iJRASET
International Journal For Research in
Applied Science and Engineering Technology

INTERNATIONAL JOURNAL FOR RESEARCH
IN APPLIED SCIENCE & ENGINEERING TECHNOLOGY

Volume: 6 Issue: XII Month of publication: December 2018

DOI:

www.ijraset.com

Call: 08813907089 | E-mail ID: ijraset@gmail.com

# Applying Floating Car Data for Real-time Traffic Monitoring

Prof. Shital Patil[1], Aditya Kute[2]
[1]Assistant Professor, Department Computer Engineering, SRTTC-FOE, Kamshet, Pune
[2]Student, Department Computer Engineering, SRTTC-FOE, Kamshet, Pune

***Abstract*: In today's routine life usage of smart devices and artificial intelligence have increased drastically, therefore, more and more images, text, videos, and audios are created day by day, however applying the current technological possibilities has led to a wide range of Real time traffic monitoring system. On the contrary, for the computation of complex features deep learning of the live geographical and surrounding factors is needed. This is because deep nets within the deep learning method have the ability to develop a complex hierarchy of concepts. Secondarily when unsupervised data is collected and machine learning is executed on it, manually labeling of data has to be performed by the human being. This process is time-consuming and expensive. Therefore, to overcome this problem deep learning is introduced because it has the ability to identify the particular data.***

***Keywords: Floating Car Data (FCD) , Intelligent Transportation System (ITS) , Real-time Traffic Monitoring***

## I. INTRODUCTION

Traffic and mobility are important ingredients in our daily routines. People are suffering from inefficiency, noise and air pollution as far as street traffic and transportation is concerned, which is quite evident from drastic increase in number of vehicles in last decade or so. Deep learning is based on an artificial neural network with multiple hidden layers and has found considerable traction for many artificial intelligence applications. It takes metadata as an input and process the data through a number of layers of the non-linear transformation of the input data to compute the output. This algorithm has a unique feature i.e. automatic feature extraction. This means that this algorithm automatically grasps the relevant features required for the solution of the problem. This reduces the burden on the programmer to select the features explicitly. This can be used to solve supervised, unsupervised or semi-supervised type of problems. The traditional neural network consists of at most 2 layers and this type of structure of the neural network is not suitable for the computation of larger networks. Therefore, a neural network having more than 10 or even 100 layers is meant for Deep Learning. In this, a stack of the layer of neurons is developed. The lowest layer in the stack is responsible for the collection of raw data such as images, videos, text, etc. Each neuron of the lowest layer will store the information and pass the information further to the next layer of neurons and so on. As the information flows within the neurons of layers hidden information of the data is extracted. So, we can conclude that as the data moves from lowest layer to highest layer (moving deep inside the neural network) more abstracted information is collected.

## II. METHODOLOGY & PROCESS FLOW

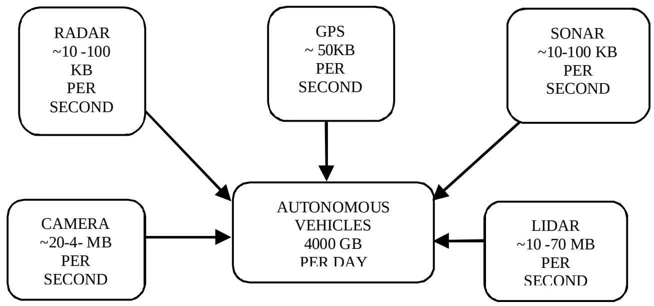
There are various methods that are introduced for the analysis of a large data set such as pattern recognition methods like K-N Algorithm, Support Vector Machine, Naive Bayes Algorithm etc. Due to the presence of a large amount of data, these traditional methods are not feasible to produce efficient results. Stationary detector data (SDD) consists of data captured on fixed points in the road network by cameras, embedded inductive loops or other measuring equipment. This offers high resolution monitoring of the specific location (often with samples generated every 10-60 seconds). A full view on the traffic state along the trajectory can be made by combining the SDD from several points with macroscopic flow theory. Kalman filtering models the traffic as flows of cars and estimates the traffic state space for each time period [7]. Further extensions to the model have been made to account for irregular sample generation by using multiple modes of filter operation [8]. While both sources separately can create a full traffic view, their combination allows a more detailed and accurate estimation of the traffic state. This is called **data fusion** and aims to fully capture the information in the individual sources. While SDD provides a detailed view on the traffic state on the monitored locations, installing and maintaining these sensors on the entire road network would require high investments. FCD is more easily used for this type of traffic monitoring as it distributed design inherently monitors large geographical areas instead of fixed locations. However, FCD accuracy depends on the number of monitored probe vehicles, often limited to a small fraction of the total traffic.

