Intelligent Transportation Cyber-Physical System: On Crowd through Event Detection for Public Urban Transportation

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Abstract: Intelligent Transportation System (ITS) has become the popular area of research since the last decade. Knowing the crowd density in every region of the city is of high importance for an ITS in delivering adequate transport facility to the public. Further, the occurrence of social events draw public crowd occasionally, in any specific region of the city. Thus, the combination of both the identification of crowd density and the social event detection lays a path to an interesting research in ITS. Having said, this paper proposes a methodology for the effective design of ITS with a primary focus on crowd sensing. The paper also presents a taxonomy of methods used to gather crowd density information through various sources. Furthermore, the research works that focused on event detection and crowd analysis are studied. Finally, the open challenges are identified and outlined which are promising research directions for ITS.

I. INTRODUCTION

The urban population is rapidly increasing in recent years due to the economic upturn, rising job opportunities, and modernization. Thus, it is very common to see a huge amount of people in public places who seek transportation facilities for their commute. It lays a critical burden on the city administrators to ensure adequate transportation infrastructure, management, and safety in an overloaded region of the city. Hence, it becomes more prevalent to design an intelligent system with an objective of resolving the aforementioned issues. Intelligent Transportation System (ITS) is emerging globally with the potential to serve this purpose and legislate current transportation. ITS offers contemporary services related to different types of transportation and management of traffic which make users be safer, more updated and enables a smarter way of transportation. The different types of transportation include road, sea, air, and rail. The idea of an ITS is to sense, analyse, and control the transportation by means of integrating sensors, information and communication technologies. A Traffic Management Centre (TMC) is used to collect and analyse transport data, and further make wise decisions to solve complex traffic problems [1].

The key objectives of ITS include minimizing traffic problems, improving traffic efficiency, conserving time, and enhancing public safety and comfort. Although ITS offers advantages to the possible extent, it faces a numerous challenges. Emergency vehicle notification system, automatic road enforcement, dynamic traffic light sequence, collision avoidance system, parking guidance, and electronic toll collection are a few important challenges to list.

Hence, the implementation of ITS brings more prominent problems, despite its promising features. Especially the increasing congestion, accident risks, building infrastructure [2], and crowd sensing make the challenges extremely difficult. H. Behruzet. al [3] state in his case study that the effective use of traffic cameras, GPS technology, and intelligent routing system for passengers make ITS implementation more challenging. On the other hand, the data acquired by the ITS is vulnerable to security threats. The breach of sensitive data can lead to a great loss, even life-threatening risks. Hence, effective security safeguards need to be in place in order to avoid security ramification.

Therefore, an effective implementation of ITS has numerous critical research issues and still remain unaddressed. In this paper, we emphasise on crowd analysis through event detection in urban areas which is the prime factor for enhancing intelligent public transportation. As mentioned above, the urbanization brings more population. Consequently, the occurrence of a social event draws the public crowd in a specified region. It is thus imperative to consider social events and density of a crowd which could be adopted in some phases of intelligent transportation.

We structure the reminder of this paper as follows: Section 2 presents a methodology to design an ITS for improving smartness. Following this, the data collection and creation along with a taxonomy of crowd sensing methods is discussed in section 3. Section 4 highlights the importance of data handling and manipulation. Section 5 presents a survey of research works carried out in crowd analysis through event detection, which emphasises on the computation and analysis of the data. Finally, section 6 concludes the paper and outlines the future research aspects of ITS.

II. METHODOLOGY TO DESIGN AN ITS

As discussed in the previous section, crowd analysis and event detection play a significant role in the effective implementation of ITS. There have been diverse technologies proposed by various researchers to address crowd analysis

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and event detection. However, they doesn't specify an end-to-end methodology to implement ITS. Here, we propose a three step methodology to design an ITS with a focus on crowd analysis through event detection to improve smartness. Figure 1 illustrates our proposed methodology.

