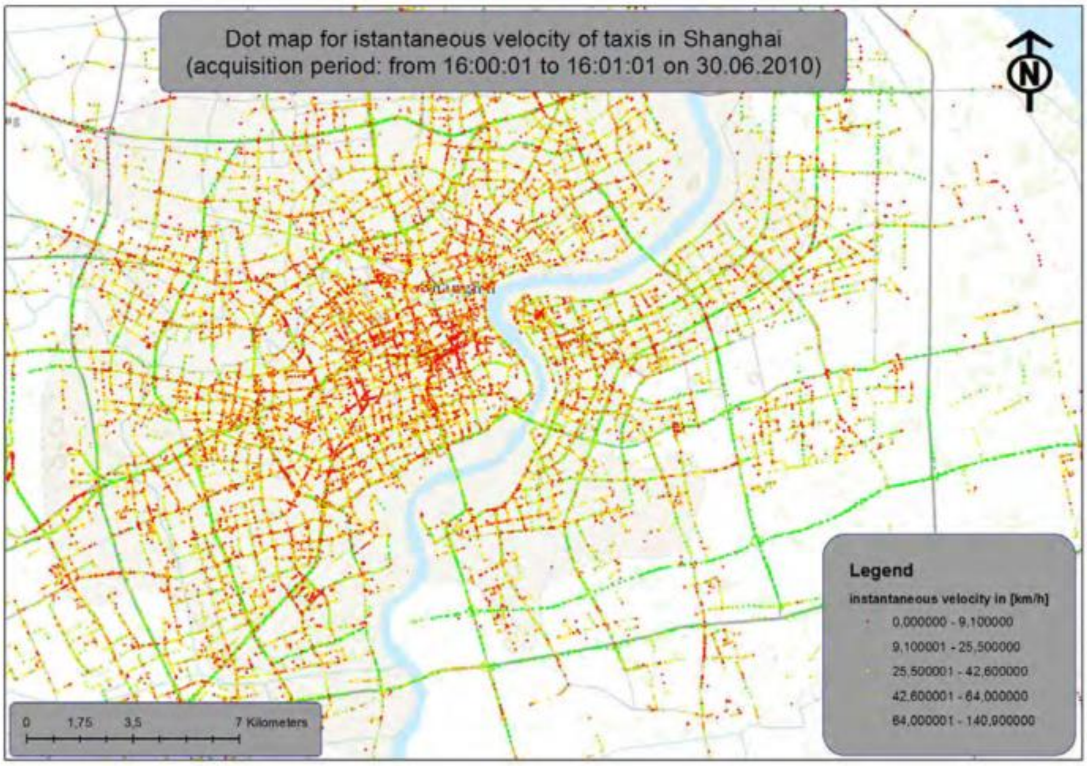



**Figure 4.1.** Dot map of taxi distribution in Shanghai based on instaneous velocity (Keler, A., 2013)

As movement data deals with data aggregation, points could be aggregated into a trajectory to build a continuous spatial aggregation which represents movement density (Dykes and Mountain, 2003; Willems N, et al, 2009). Kernel density estimation (KDE) proposed by Willems N, et al (2009) is common technique for estimating surface density in trajectories, as it can easily illustrate density and expose large patterns and fine features from a combined density fields from different radius. Color coding and/or shading by means of an illumination model are used to visualize density. An example of kernel density is shown in Figure 3.2.

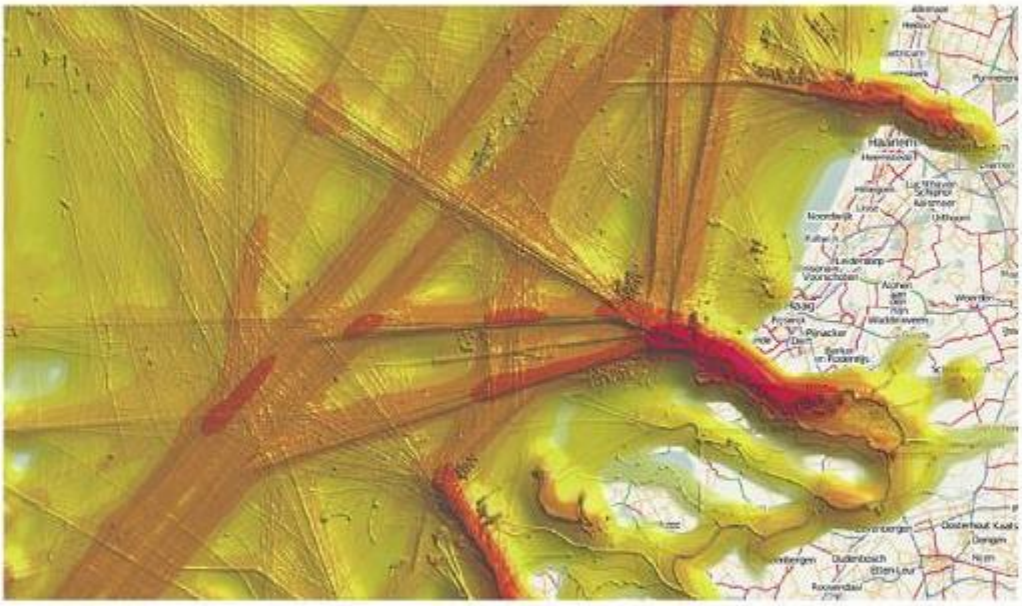


**Figure 4.2**. Continous spatial aggregation of vessel trajectories using Kernel Density Estimation method (Willems et al, 2009)

Another possibility for aggregating movement data is clustering. Clustering is one approach to analyze geo-temporal data at higher level of abstraction by grouping the data according to its similarity into meaningful clusters (Kisilevich. et al, 2010). The important part of clustering is defining the degree of similarity between movement data. Distance-based clustering methods is one of most common approaches to be used in clustering which consists of distance functions that encapsulate the concept of similarity among data items. Choosing a generic clustering algorithm, a distance function and criterion of how trajectories are chosen to be in the same cluster, is a problem for this method as the concepts of similarities may vary depending on the considered application scenario and the analyst.

Xintao Liu and Yifang Ban (2013) are using clustering methods to uncover spatio-temporal patterns of traffic congestion from floating car data. Spatio-temporal clusters is generated in two steps: generate spatial clusters based on coexisting GPS points at different time slices and connect spatial clusters which are continuous over time and space to form spatio-temporal clusters. The first spatial clusters is using 20 meters as the radius and mean speed less than 20 km/h as a base to describe a congestion. The spatio-temporal cluster is described by two measurements: the time duration, which is 2 minutes and the number of taxi cab. A high-density value of vehicles in a duration less than 2 min is considered as traffic congestion. The clustering could be seen in Figure 4.3., in which the red area represented the longer congestion period.

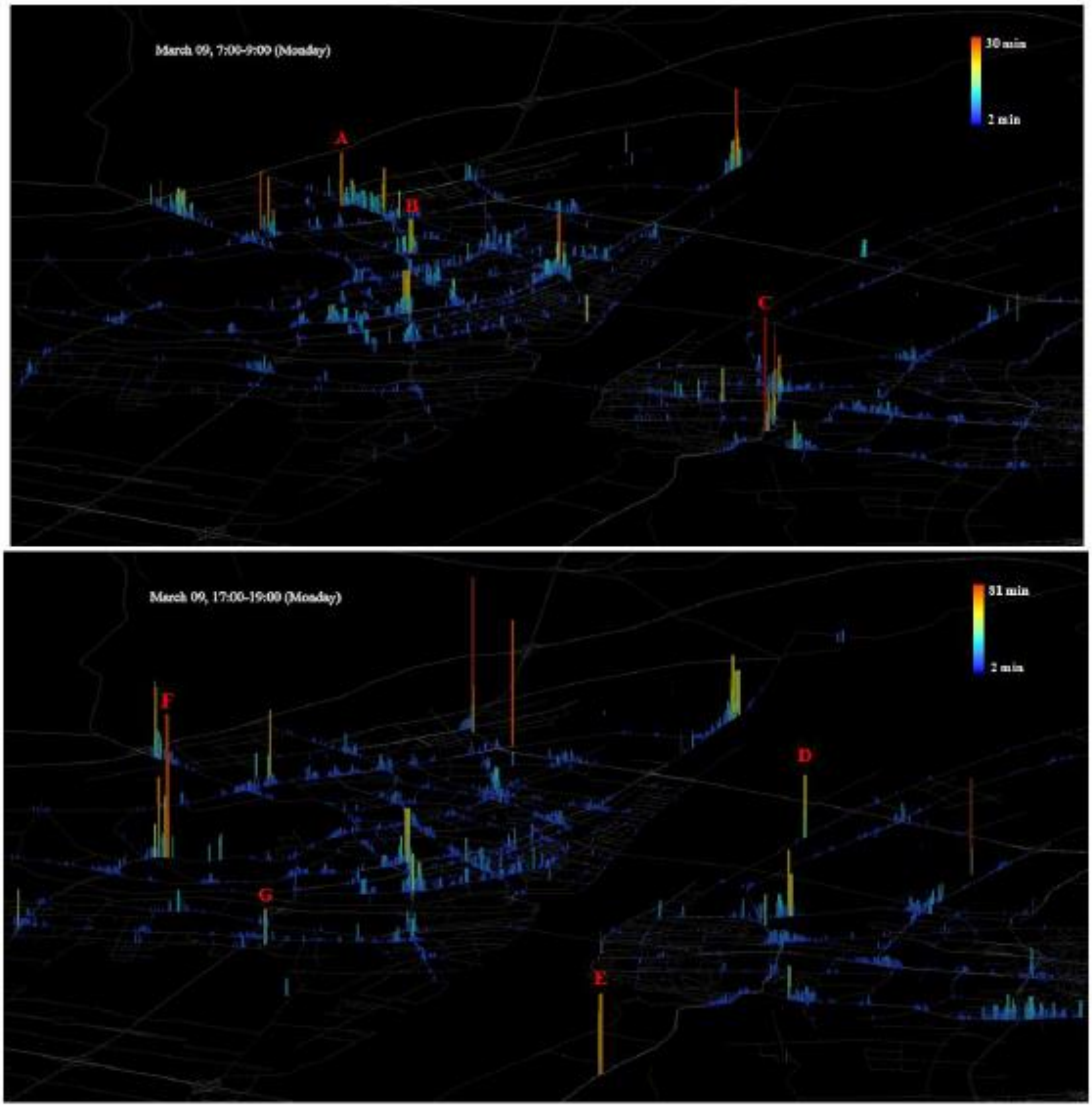



**Figure 4.3.** Spatio-temporal cluster visualized according to taxi lifetime during rush hour (Xintao Liu and Yifang Ban, 2013)

Another function of clustering methods is to identify hotspots of the events. Prasannakumar, et al (2011) evaluated road accident hot spots based on spatio-temporal clustering of road accidents. This research goal is to find patterns of localization and distribution of hotspots to determine whether spatial or temporal factors, such as the proximity to the school or the season, have influences to the road accidents. They are using Moran's I method for spatial autocorrelation and Getis-Ord GI* function and Kernel density for clustering method.