©IJRASET: All Rights are Reserved 

International Journal for Research in Applied Science & Engineering Technology (IJRASET)
ISSN: 2321-9653; IC Value: 45.98; SJ Impact Factor: 6.887
Volume 6 Issue XII, Dec 2018- Available at www.ijraset.com

Data fusion itself has be done with a wide range of techniques, e.g. neural networks [9-12] or Kalman modelling [13], fusing additional data sources e.g. automatic license plate recognition [14]. More example techniques and an overview of applications can be found in [15,16]. In this paper, we focus on an adaptive smoothing technique proposed in [17,18], also known as the extended and generalized Treiber-Helbing filter (EGTF). This filter uses kinematic wave theory applied to road traffic to merge individual samples to a full traffic state estimation.

Self-driving cars will create significantly more data than people—3 billion people's worth of data.




Generated data will be used for lane control and road hazards, so they will need to be continuously updated and splits the continually changing intelligence into three data sets:

1) *Technical data:* cones in the road and other hazards,
2) *Societal data( Crowd-Sourced Data):* It includes an automatic version of platforms such as Waze, for example. Waze is a community-based traffic awareness app that is heavily reliant on crowd-sourced traffic reports.
3) Personal data will make up the third classification. That includes locations and stop time.

## III. BASIC DATA FUSION ALGORITHM

For this EGTF technique, the road network is modelled as a dynamic system in which traffic flows along the roads, with cars driving from position *A* at time *tA* to position *B* at time *tB*. In free-flow traffic, the traffic conditions move along with the traffic, meaning that the traffic condition at position *A* at time *tA* will be very similar to the traffic conditions at position B at time tB. This implies that the traffic state at position B at a certain time tx (possibly in the near future) can be predicted by using a traffic state from position A at an earlier time ty. In congested traffic, however, the traffic conditions move in the opposite direction of the traffic. While the traffic at the head of a traffic jam starts to move again, the back of the traffic jam is still stationary, with even more cars queuing on. This results in the head of the jam moving backwards and causes stop-and-go waves. More importantly, the prediction of the traffic state at position A should take into account the traffic state at position B (further along the highway in the normal driving direction). These two mechanisms are modelled as separate waves in the Treiber-Helbing filter, moving at different speeds and in different directions. A schematic representation of the system is shown in Fig. 1. To estimate the traffic state for the position denoted by the diamond, the loop samples (denoted by triangles) on positions further along the route are taken into account by the backward propagating wave (denoted by the ellipsoid going from the top left to the bottom right). Analogously, the loop samples contributing to the forward wave are found in the forward ellipsoid (bottom left to top right). Following the above reasoning, the data samples within both ellipses are considered most relevant to the traffic state and will therefore be weighted more in the estimation of the traffic state at position P.