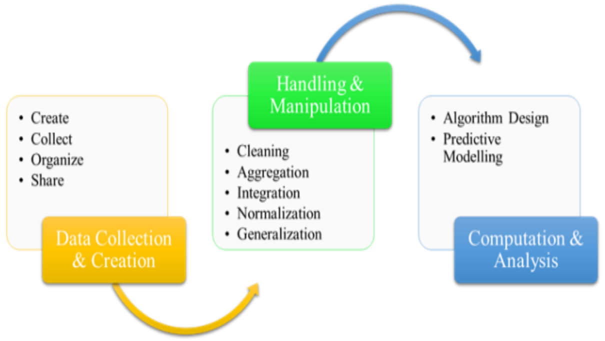

Figure 1. Methodology to design ITS using Crowd Analysis through Event Detection

The methodology begins with data collection and creation through various sources, continues with the handling and manipulation of the acquired data using cloud computing technologies, and performs computation and analysis using machine learning or deep learning approaches to take smart decisions. Following sections discuss each of these steps in detail.

III. DATA COLLECTION AND CREATION

Data is an integral part of ITS. The details such as the number of vehicles, position of the vehicle, number of people (a.k.a crowd), speed, and roadway play a crucial role in ITS decision making to improve smartness. Acquisition of these data could be historical or real-time and can be in the form of text, images and videos [4]. In short, the data is heterogeneous in nature. Historical data notifies the past event while the real-time data is delivered instantly after acquisition. The data collected through toll gates, parking management systems, and surveillance camera contribute to historical data. On the other hand, real-time data can be gathered by means of sensors, Global Positioning System (GPS), smart cards, etc. Historical data can also be fetched from social events, tourist spots, and urban sensing. Such data can be fetched by monitoring surveillance camera installed at public places such as train station, bus stand, hospital, and shopping malls. It is to be observed that the data collected is not only useful for detecting the crowd, but also to predict a suitable model for intelligent transportation.

The combination of historical and real-time data provides the accurate prediction of future events. Historical and real-time data can be collected in the following six ways [5].

A. Manual collection

It is the traditional method of collecting transportation information. The number of vehicles, and the number of people are manually collected for the purpose of documentation and financial records. It also involves extracting pre-planned public event information from newspapers, websites, radio, television, websites and social media. Such a process is difficult, slower, and involves high manpower. Moreover, the accuracy of the data is of no guarantee. Hence, the manual data collection is disregarded, and the incorporation of a variety of automated devices are recommended. In [16], the authors manually collected the dataset named as crowd-11 from web using keyword search for behaviour analysis of crowd.

B. Open crowd-sensing

Open crowd-sensing [6] directly estimates the density of the crowd using electronic toll data, probe vehicles or devices, on-board units and even, surveillance camera. A typical example would be a vehicle equipped with wireless technology. It is used to find the speed and location of that particular vehicle. But still it has some infrastructure constraints. The sensors described in section 3.D also contribute to open crowd-sensing. From this, it is apparent that the methods fall in each of the other methods. A people counting method is proposed in [13], that effectively uses airport surveillance camera. A sample of 1000 images and 474 videos is taken as a data set.

C. Hidden crowd-sensing

This method [7] is an indirect way of extracting crowd information which primarily relies on GPS. In recent days, the number of mobile phone users continues to increase. Most of the mobile phones are equipped with GPS, offering location information of the users. It enables one to collect real-time and accurate data. This results in trouble-free and infrastructure less mechanism. Besides the gained advantages, fetching the travel time, vehicle speed, route details, and location information without user's knowledge is yet a significant threat.

D. Sensor-derived

The shortcomings of manual data collection enforce the need for automated devices for smooth data collection. The range of such automated devices include [1] IR (Infra-Red) sensor, people counter sensor, horizontal beam sensor, video graphics (CCTV), and passenger counter sensor. These sensors gather the roadway information in real-time with greater accuracy. Even though it reduces the manpower, the implementation and maintenance are costlier and the coverage area is limited. The sensor-derived data is real-time and provides exact figure about the crowd. In [17], a bus arrival prediction model is proposed using RTI method. In this framework, GPS data of bus is used for the prediction. A similar work is carried out in [18], in which a framework for smart transportation is proposed, where the GPS data, mobile phone network, and Bluetooth information are collected without the knowledge of the user to find the vehicle's location.