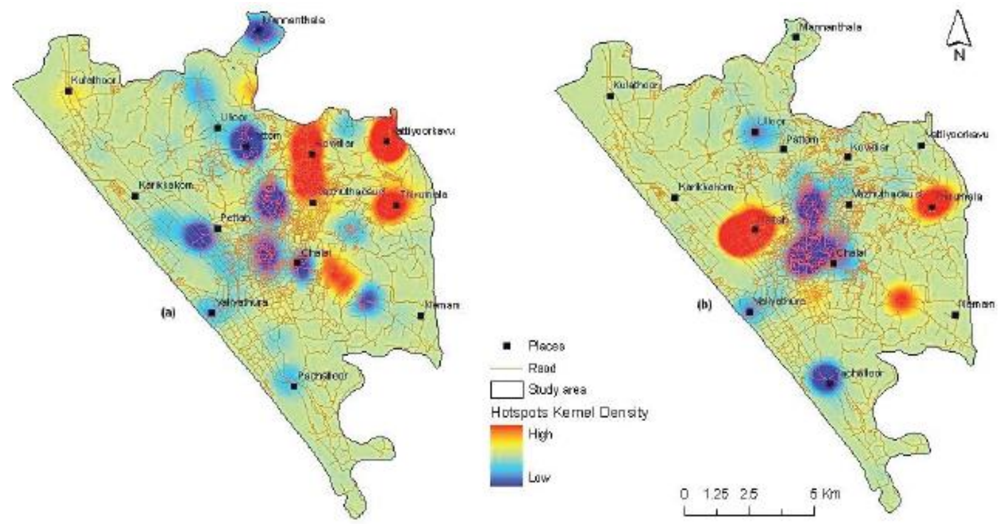



**Figure 4.4.** Hotspots distribution of road accidents associated with educational institutions (left) and religious place (right) (Prasannakumar, et al., 2011)

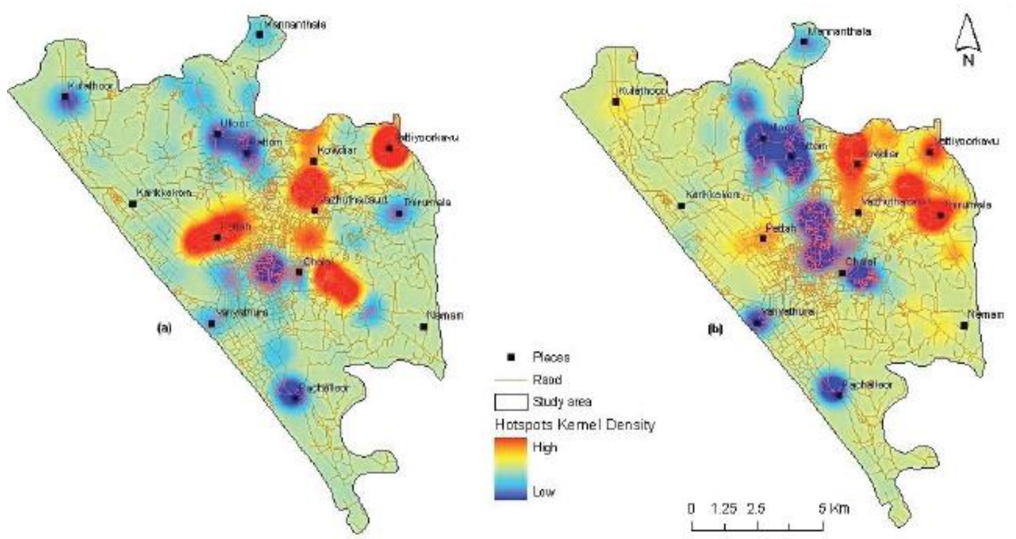



**Figure 4.5.** Hotspots distribution of road accidents associated with monsoon period (left) and non-monsoon period (right) (Prasannakumar, et al., 2011)

## 4.2. Visualization of Traffic Congestion on Road Network

Traffic congestions occur in the road network, thus a visualization of traffic congestion on road network is the most suitable representation. By using this visualization the spatial distribution and traffic congestion patterns for each road segment could be observed directly on the map. Information about traffic congestion becomes the attribute for each road segment, which then could be used to build a time slider animation based on the different time periods.

Traffic congestion classes could be represented by using different colors to distinguish each class. The use of colors will help the analyzing process as colors could easily depict different features which could be seen easily with bare eyes. The changes for each segment could also be observed by the changes of color for different periods of time. Patterns and trends of traffic congestion could be determined by observing the frequent congested road segments.

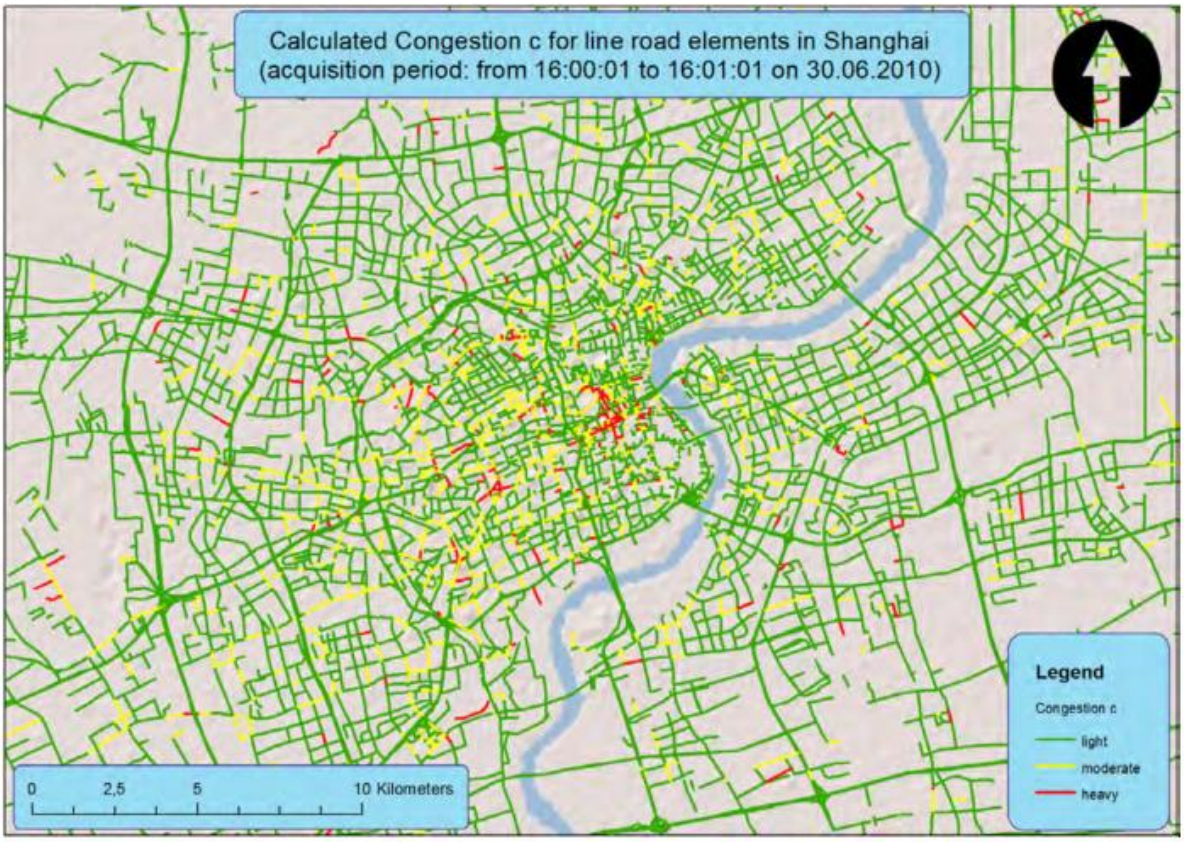



**Figure 4.6.** Traffic congestion visualization on road segment (Keler, A., 2013)

## 4.3. Three-Dimensional Spatio-Temporal Data Visualization

Traffic congestion could also represented by using 3D space. 3D view provides a better overview for certain quantitative values (Andrienko N, Andrienko G, 2007). By using 3D data visualization, the dynamic nature of social events such as traffic could interactively explored. In GIS, temporal data is commonly visualize by animations which represent changes in data (Tominski, et al., 2005). Animation is a useful technique to scan data from different period of time, and if the data from each time period is correlated then the animations will show smooth evolution. With animation map, users can catch the change of the object easily and have a deep impression. A simple animation map could be built from series of static maps that are put in order of temporal sequence. With the addition of a time-slider, users can navigate back and forth through different time periods to derive information about the data.

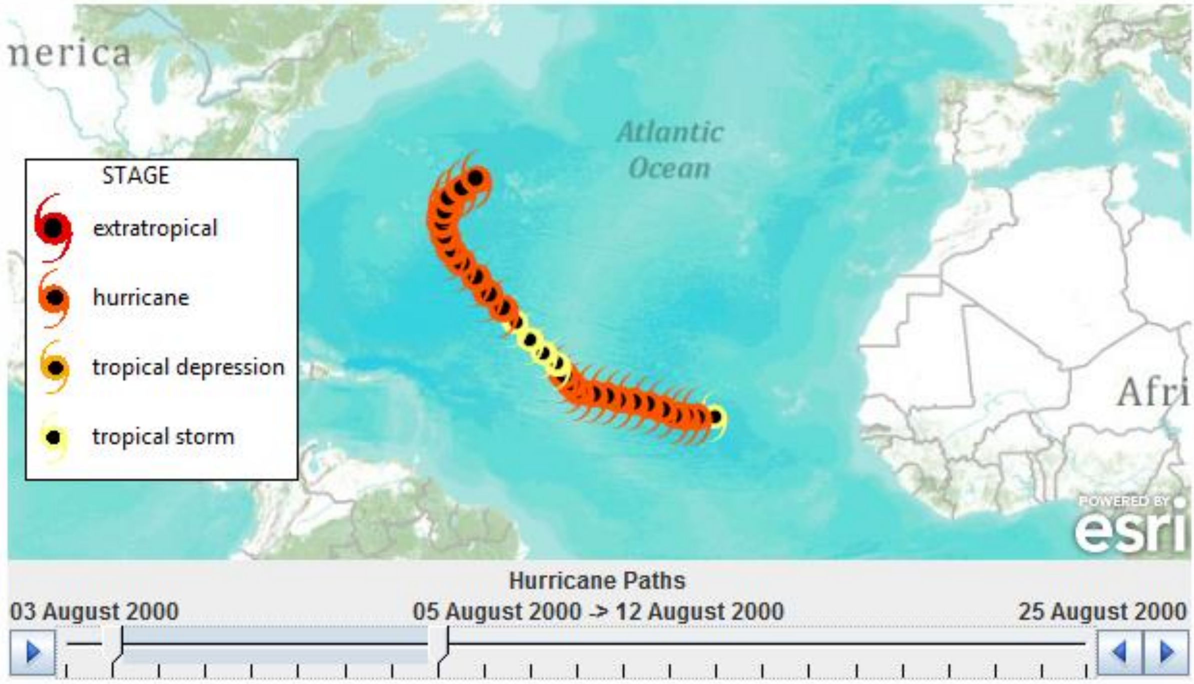



**Figure 4.7.** Time slider animation of hurricane paths changing with the passage of time
**Source:** https://developers.arcgis.com/java/sample-code/time-slider/

Figure 4.7. is an example of a basic time slider animation. In this example, there is a time slider function which show the start date and end date with several lines in between which indicates different dates. The time slider function could be played automatically by pushing the play button, or manually manipulated by moving the slider. This animation is also equipped by information box to show information about different stages of hurricane. While Figure 4.8. shows more sophisticated animation of taxis distribution on rainy days in Singapore. This animation does not only show the taxis distribution on the road network but also present a visualization of rain above the area of study to give more real feelings to the user. This animation is not only have a time slider function to show different timeline of events but also a rotate function to make it easier to explore by the users.