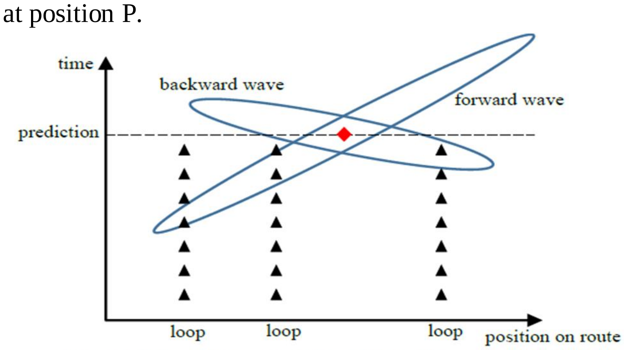


Figure 1: Schematic representation of the traffic wave in the EGTF

©IJRASET: All Rights are Reserved

To calculate the traffic state, the available samples are processed in a weighted sum. The estimated speed *s(x,t)* at position *x* and time *t* for one wave is then calculated as a weighted sum of the speed of all samples in the region of interest around the *(x,t)* point. This weighted sum is given by

$s(x,t) = \Sigma i\ (wi(x,t) \cdot si) / \Sigma i\ wi(x,t)$ … (1)

with *wi(x,t)* the weight of a sample at position *xi*, taken at time *ti*, contributing to the state at position *x* at time *t*. The individual weights *wi(x,t)* are calculated as follows

$wi(x,t) = exp( -|x-xi|/\sigma - |t-ti-((x-xi)/v)|/\tau )$ …(2)

with σ and τ denoting the width and time window, respectively, of the region of influence around the (x,t) point under estimation. This weight function favors samples according to the ellipsoids shown in Fig. 1. The σ and τ are tuned to the availability of samples, which depends on the average distance between installed detectors and their sampling interval. The v in the formula denotes the propagation speed of the wave and differs between the forward free-flow wave (vFF) and the backward wave (vCONG). This results in 2 speed estimates sFF(x,t) and sCONG(x,t).

To obtain a single speed estimate v(x,t) from the 2 estimates, they are combined using the following equations

$v(x,t) = z(x,t) \cdot sCONG(x,t)+(1-z(x,t)) \cdot sFF(x,t)$ …(3)

$z(x,t) = 1/2 \cdot (1+\tanh((Vc-\min(sCONG\ (x,t),sFF(x,t)))/dV)$ …(4)

with Vc the speed at which free-flow traffic transitions to congested traffic and dV the sensitivity around this threshold.

In Eq. 4, the two speed values (from the different propagating waves) are combined to estimate whether the traffic is in congestion ($z > 1/2$) or in free-flow ($z < 1/2$). If scong(x,t) or sFF(x,t) are below the transition threshold, the congested estimate becomes more dominant in the calculation of the final speed estimate v(x,t).

The input layer will consist of log messages and training is performed with the algorithm, whenever the abnormal behavior is depicted by the hidden layer, an alert will be given. This is one of the best approaches for the analysis of log files. Now let's discuss how log analytics is performed in the Big Data Platform using Deep Learning. Firstly, all types of log data are taken as input. Data integration is performed by collecting all log data at one location.

## IV. CONCLUSION AND FUTURE WORK

There are various data integrated tools in Big Data platform such as Apache Flume, Apache Nifi, and Apache Kafka. After the data collection, next step is to store the log data into the storage system such as HDFS (Hadoop Distributed File System), No-SQL Database like Hbase etc. After storage, processing of the data is performed by the corresponding tool engine like Apache Spark, MapReduce and much more. Then deep learning techniques are executed and patterns are identified as output. The obtained output of Deep Learning in CSV format is stored in the storage system. While executing Deep Learning security use cases are also performed simultaneously. After that, the output is visualized in the form of Graphical User Interface (GUI).

With more and more heterogeneous traffic monitoring, the traffic state estimation has to incorporate these individual sources in a consistent framework. By normalizing the individual data samples to take into account the measuring properties, they can be combined in a single data fusion algorithm to estimate traffic state. This approach was applied to fuse stationary detector data with floating car data, both gathered and processed real-time. Results show that this corrects individual data source bias, resulting in a cleaner traffic state estimation. While our study was limited to the well-monitored A58 highway, most road infrastructure is not equipped with traffic sensors, thereby limiting the availability of SDD. However, the data fusion algorithm does not require a single source to provide a full traffic view. As samples from different sources can be merged, the algorithm can be applied to roads with fewer sensors. More interestingly, it may also be used to avoid having to install an extensive network of detectors, thereby lowering infrastructure cost.

