Trajectory Prediction in Vehicular Environment using AI: A Review

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Abstract
A vehicular network is an assisting technology that supports many applications. Safety is one of the most crucial among all the applications. Vehicles generally exchange emergency messages through direct communication. But in the real world, this type of communication is not possible to build among vehicles because of obstacles that can be static or dynamic. This situation is normally called non-line of sight. As a researcher, we aim to develop an approach for improving awareness among neighboring vehicles, reducing latency and mean square error rates. In this paper, we describe various methodologies related to vehicular network systems. Deliberation of various techniques with different datasets and corresponding performance metrics for improving the system performance are described here.

Keywords: *Trajectory, Prediction, Vehicular, VANET.*

Introduction
A vehicle's trajectory is different from other regular dynamic nodes as it is much affected by latent factors like road structure, driver's driving skills, intention, traffic rules etc. Some existing approaches use a vehicle's behavioural model in a sophisticated manner and present many complex algorithms. Such algorithms need skilled system designers to use complicated optimization for the practical use of these algorithms in real-world scenarios. The behaviour prediction function can predict the future states of the nearby vehicles based on their present and past information about the surrounding environment. This enhances the awareness of upcoming hazards. People are adopting autonomous cars to reduce the number of accidents and for safety points. Such a vehicle must understand the present state of all the neighbouring cars and their future behaviour. There are many survey papers on monitoring and behaviour analysis of vehicles [1-5]. Researchers have already applied various approaches and algorithms such as Hidden Markov Models and Support Vector Machines. Deep learning- based approaches are new and powerful tools that provide superior results in complex environmental conditions and good performance results for complex and realistic scenarios. Fig. 1 provides state-of-the-art deep learning approaches for the behavioural prediction of vehicles. It gives the classification mentioned above based on three criteria: input representation, output type and prediction approach. The first criteria describe how input data can be represented. The vehicle's position, acceleration, and velocity are mentioned here. In the second section of this paper, classification and approaches are mentioned based on predicted output. The emergency message delivery rate must be improved to avoid accidents by sending vehicle-related information to all the neighbouring nodes. Vehicle trajectory prediction provides accurate location services and

monitors traffic conditions in advance. Also, recommend the best suitable path to avoid an accident-like situation. The estimation of vehicle-related information is very important in Advanced Driver Assistance Systems (ADAS). It can be used in safety tasks like the collision avoidance monitoring system and hazardous road warnings. In network protocol designing, routing and security, it can be used. This paper compares the various techniques and simulators used for trajectory prediction. Simulators NS2 and NS3 utilize CPU very well, but in terms of computation time, NS3 gives fast performance responses wrt ad-hoc on-demand distance vector routing algorithm.

I/P Representation	Track history Raw sensor data
O/P Type	Trajectory: unimodal, multimodal Occupancy map
Prediction Approach	RNN CNN

Fig 1. Deep Learning based Vehicle behavioural prediction classification

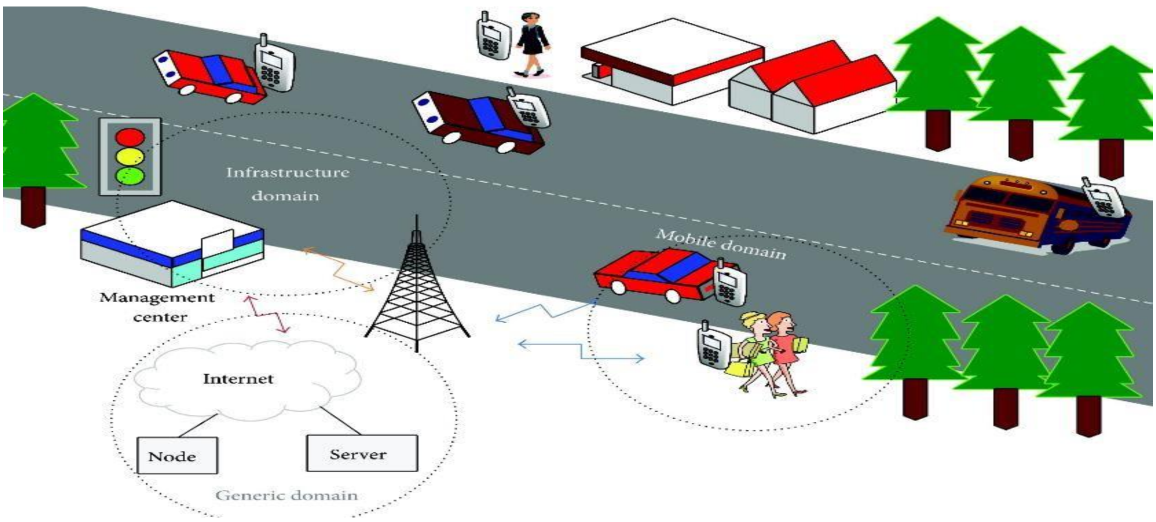


Fig 2. VANET System Domain [8]

Vehicular networks are nowadays becoming the most promising and valuable research area [6-8] in terms of safety. Vehicular applications are classified into two categories:

1. Safety applications,
2. Comfort applications.

Section third will be discussed shortcomings and their modifications as alternatives for constructing a good model and getting better results. The last section consists of a conclusion and future scope related to the particular problem of trajectory prediction.