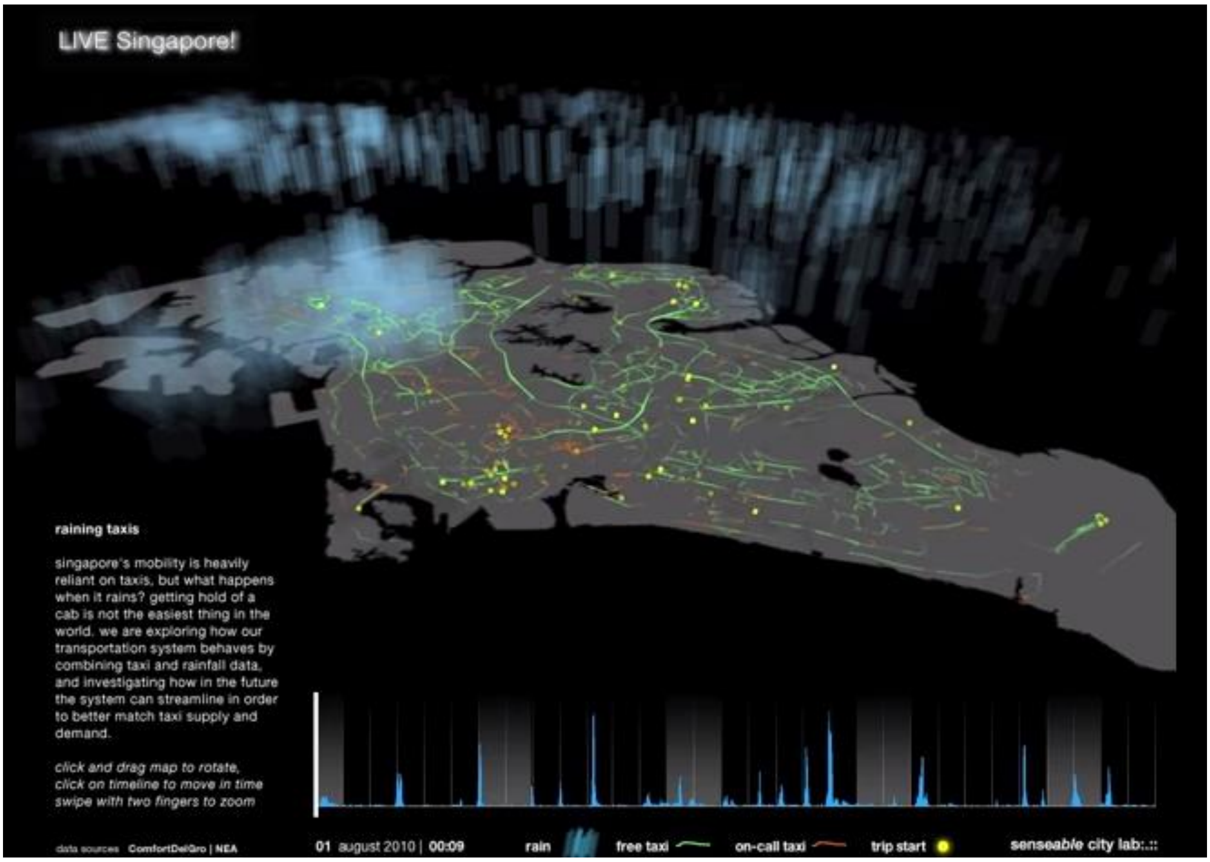



**Figure 4.8.** Animation of taxis distribution based on time series in raining day in Singapore

**Source:** *http://senseable.mit.edu/livesingapore/visualizations.html*

Another possible 3D visualization is by using 3D graphs or extrusion method. For example in Figure 4.9., the Wasatch Front Regional Council (WFRC) in the Salt Lake City use a 3D graphic both in color and vertical height to display regional delay patterns which create an effective visual representation (Grant M. et al, 2011). The 3D graphs are placed above the road network which symbolize the level of delay of each road. The height and the different color give a deeper meaning of the information as users could easily distinguish the delay level and pattern based on the height.

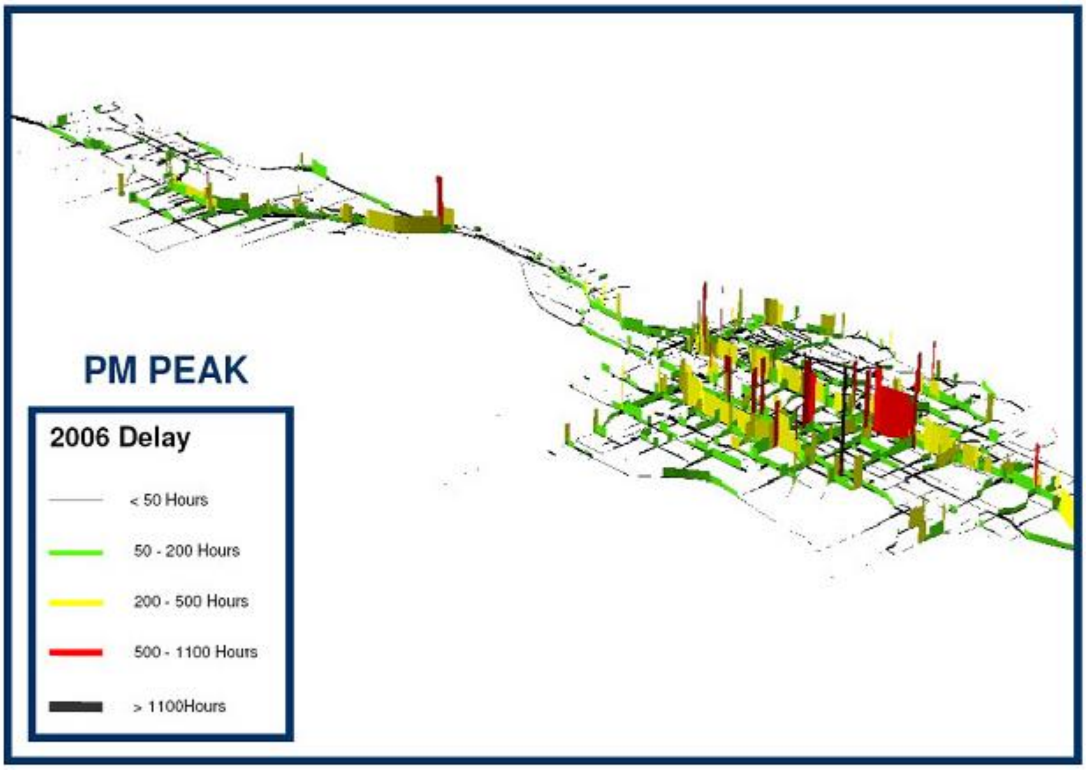



**Figure 3.9.** 3D visualization of transportation delay in Salt Lake City in 2006 by Wasatch Front Regional Council (Grant M. et al, 2011)

Another example of this method could be seen in Figure 4.10. While extrusion method in Figure 4.9. is based on the road network, extrusion method in Figure 4.10 is based on grid elements on the road network. The grid cells are classified based on the number of points inside it within a certain period of time. The grid cells are then extruded with different height that correspondent to the relative density. Different coloration is also used to represent different class range. With the combination of extrusion with different height and different coloration, the overview of distribution of events could be provided which could be used to generate interesting patterns of the data. In addition, comparison between two different time window could be provided to explore the temporal density distribution.

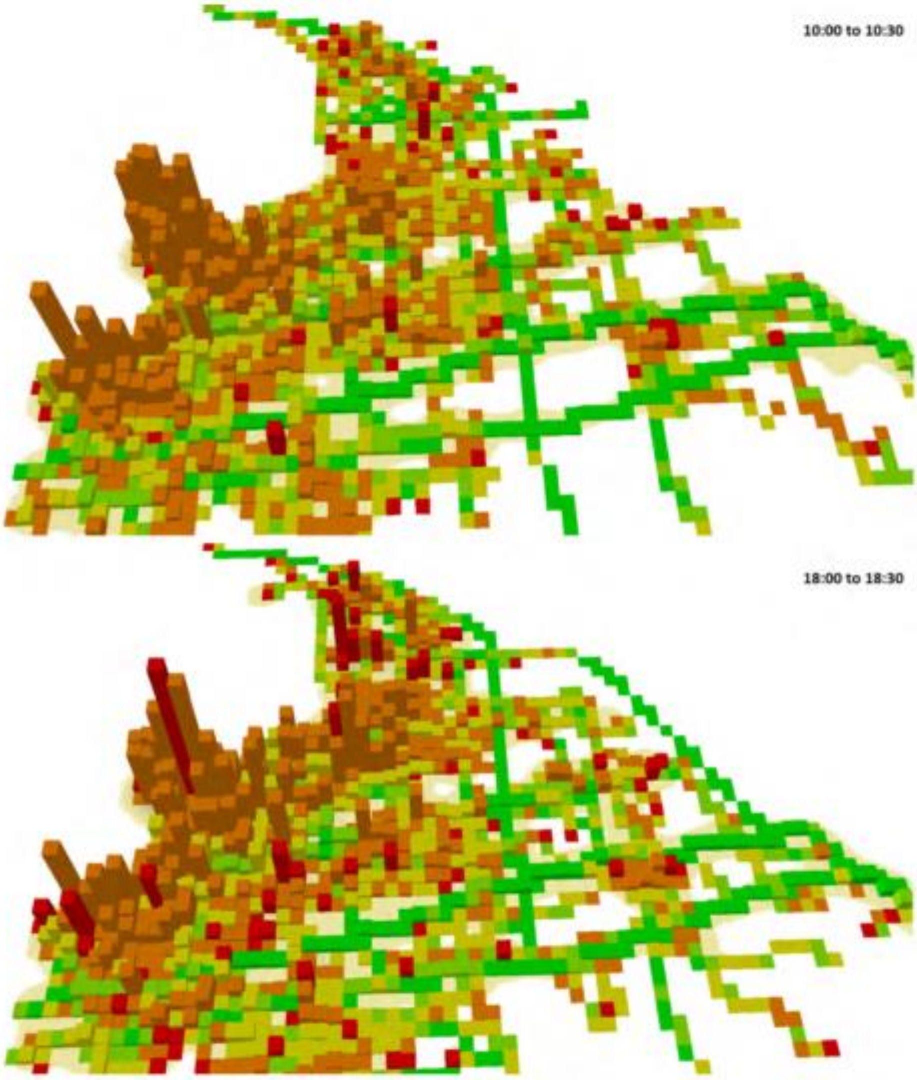



**Figure 4.10.** Comparison of two different time window of taxis density based on grid elements extrusion visualization (Keler, A., 2013)

# 5. RESULT AND ANALYSIS

This chapter discusses the result and analysis of the study for the visual analytics of spatio-temporal traffic congestion pattern in Shanghai based on Floating Car Data. This section consists of two main sections: data pre-processing and analysis and discussion. The analysis and discussion section consists of two subsections: temporal analysis and spatial analysis.

## 5.1. Data Pre-Processing

Before the data could be used for traffic congestion visualization, several steps must be done to prepare the data. First of all, the raw data must be filter to eliminate errors. The GPS points were first filtered by the bounding box of the study area. Then it is filtered by the limited maximum speed on the road, therefore the GPS points with instant speed over than 150 km/h are removed. The low speed and stop taxi GPS points are also removed from the data to eliminate the taxi which stop or waiting for passengers that could give great influence on the calculation of the vehicle speed in the road segments. Therefore the taxis that have speed less than 5 km/h were eliminated. Another errors also need to eliminate, such as time which has number more than 6 digits or date which is not the date of the experiment.

| FID | Shape * | Date | Time | Car ID | Instant Ve | Car Status |
|---|---|---|---|---|---|---|
| 1052 | Point | 2010000 | 17003723 | 10389 | 9,9 | 0 |
| 1053 | Point | 2010000 | 17101043 | 15404 | 7,5 | 1 |
| 1053 | Point | 2010000 | 17111522 | 15980 | 6,6 | 0 |
| 1054 | Point | 2010000 | 17150541 | 14840 | 8,5 | 1 |
| 1054 | Point | 2010000 | 17151318 | 10944 | 8,1 | 1 |
| 1054 | Point | 2010000 | 17160301 | 15012 | 7,9 | 1 |
| 4248 | Point | 2010000 | 17171638 | 15819 | 9,9 | 1 |
| 6484 | Point | 2010051 | 17254549 | 14095 | 9,5 | 0 |
| 1471 | Point | 2010000 | 17180307 | 12776 | 6,5 | 1 |
| 1471 | Point | 2010051 | 17185142 | 10450 | 7,9 | 1 |
| 1471 | Point | 2010000 | 17210023 | 14045 | 8,2 | 1 |

**Figure 5.1.** Exampe of data errors of the time attribute

After filtering, the data is divided into small partitions of about one hour acquisition time to simplify the work and to easily define the peak hour of the traffic congestion. Map matching process then needs to be done to associate the GPS points with the road network in the digital map. The general purpose of map matching is to identify the correct road segment on which the GPS points are. The map matching algorithm that has been used is based on distance and driving direction of the taxi. Distance means the distance of the matched road must be the closest to the GPS points. While driving direction means the matched road direction is most similar to the vehicle's travelling direction which could be calculated by the angle between the tangential direction of the candidate road and the direction of the GPS points. After all of these processes have been done, the data could be used in the next step.