## V. RESOURCE-DEMANDING TECHNOLOGY

Deep learning is a quite resource-demanding technology. It requires more powerful GPUs, high-performance graphics processing units, large amounts of storage to train the models, etc. Furthermore, this technology needs more time to train in comparison with traditional machine learning.

### *A. Summary*

As more autonomous vehicles enter the scene, big data will only get bigger and consequently the potential for autonomous technology will rise, resulting in a vastly more data-centric automotive industry. The importance of deep learning is growing day by day due to the advancements in the technology and increasing availability of digital data. Opportunities will likely go beyond marketing, into autonomous driving, usage-based insurance, and other businesses.

©IJRASET: All Rights Reserved

As more autonomous vehicles considered into the picture, big data will only get bigger and consequently the potential for autonomous technology will rise, resulting in a vastly more data-centric automotive industry.

By 2020, the connected car market report states that connected car services will account for approximately $40 billion annually. These services include infotainment, navigation, fleet management, remote diagnostics, automatic collision notification, enhanced safety, usage based insurance, traffic management and, lastly, autonomous driving. The root of these applications is big data, as increasing amounts of data are collected from remote sensors; this information is being interpreted and leveraged to transform the automotive industry into one of automation and self-sufficiency.

## REFERENCES

[1] M. Vanlommel, M. Houbraken, P. Audenaert, S. Logghe, M. Pickavet, and P. De Maeyer, "An evaluation of section control based on floating car data", Transportation Research Part C: Emerging Technologies, in press, 2015.

[2] B. S. Kerner, C. Demir, R. G. Herrtwich, S. L. Klenov, H. Rehborn, M. Aleksic, and A. Haug, "Traffic state detection with floating car data in road networks", Proc. 2005 IEEE Intelligent Transportation Systems, pp. 44-49, September 2005.

[3] M. Vanlommel, P. De Maeyer, and S. Logghe, "Dynamical network management and historical analysis based on floating car data", 2nd international conference on Models and Technologies in Intelligent Transportation Systems, june 2011.

[4] E. Brockfeld, B. Passfeld, and P. Wagner, "Validating travel times calculated on the basis of taxi floating car data with test drives", Proc. 14th World Congress on Intelligent Transport Systems, October 2007.

[5] Reinthaler, B. Nowotny, F. Weichenmeier, and R. Hildebrandt, "Evaluation of speed estimation by floating car data within the research project DMotion", 14th World Congress on Intelligent Transport Systems, 2007.

[6] D. Schmidt, B. Friedrich, and F. Weichenmeier, "Data fusion techniques for traffic state estimation–DINO within DMotion", 15th World Congress on Intelligent Transport Systems, pp. 15-20, November 2008.