Possible techniques

Vehicular Adhoc Networks (VANETs) have been a rapidly growing research area in the last few years and have attracted much attention in academia and industry. Before implementing VANETs on the real road network, realistic computer simulations of VANETs using a combination of mobility simulation and network simulation are necessary. A road traffic simulator and a network simulator are combined to study the performance and implementation of VANETs. Python can be used for implementation purposes.

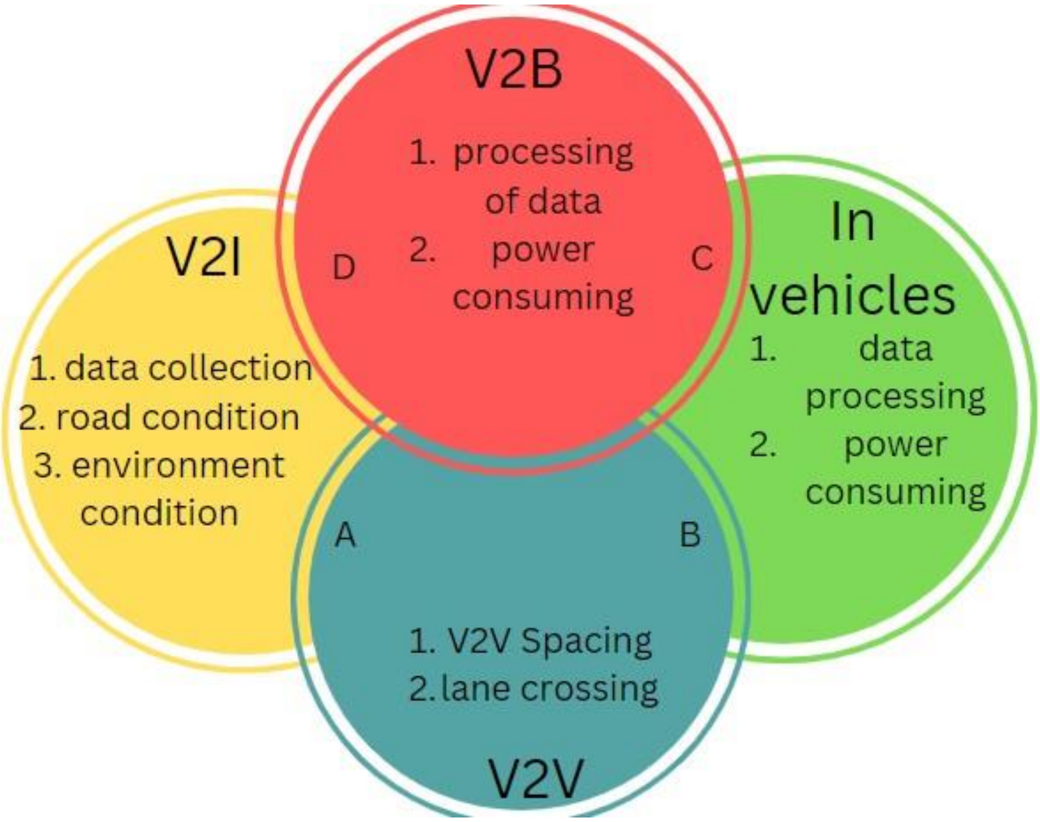


Fig 3. Key function of communication type (A. Obstacle detection, B. Cooperative driving, C. Vehicle condition GPS and D. Traffic control)

Following are a few possible existing techniques that can be further modified according to requirement. Fig. 4 shows various existing techniques related to trajectory prediction. Table 1 describes various frameworks and corresponding features. Table 2 compares the already existing approaches in terms of parameters to design a novel approach. Out of all these, one approach, i.e. based on Gaussian Mixture Model (GMM) is the most suitable one to apply for vehicle detection. For object tracking purposes, the Kalman filter method can be used.

Table 1: Different Frameworks

Keras	**Tensor Flow**	**PyTorch**
-Small dataset -Multiple back-end support -Rapid prototyping -Fast experimentation	-Large dataset -Object detection -High performance -Functionality	-Flexibility -Short training duration -Debugging capability