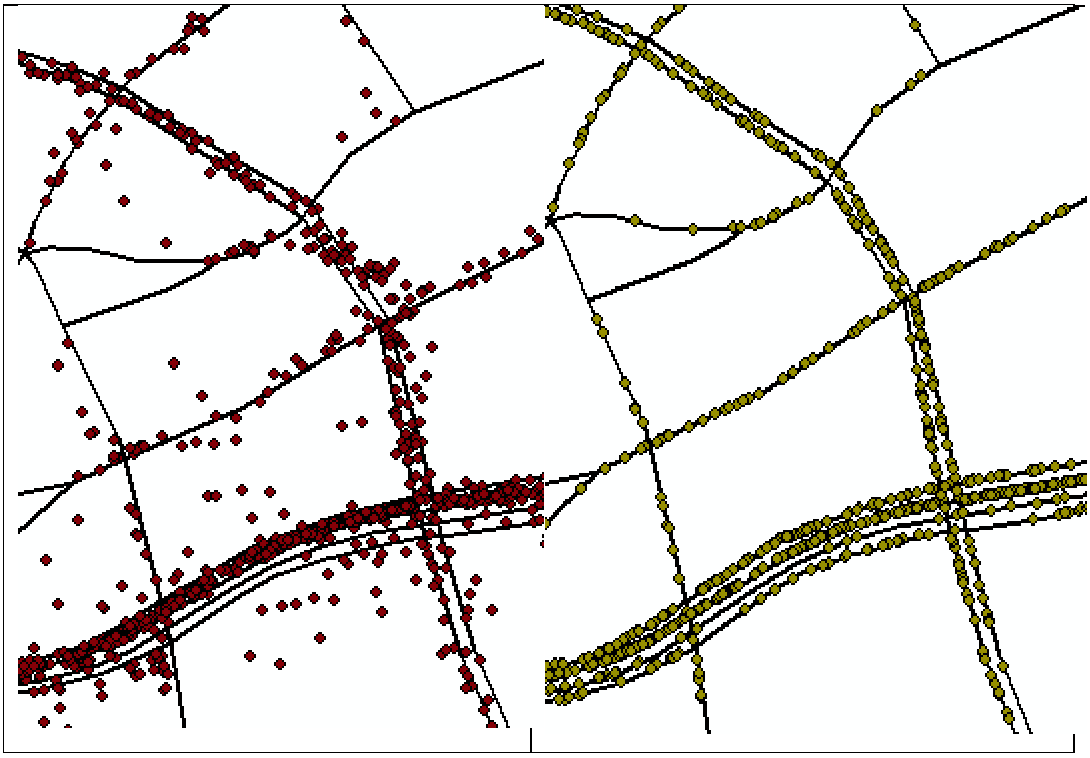


**Figure 5.2.** Map matching result for GPS points from FCD

## 5.2. Result and Discussion

### 5.2.1. Temporal Analysis

The mean speed of all GPS points for each period of time could be calculate from the data. By compairing the results of each period of time, the trends of traffic congestion in Shanghai city could be reflected. The rush hour periods have mosly lower mean speed than the other periods which means that traffic congestions are mosly occur in these period of times. The start and the *idle* time of traffic congestion could also be detected from this data. From the graphic in Figure 5.2., the lowest mean speed occur between 07:00 – 09:00 in the morning and between 17:00 – 18:00 in the evening. According to this result, the traffic congestion are mostly occur at this period of time.

It mostly happen because in these time period people are starting to do their activity therefore many people are traveling from their home to their office or schools and vice versa. Another interesting pattern that could be seen in this graphic is how extreme the changes of the mean speed at 06:00 – 07:00 AM period to 07:00 – 08:00 AM period, which means that the traffic congestion is started to take place in the beginning of the 07:00 – 08:00 AM and continue until 09:00 AM then start to dissolve at 09:00 – 10:00 AM. A little change of mean speed also happen after 13:00 – 14:00 time which could indicate that a moderate traffic congestion might occur in this period of time as this is a period of time when people take a little break for lunch or students finish their school and travelling back to their house.

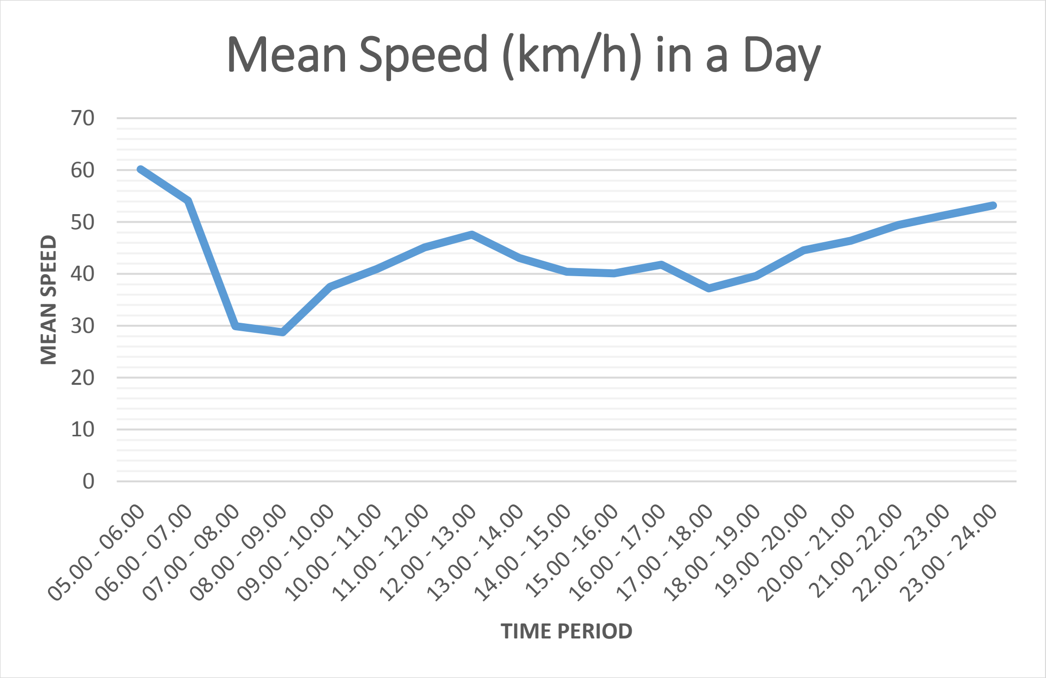



**Figure 5.3.** Mean speed (km/h) which calculate from a different time period in a day

Another indicator that could be used to detect traffic congestion for different time periods is by comparing the precentage of speeds for each period of time. In Figure 5.4., for 08:00 – 09:00 AM period the biggest percentage of speed is the speed which less than 20 km/h (60 %), while in the 12:00 – 13:00 PM period is the speed which more than 60 km/h (37 %). From this result, it indicates that 08:00 – 09:00 AM has more low speed which indicate that traffic congestion most likely occur in this period of time than at 12:00 -13:00 PM period.

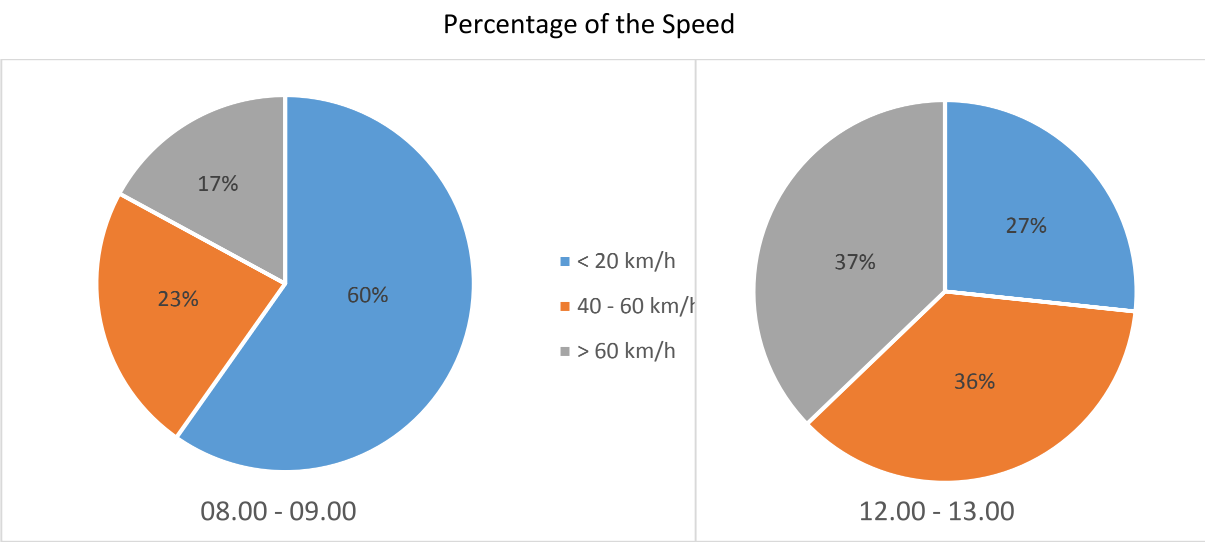



**Figure 5.4.** Comparison of percentage of speed for different time periods

From the identification of traffic congestion which is done by using classification method proposed by Duan, Liu and Sun (2009), the traffic congestion mostly happen for about 10 – 25 minutes. Figure 5.5. is the visualization of the temporal distribution of the data in a certain road segment which has heavy congestion level. The congestion begin at 17:02:00 PM and last until 17:24:00 PM, the second congestion begin at 17:25:00 PM and last until 17:45:00 PM and the last congestion begin at 17:47:00 PM until 17:59:00 PM.