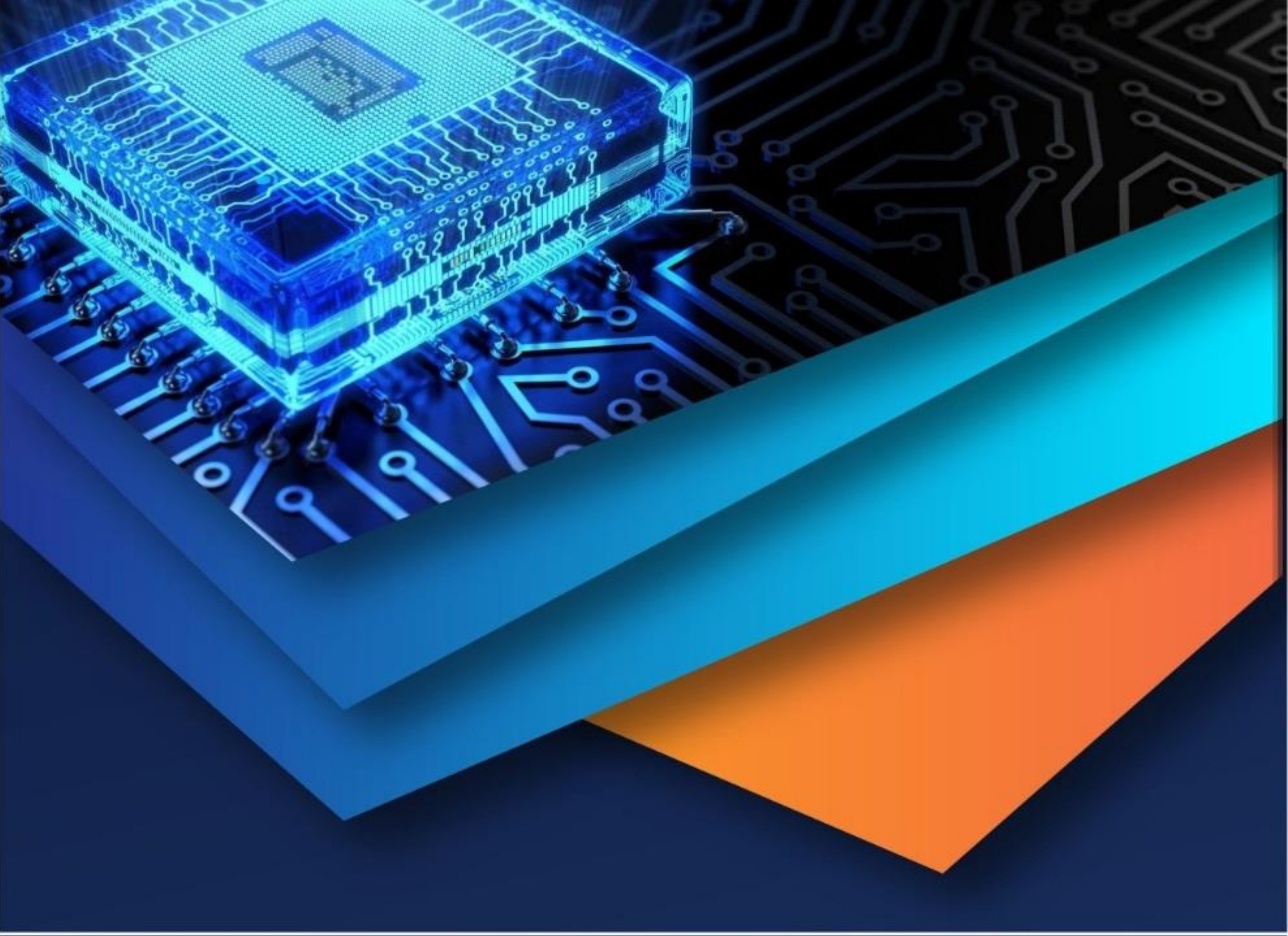
[7] N. E. El Faouzi, H. Leung, and A. Kurian, "Data fusion in intelligent transportation systems: Progress and challenges–A survey", Information Fusion, vol. 12(1), pp. 4-10, 2011.

[8] B. Kerner, C. Demir, R. Herrtwich, S. Klenov, H. Rehborn, M. Aleksic, and A. Haug, "Traffic state detection with floating car data in road networks," in IEEE Proc. on Itelligent Transportation Systems, 2005, pp. 44–49.

[9] B. D. Greenshields, "A study of traffic capacity," Highway Research Board Proc., vol. 14, pp. 448–477, 1935.

[10] Neumann, T. (2009b), 'High-quality urban traffic monitoring – Theory and evaluation of a promising data fusion methodology', European Transport Conference, 5-7 October 2009, Leeuwenhorst, The Netherlands.

©IJRASET: All Rights are Reserved




10.22214/IJRASET

45.98

IMPACT FACTOR: 7.129

IMPACT FACTOR: 7.429


# INTERNATIONAL JOURNAL FOR RESEARCH

IN APPLIED SCIENCE & ENGINEERING TECHNOLOGY


Call : 08813907089 (24*7 Support on Whatsapp)