E. Data repository (Service provider)

The data repository is a data library or an archive that stores related information. It is a historical data that helps in effective data analysis, sharing and reporting. ITS is used globally and implemented for a specific requirement. For example, countries like USA, Japan, UK, Europe, and Canada implement intelligent transportation [6]. These ITS datasets are publicly available and can be used for a variety of

ITS research. An example of such a dataset is USDOT (U.S. Department of Transportation). In a work proposed in [10], a large crowd information is detected in order to aid the transport managers and the travellers to plan transportation accordingly with the help of Singapore public transport system data set. In [11], an unusual social event prediction model is proposed which makes use of non-sensitive data of smart card users for the purpose of city administration. The model is evaluated by China's public transportation data.

F. Social media

Social media is of great interest today. It accumulates a myriad of information about the occurrence of real-time social events. The social media users frequently post everyday activity of their life and public events on Facebook, Twitter, and Whatsapp [8]. Therefore, such data present in social media is of great value in extracting event information. The captured event information is useful to determine the traffic incidents, the purpose of visit, mode of commute, source, destination, and time period. The counties like China use an Android-based mobile application to collect traffic information from social media. In [20], the authors developed a data fusion model for detecting the traffic events, where the social media data and GPS information are extensively used. Table 1 summarizes our review and compares various factors involved in identifying crowd and event information.

Table 1.

Ref	*MN*	*OCN*	*HCN*	*SD*	*DR*	*SM*	*DS*	*Image*	*Text & Number*
[10]		✓			✓	✓			
[11]		✓			✓	✓			
[12]		✓			✓			✓	
[13]		✓			✓				
[14]		✓					✓		
[16]	✓							✓	
[17]			✓	✓	✓				✓
[18]		✓	✓	✓		✓			✓
[19]		✓							✓
[20]		✓				✓			✓

Legends: Manual collection (MN); Open crowd-sensing (OCN); Hidden crowd-sensing (HCN); Sensor-derived (SD); Data repository (DR); Social media (SM), and Data sharing (DS).

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G.Data organizing and sharing

Sensors and camera are the widely used data collection equipment in ITS [13]. The collected data is pre-processed and is uploaded in a cloud environment. The cloud environment performs analysis on the data and the results can be downloaded for further process. Instead of performing all data analysis processes on a device, a cloud platform is used in order to reduce the energy consumption and increase the accuracy.

IV. HANDLING AND MANIPULATION

The real-time collected data is crude, and demands only the essential data to be selected for further processing. Before taking the data for analysis, it must undergo a few pre-processing steps including cleaning, integration, aggregation, generalization, and normalization. Data cleaning either removes missing data or fills relevant value. It removes noisy data as well. During the process of integration, the data collected from various sources are combined. This perhaps results in data duplication, which can be resolved using correlation analysis. Subsequently, aggregation summarizes the data for processing. Generalization normally identifies the low level data from the aggregated data and replaces them with high level data. Furthermore, the scaling of a parameter value to a specific range is vital, since it is a primary requirement of processing phase. This process is called as normalization [9].

V. COMPUTATION AND ANALYSIS& RESULTS

In this section, we review recent research works that focus on event detection and crowd analysis through various technologies and data acquisition methods discussed in section 3. The study reveals several interesting factors for future research in ITS, which are outlined in our conclusion section.

In [10], Francisco C. Pereira et. al. proposed a machine learning model to breakdown unhabitual overcrowded hotspots. The statistics of the habitual crowd along with event dataset collected from five different websites (public events announced in the web) is used to predict the unhabitual crowd and provide an explanatory component to each. Moreover, their model enables a transport manager to supply an adequate transport system on demand. The model is validated against the real-time data collected from the EZLink public transport system, Singapore and their findings show that the model is more accurate in terms of generating explanatory components. Incorporating seasonality effects, baseline demand, spatial correlations, and simultaneous events could overcome the shortcomings of their model.