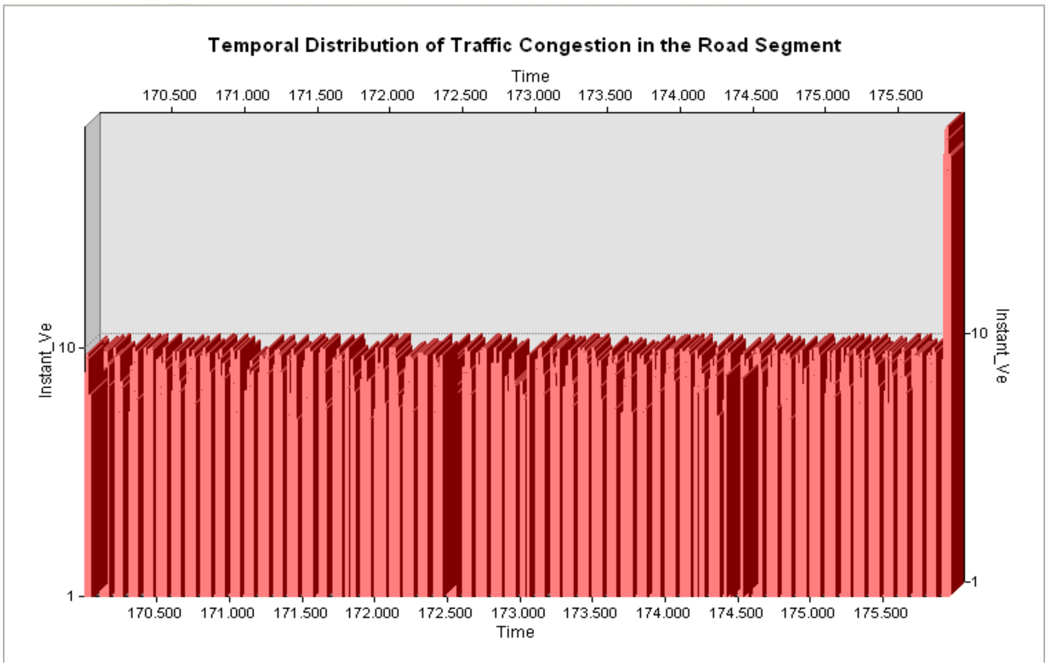



**Figure 5.5.** Temporal Distribution of Traffic Congestion in the Road Segment

### 5.2.2. Spatial Analysis

The spatial distribution of the road congestion could be identified directly on the map. Based on the distribution, the most congested road segment could be identified. In this cpahter, the congested segment will be identified using various type of visualization.

#### 5.2.2.1. Density Mapping

Point density map describes the closeness of GPS points which situated in the same area. Therefore only points that fall within the neighborhood area considered in this method. This visualization is choosen to smooth out the information represented by a collection of points. In this visualization, kernel density method is used to produce a smooth visualization of the point density. With this visualization and then combined with the road network visualization, the spatial distribution of taxi density in a certain period of time could be seen. This density map could be seen in Figure 5.6.

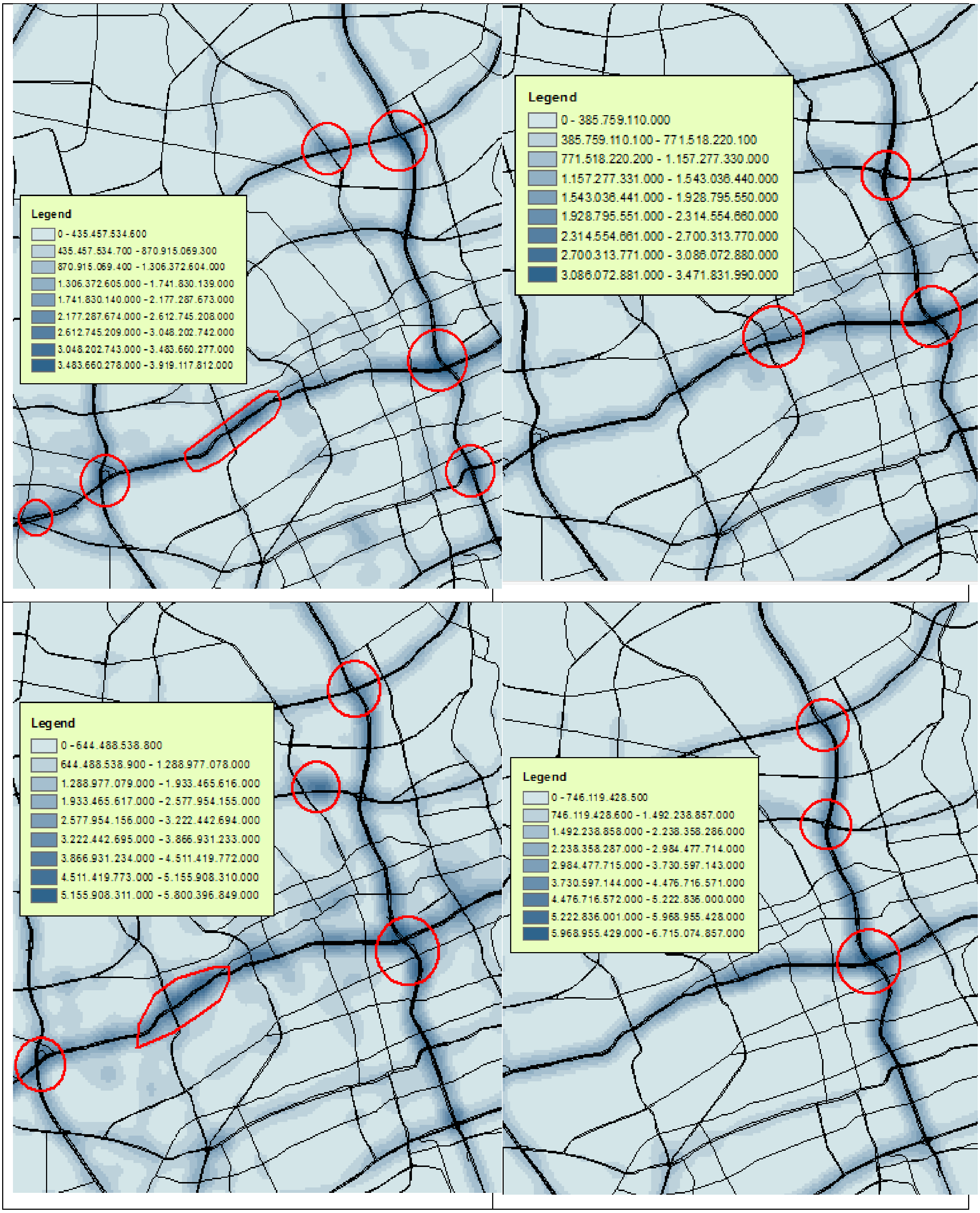



**Figure 5.6.** Kernel Density Map of Taxis Distribution in Shanghai at 08:00 – 09:00 AM (top left), 12:00 – 13:00 PM (top right), 17:00 – 18:00 PM (bottom left), and 22:00 – 23:00 PM (bottom right)

From the comparison of the kernel density results of the taxi distribution for different time periods in Figure 5.6., the congestion mostly occur in the intersections and in the arterial roads. The distribution patterns of traffic congestion is different for each period of time. From 08.00 AM to 09.00 AM, which is the morning peak of traffic congestion, the traffic congestion mostly happen along the expressway/elevated roads and main arterial roads and intersections, especially near the down town area. There are also many hot spot areas of the high density of taxis distribution in this time period compared with other time periods. The traffic congestions are nearly happen in all road segments of expressway/elevated roads and main arterial roads along the expressway which means that the level of traffic congestion in this period of time is heavy.

From 12:00 PM to 13.00 PM, which is the highest *idle* time between the morning and evening traffic congestion, the traffic congestion only happen in the intersection which close to the city center. Some parts of the expressway/elevated roads and main arterial roads are having a slight traffic congestion, especially the parts of the road which will lead to city center direction. The traffic congestion level in this period of time is low or no traffic congestion until minimal congestion.

In the 17:00 PM to 18.00 PM time interval, which is the evening peak of traffic congestion, the traffic congestion happen along the expressway/elevated roads and main arterial roads and intersections, just like the morning peak period. The traffic congestions level in this period of time is heavy, as mostly all of the road segments of expressway/elevated roads and main arterial roads are congested. However, the level of congestion in this period time is slightly higher than at 08:00 AM – 09:00 AM period because in this time period, the number of roads in congestion are higher. The distribution of the hot spot areas of the high density of taxis are also different and more dispersed than from the morning peak period.

In the 22:00 PM to 23:00 PM time interval, the traffic congestion only happens in the intersections which are close to the city center and expressway/elevated roads along these intersections. The traffic congestion level in this period of time is minimal. The distribution of high density taxis is only along in one particular expressway segment which started from the city center heading to the outer city.

The density map could also be represented by using line feature, corresponding to the trajectories of the taxis. The trajectories are built from the GPS points of each vehicle identification numbers and the time stamps inside of the time partition of FCD set. The trajectories are mostly intersect with each other, therefore the area which have the most number of intersecting trajectories will be marked as a dense area. By using this method, the intersecting trajectories lead to more dense areas which means that these areas are mostly passed on by the taxis. This method could be used to identify the most used roads and routes by the taxis.

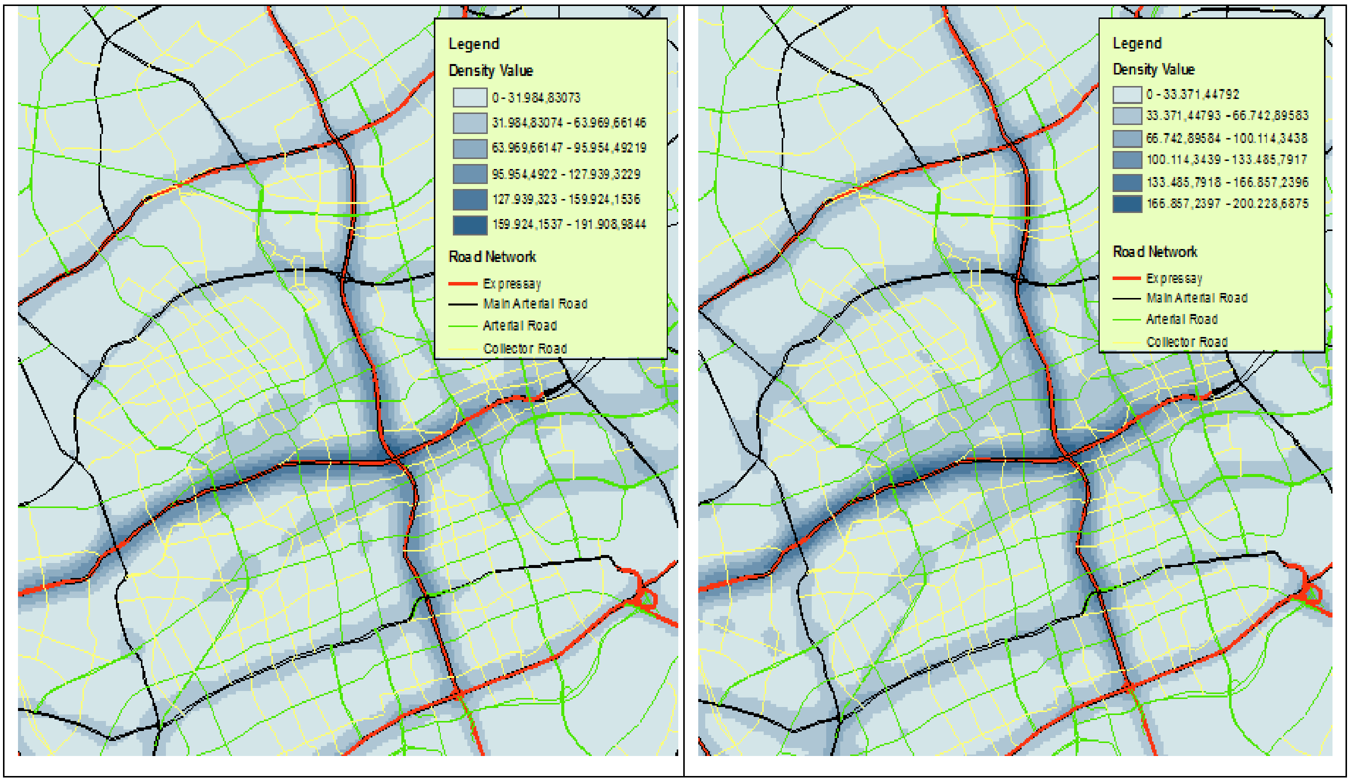



**Figure 5.7.** Kernel Density Map of Trajectories of Taxis in Shanghai at the morning peak (08:00 – 09.00 AM) (left) and at the evening peak (17:00 – 18:00 PM) (right)

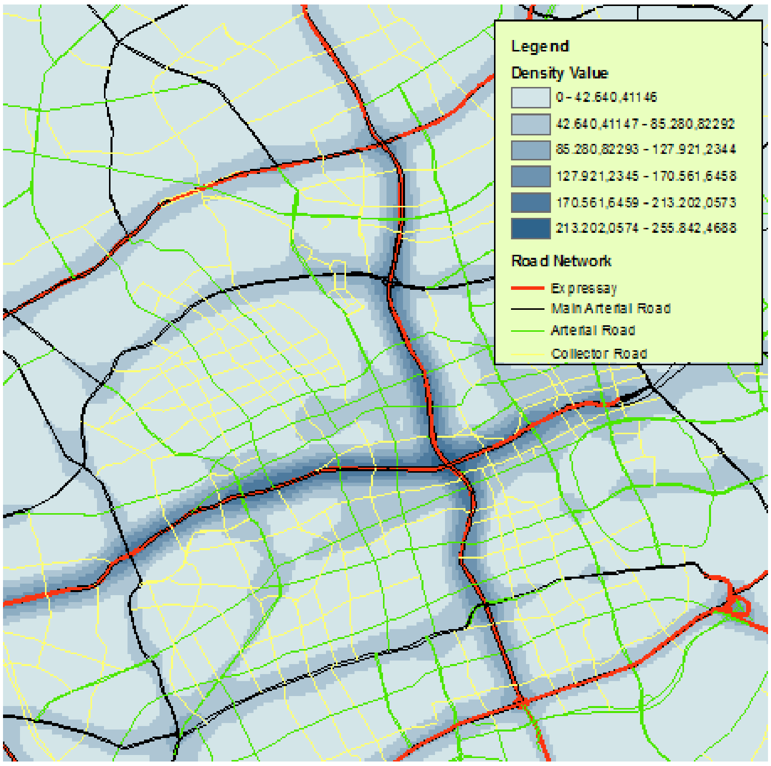



**Figure 5.8.** Kernel Density Map of Trajectories of Taxis in Shanghai at 12:00 – 13:00 PM

From Figure 5.7., the expressway/elevated roads and main arterial roads have the highest density comparing with the other road types. This means that these roads have the highest frequency to be used for travelling by taxi users. Therefore these types of roads have the greatest possibility to be congested. In the morning peak period, the frequently used roads are the expreesway/elevated roads and the main arterial roads alongside the expressway. Some main arterial roads and arterial roads which are located closed to the expressway/elevated roads and city center are also used frequently in this time period.

The evening peak period has the slightly different patterns from the morning peak period. The number of the frequent roads is higher than the morning peak, thus the distribution of the frequent roads is more dispersed. This might be because people tend to not use the expressway/elevated road to avoid the traffic congestion or people are having gathering or dinner in the area near city center before they are going home so that the traffic flow are not really concentrated in the expressway/elevated roads and the main arterial roads alongside it.

In the Figure 5.8, the highest peak of *idle* time between morning peak and evening peak (12:00 – 13:00 PM), the pattern of the frequently used roads is almost the same with the morning peak period. But the intensity of the frequent roads is different from the morning peak period and more main arterial roads and arterial roads are used in this time period. This could mean that not so many people are travelling to the city center or just travelling around the down town area of the Shanghai city.

From the low speed and stop taxis information, a clustering method could be performed to depict the stop-and-go traffic pattern (Xintao Liu and Yifang Ban, 2013). When the result of this clustering method is combined with the traffic congestion visualization on the road network, the clusters which located closely to the heavy traffic congestion level will show the stop-and-go traffic pattern. Grid based clustering technique is used to cluster these points. This method divides the area into some cell grids and cluster the points that inside the cell into one class. The GPS points that has been used only for with car status equal to one which has passenger on the taxi to make a certain that the taxis could included in the traffic flow. From the result in Figure 5.9., the clusters of stop taxis are mostly located near the congested roads, especially near the intersections. This could mean that these taxis are waiting for traffic lights or could be stuck in the traffic congestion. Based on this result, it could be concluded that the stop taxis has a high correlation with the traffic congestion, as most stop taxis which has passengers are located close to the congested roads.

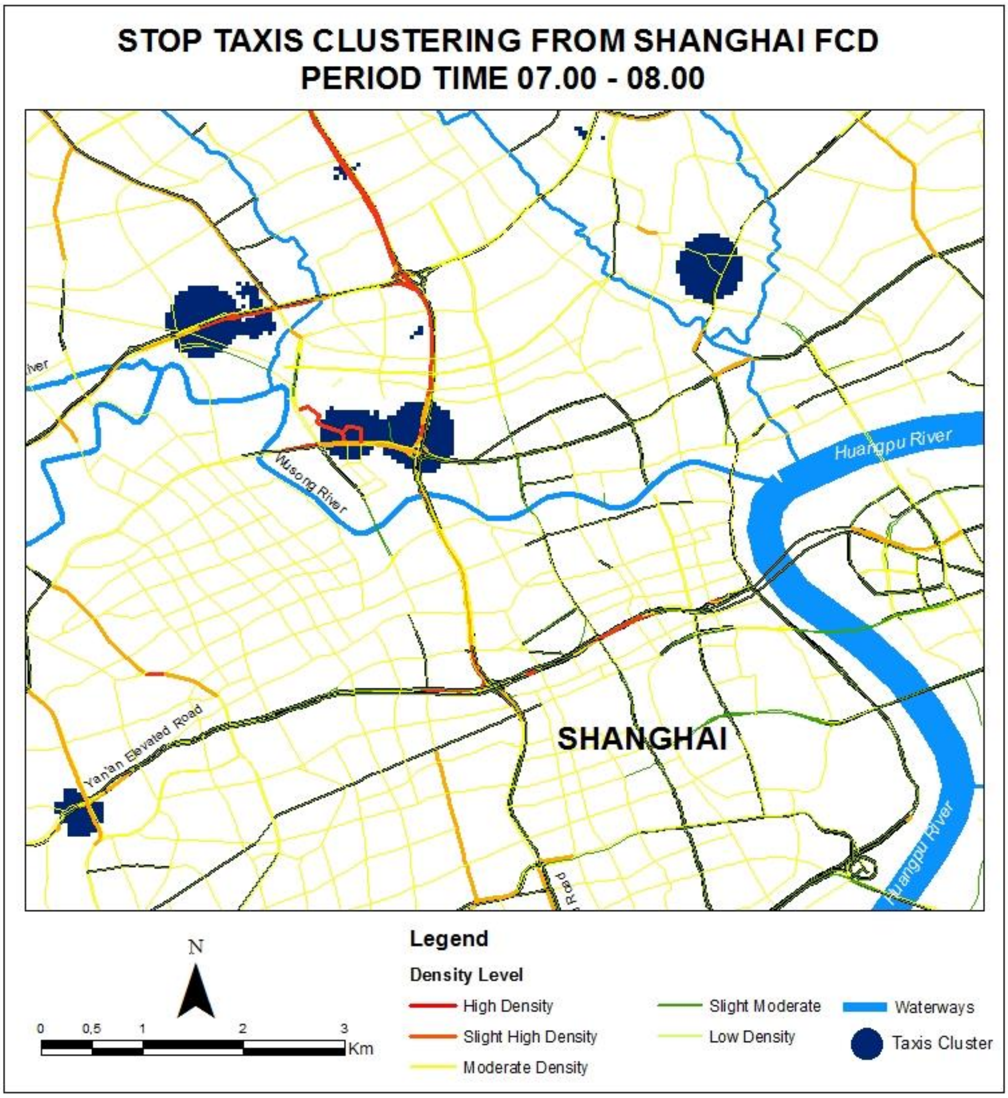



**Figure 5.9.** Stop Taxis Clustering at 07:00 – 08:00 AM time period

### 5.2.2.2. Visualization on Road Network

Visualization of traffic congestion in road network will give an actual representation of traffic condition in real world as traffic congestion happened in the road network. The spatial distribution of road congestion could also be easily depicted by using different color for each level of congestion on the road network. With this visulization, indetifying which road segments are congested would be easier.

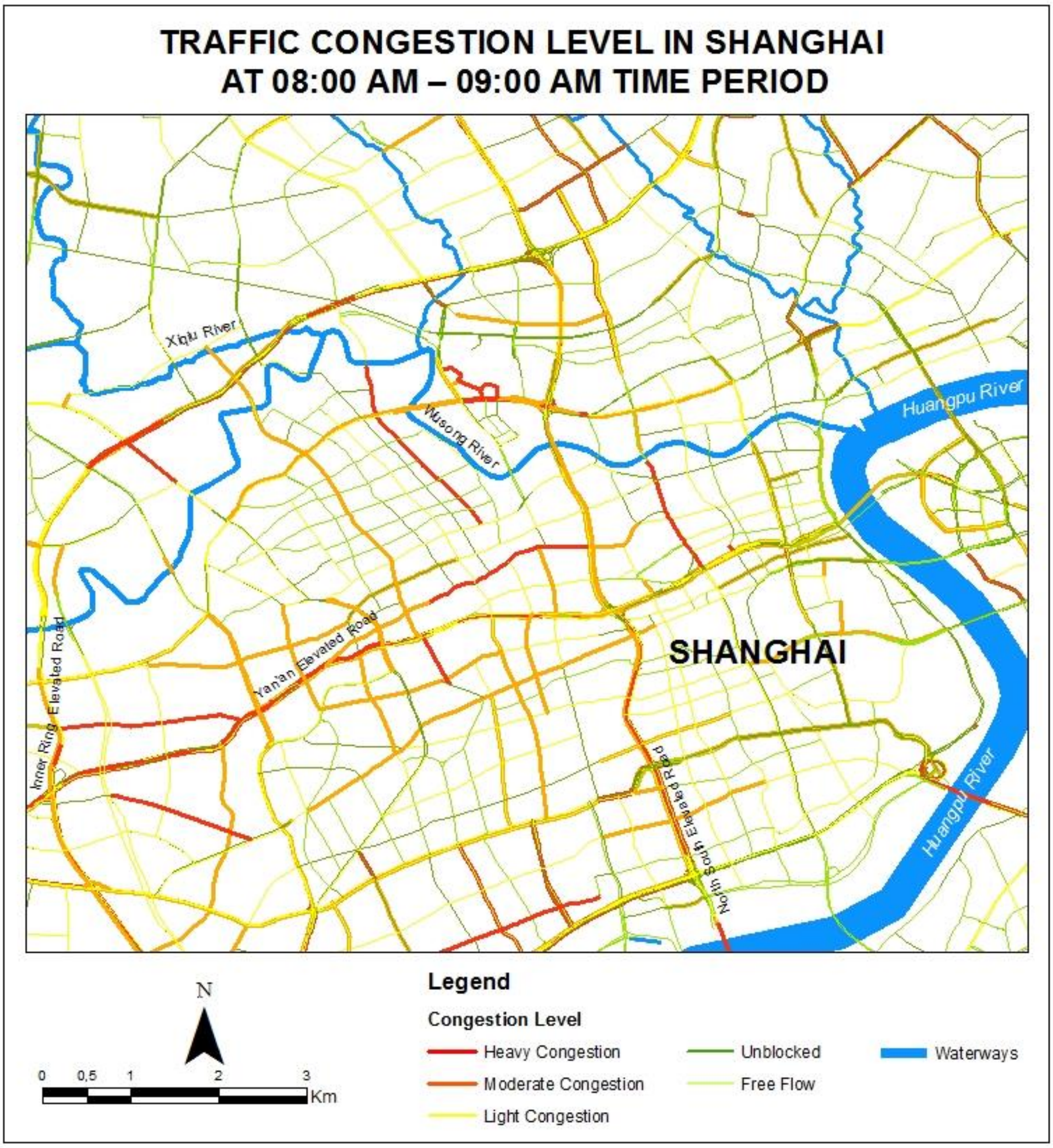



**Figure 5.10.** Traffic Congestion Level in Shanghai 08:00 – 09:00 AM Time Period

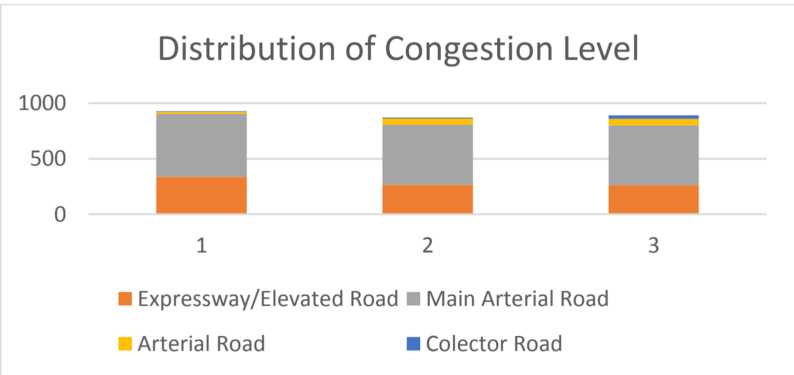



**Figure 5.11.** Distribution of Traffic Congestion Level in Shanghai at 08:00 AM - 09:00 AM for Each Road Type

Figure 5.10. depicts the traffic congestion level in Shanghai in the morning peak, which shows that in this period of time the heavy congestion mostly occur in the expressway/elevated road segment, especially in Yan'an Eleveated Road and near the intersection of the city center. While from the distribution of the traffic congestion, main arterial roads have more frequent traffic congestion event compare with other types of road.