Haiyang Wang et. al. [11] proposed a detection-based prediction framework for the early detection of unusual social crowd events. The aim of their model is to provide adequate information to the city administration team, in order to take necessary actions for traffic management, emergency management, and public safety. Given the history smartcard data and social crowd event data from the Internet, the model effectively predicts an unusual gathering. They find a 'two-peak' pattern of gathering flow and departing flow before and after a public crowd event. The model is evaluated against real-time public transportation data of Shanghai, China and validated with social crowd event data collected from the Internet. Furthermore, the model uses non-sensitive data from the smart card which improves security and privacy.

Depth Information Guided Crowd Counting (Digcrowd) model is proposed by MingliangXu. et. al. [12] to accurately count people in a crowd. Their contribution is of threefold: crowd density detection system, image segmentation method, and a dataset of complex crowd scenes from an airport. They implemented the model with a deep convolutional neural network which applies image segmentation. The neural network is trained by CIISR (airport) dataset with 1000 images captured by surveillance camera. Their model is compared with two other existing datasets, Mall dataset and Shanghaitech dataset (data of a busy street). The model outperforms with CIISR dataset. The security parameter is not considered, which is viewed as a typical downside of their work.

Beacon technology deploys a small device that broadcasts a unique ID number which can be sensed by a Bluetooth equipped smartphones, once it's in range. DaniloCianciulliet. al. [15] developed a distributed software system which utilizes personal mobile devices along with beacon technology. The mobile devices are used as both mule sensor and client to obtain real-time bus information. The framework provides the users with bus positions, travel time and other recommendations. Less human intervention, no infrastructure costs, and self-learning are the potential advantages of the model. However, incorporating incentive techniques, security considerations, and user's feedback will enhance the model.

Jens Weppneret. al.m [21] proposed a Bluetooth scan based crowd density sensing technique using mobile phones. In addition to the number of devices identified through a Bluetooth scan, they focus on the ratio of the present scan window to the previous scan window, diversity of the identified devices, device visibility periods and duration. They also take into account the relative features based on the values observed by different devices and the actual number of Bluetooth IDs gotten during the scan. This makes the system more efficient in terms of determining the crowd density. The system is evaluated with a real-time event, European soccer championship held at Kaiserslautern (Germany) for three days during 2012. The system achieved 75.3% of accuracy using decision tree classifier. Nonetheless, their model is designed to estimate the crowd density in an area of 2500m2.

Table 2 depicts different models used for event detection and crowd analysis.

Table 2. Event detection and crowd analysis methods

Ref	Model	Purpose
[10]	Bayesian Hierarchical Additive Model	Recognise unhabitual overcrowding
[11]	Multi Regression Prediction Model	Detect of unusual social crowd events
[12]	Convolutional Neural Networks	Determine the count of people in a crowd
[15]	Beacon based Context Aware Model	Provide the users with bus positions, travel time and other recommendations
[21]	Bluetooth Scan based Crowd Density Estimation Model	Estimate crowd density through mobile phone Bluetooth

VI. CONCLUSION

Crowd sensing is an essential and a challenging research component in ITS. In this paper, we outlined a methodology to design a crowd sensing based ITS that gathers and analyses crowd information and provide useful insights to the city administrator. In addition, the paper reviewed various data acquisition methods available to collect public crowd information, social event detection methods, and shortcomings of the existing methods, vulnerabilities, and security challenges. It is observed that the incorporation of security and privacy algorithms in ITS is of great significance to avoid data breach and cyber-attacks. To achieve high speed computation, manage huge volumes of data, the ITS can be integrated with a cloud computing framework. Moreover, the size of the crowd sensing area plays a vital role in the accurate identification of crowd information. These suggestions undoubtedly constitute a secure, effective, reliable and robust ITS.

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