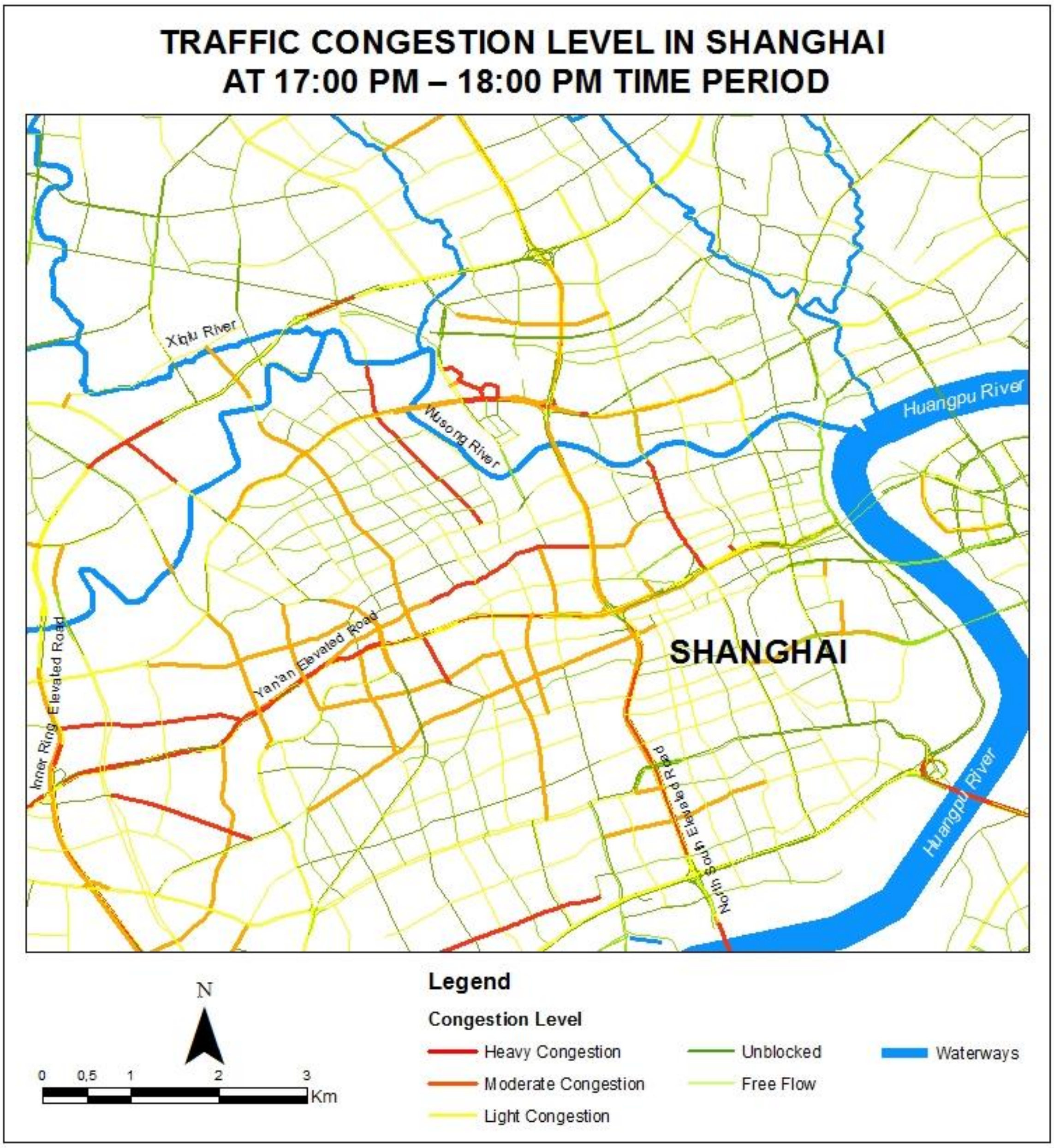



**Figure 5.12.** Traffic Congestion Level in Shanghai 17:00 PM – 18:00 PM Time Period

In the evening peak period (17:00 PM – 18:00 PM) that is visualized in the Figure 5.12, the heavy congestion only occurs in some part of the expressway/elevated road segment and most of the congestion are at moderate congestion level, especially in the North South Elevated Road. From the distribution of the traffic congestion, main arterial road still have more frequent traffic congestion event compared with other type of road and the number of the heavy congestion in expressway/elevated road is smaller than that in the morning peak period. The collector roads also have bigger number of the traffic congestion event compare with in the morning peak period.

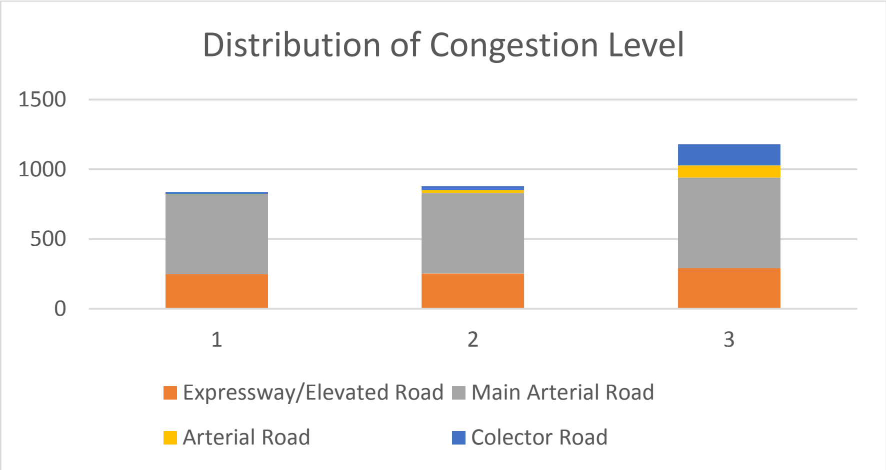



**Figure 5.13.** Distribution of Traffic Congestion Level in Shanghai at 17:00 PM – 18:00 PM Time Period for Each Road Type

From the distribution of the congestion level for each road type, the daily average congestion for each type of road in a day could be calculate. It shows that the that the heavy congestion mostly occured in the main arterial road, with the frequency of 58,85%. While arterial road and collector has almost the same number of heavy traffic congestion. In some period of time, such as from 17:00 PM to 18:00 PM, the collector roads have a larger number of road segment with the heavy traffic congestion.

| Type | Traffic Events | Percentage |
|---|---|---|
| Expressway/Elevated Road | 1009 | 34,22659 |
| Main Arterial Road | 1464 | 49,66079 |
| Arterial Road | 238 | 8,07327 |
| Colector Road | 237 | 8,039349 |

**Table 5.1.** Daily variation of traffic congestion events on road network

Another advantage by using this visualization is we could calculate the absolute density of the road from the traffic flow theory by dividing the number of vehicles on the road with the length of road. This calculation could also be used to define traffic congestion, as traffic congestion happens when the demand of the road exceeds the capacity of the road. Therefore the higher the number of the density, the higher the possibilty of traffic congestion occurs on the road segment. The length of the road could be calculated directly by using *Calculate Geometry* tools in ArcGIS, while the volume of vehicles could be calculated from the number of points which are located on the road segments for one hours period. The density number then is classified into 5 different levels to differentiate the high and low density road.

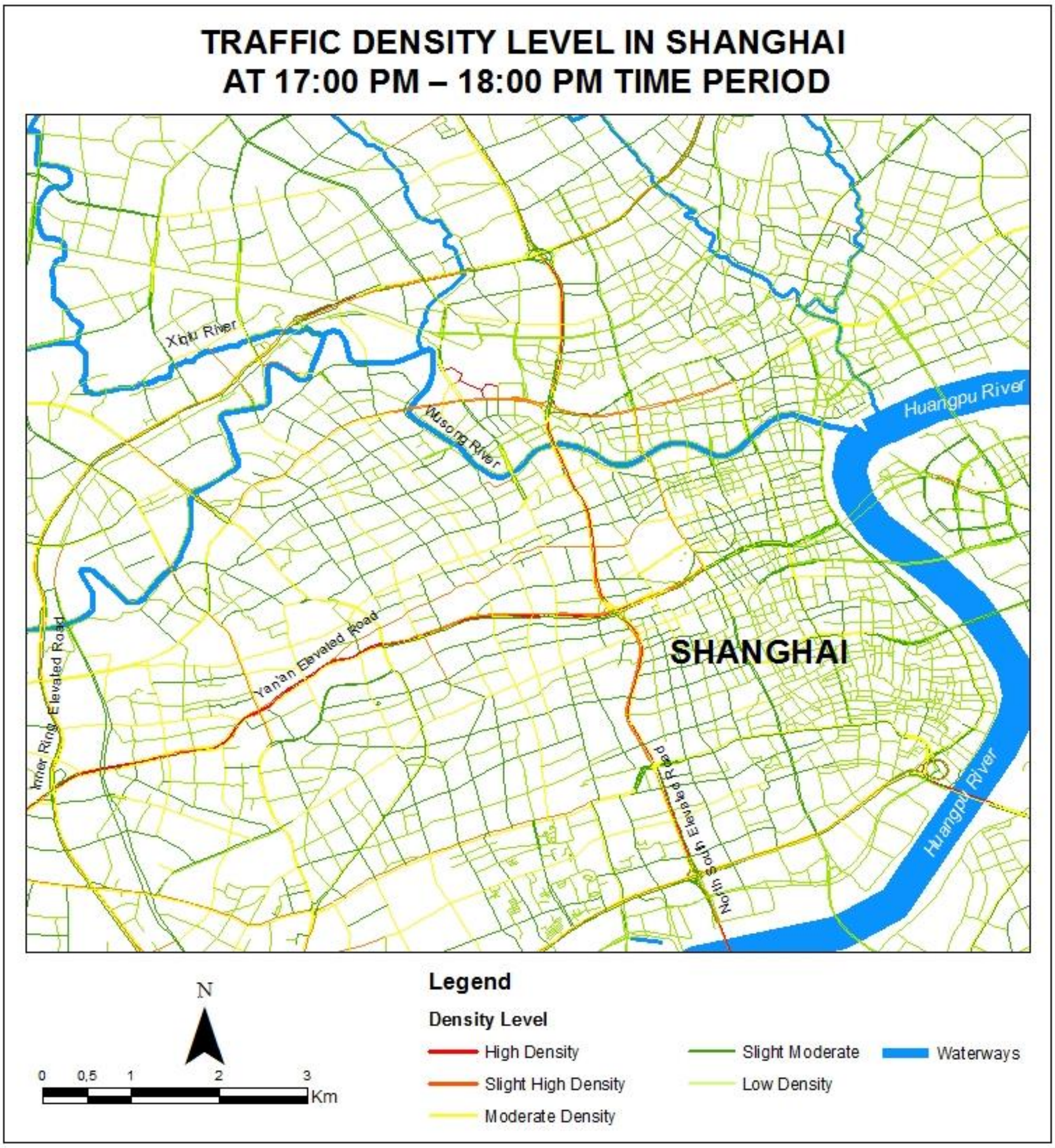



**Figure 5.14.** Traffic Density Level in Shanghai at 17:00 PM – 18:00 PM Time Period

From the result of calculating density on the road network, the highest density roads are mostly located in the expressway/elevated road. The Yan’an Elevated Road and North South Elevated Road has the highest density compared with other roads. The reason is because most of the road users choose these roads in their route, which might be because these roads have bigger capacities than other types of roads and they can avoid the traffic congestion. These types of roads are also free from the traffic lights so that the queing events are less to happen. The results from this method could be combined with the results from traffic congestion level detection on the road network to derive interesting correlations between the road density and the congestion level because the basic theory of traffic congestion stated that traffic congestion is occured when the demand of the road exceeds the road capacity. Therefore the higher the density, the higher the probability of the congestions might occur in the road segments. The Yan’an Elevated Road and North South Elevated Road which have the highest density are also have the most frequent traffic congestion, which means that the road density more or less affects the traffic congestion level.

#### 5.2.2.3. Animation and 3D graph

For 3D visualization of spatio-temporal traffic congestion in Shanghai, animation with time slider function is chosen. With this visualization, the trends and changes or evolution of the traffic congestion for each road in a different time periods could be seen easily. Temporal dimension is represented by a time slider function of the animation, while the spatial dimension which is the spatial distribution of the traffic congestion could be seen from the map. This animation actually consists of a temporal series of static map.

From the animation, we can observe the changes of the trafffic congestion level on the road segment by watching the color changes of the road segments. Most part of the road segments usually change at different period time. However some part of road segment remains the same for different time periods, such as a part of road segment in Yan’an Elevated Road with heavy congestion level, which means that this road segment is a frequent congested road. With this visualization, the user could observe the changes of traffic congestion level only in one window which makes it easier than if they have to go back and forth from one layer map to another to observe the changes. The time slider function allows users to stop the view of the map on the chosen time interval.

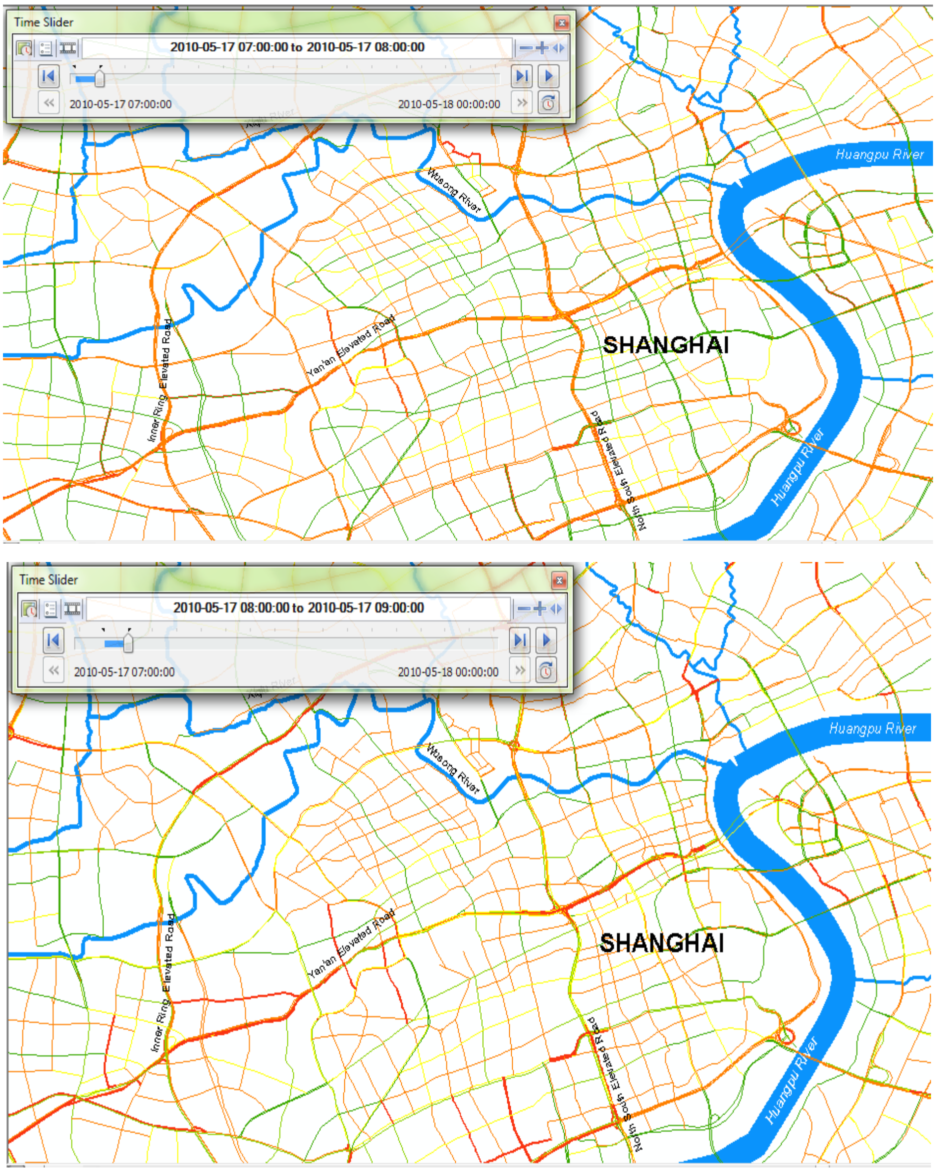



**Figure 5.15.** Time Slider Animation of Traffic Congestion Level in Shanghai at 06:00 AM to 23:00 PM in different time interval

Another method is by using 3D graph or extrusion of the attribute value on the surface of the road network to depict the level of congestion by using height and color. By using this visualization, the differences between each level of traffic congestion will be shown clearly by the height of the extrusion. The color also emphasize the differences between each level, especially if the road segment is located close to each others. In the Figure 5.15, the heavy congestion level is depicted by using the heighest extrusion and the red color. From the result we could see that most of the heavy congestion roads are on the expressway/elevated roads, especially in Yan'an Elevated Road.

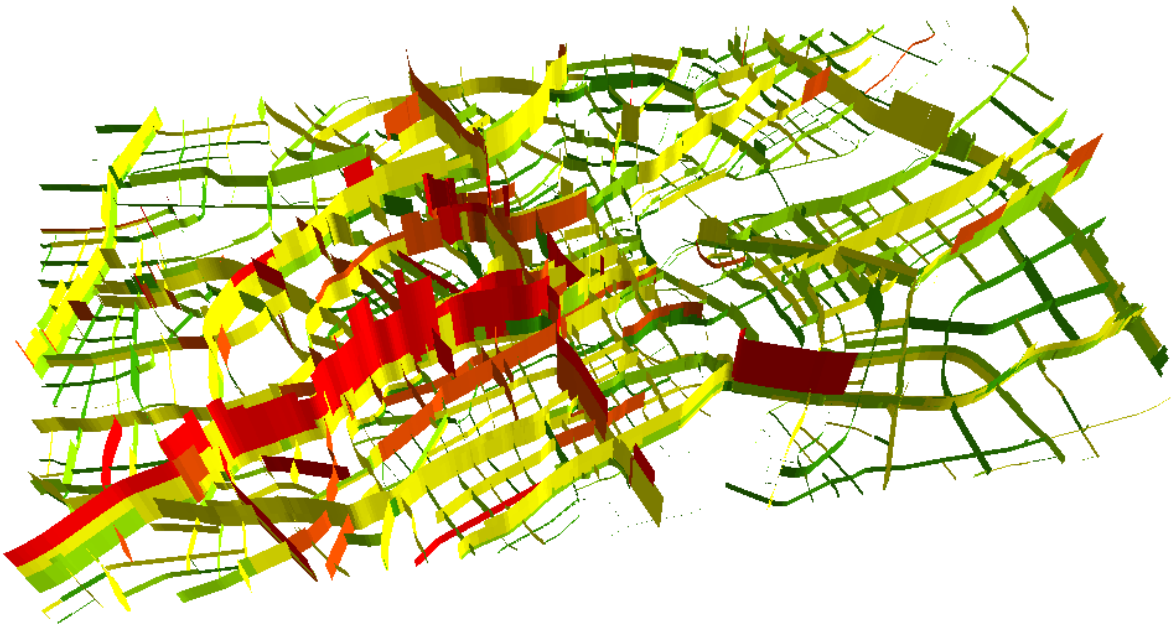


**Figure 5.16.** Extrusion Graph of Traffic Congestion Level in Shanghai at 17:00 PM – 18:00 PM Time Interval

# 6. CONCLUSION AND OUTLOOK

In this thesis, a one-day test dataset of FCD from taxi trajectory in Shanghai city is used to extract information about traffic congestion level in the city. The extracted information could be visualized and analyzed to provide deeper knowledges about the spatial and temporal patterns of the traffic congestion. The visualization technique that have been used are density mapping of the point data and trajectories, visualization of traffic congestion level based on the road surface network, animation using time slider and three dimensional visualization based on the extrusion of the attributes.

From the result by using visual analytics methods for spatio-temporal data, it can be concluded that FCD is a very useful data source to derive information about spatio-temporal patterns of traffic congestion in the city area. From the calculation, the traffic congestion in Shanghai city have two peak time periods, which are from 07:00 AM to 09:00 AM in the morning and from 17:00 PM to 18:00 PM in the evening, while the highest *idle* time between these two peak is from 12:00 PM to 13:00 PM in the afternoon. The congestion on the road network mostly last about 15 – 25 minutes. In spatial dimention, the congesstion mostly occured in the expressway/elevated roads and the main roads. The frequent congestions road segment are located in Yan'an Elevated Road, North South Elevated Road and the intersections which are located near the city center. In conclusion, the result of this study could answer all the research goals of this study which means that FCD set is useful as a data source to calculate the traffic congestion level on the road network and visual analytics method could be applied to extract more information such as spatio-temporal pattern from the traffic congestion information.

FCD sets could also be used to calclulate the road density based on the traffic flow theory by dividing the number of the points on the each road segment which represented the number of vehicles within the length of the road. The results from this method could be combined with the results from traffic congestion level detection on the road network to derive interesting correlations between the road density. The Yan'an Elevated Road and North South Elevated Road which have the highest density are also have the most frequent traffic congestion, which means that the road density have a possitive correlations with the traffic congestion level.

From the pre-processing and processing steps, map-matching and clustering techniques should be chosen wisely so that the results could really represented the actual condition of the traffic congestion. A suitable time ranges and classfication ranges should be chosen according to the data set to give a better representation of the traffic congestion as the result will be different with the different time ranges and different classification.

For the further study about visual analytics of spatio-temporal data derived from FCD set, a larger dataset which contain more than a day data could be used to detect a different pattern of traffic congestion. More sophisticated data mining and visualizations methods could be used to explore in depth about the result from the processing of FCD set. The result could then be compared with result from different methods to give an insight which method could extract a better and actual information about traffic congestion.

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