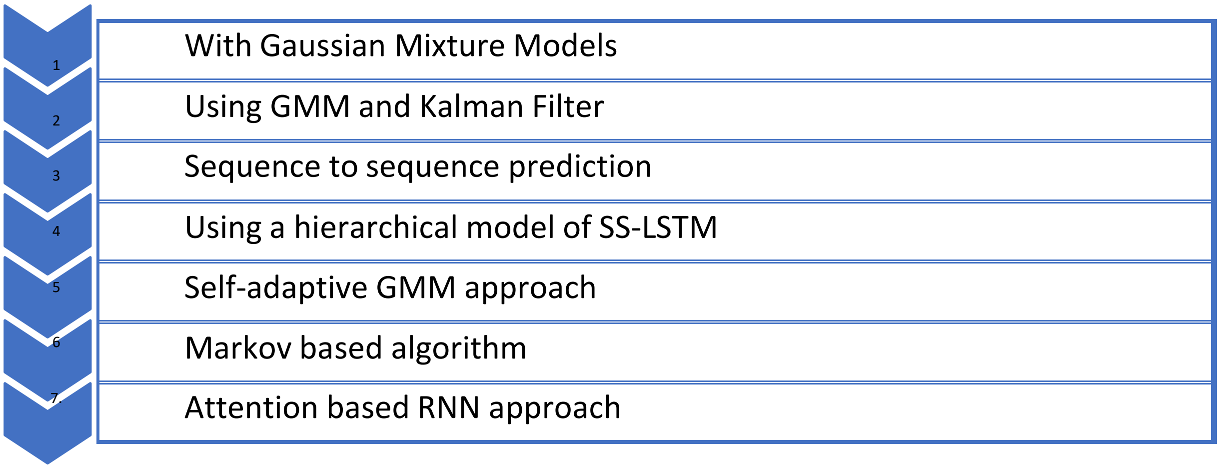


Fig. 4 Existing Techniques

Table 2: Comprehensive comparison of existing approaches

Approach	**Description**	**Performance Metrics**	**Dataset**	**Pros. & Cons.**
SS-LSTM [9]	Social Science Long Short-Term Memory It uses three LSTMs for capturing people (pedestrian), social (neighbouring information) and scenic information (scene layout features).	ADE, FDE	ETH, UCY, Town centre	Prediction results in this approach are not accurate for the short trajectory ranges.

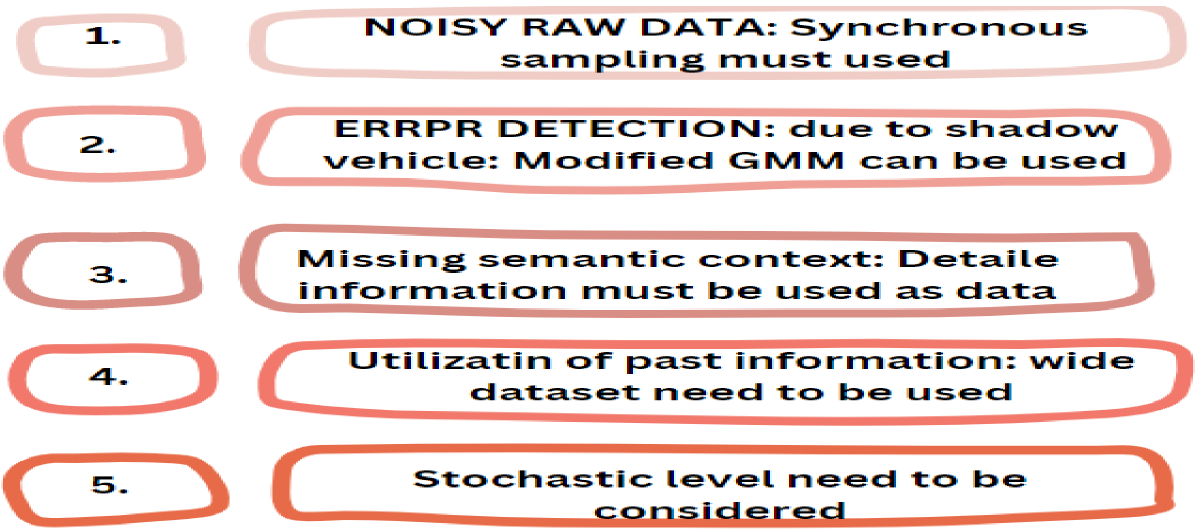
Seq2seq[10]	LSTM encoder and decoder architecture is used in this approach to analyse past measurements and to generate future trajectory paths respectively.	MAE	Highway Seoul Korea	Provide improved results in terms of prediction accuracy
GMM based [11]	Video data in .mov format and resolution 640x480 pixels isused in this method. Moving objects in a region of interest is considered only and outside that region all the objects areignored completely (considered as background).	Precision, accuracy, sensitivity, specificity	Vehicles video for light and heavy traffic	Provide good results for light traffic using Gaussian mixture model approach
SAGMM[12]	Self -Adaptive GMM approach It uses block wise process and not pixel wise, uses dynamic learning rate for detection in real time application	Sensitivity, F-measure, precision	Wallflower dataset	Dynamic learning rate is used in this method to adapt the changes in illumination.
LSTM-M[13]	This approach is used for missing data of values for short and long period runs. Linear model is used for predicting the missing terms in the given data information.	MAE, MRE, RMSE	Hangzhou PeMS dataset	Accurate inference is the need to incorporate attention mechanisms.
Saptio-Temtoporal LSTM [14]	In this approach a model is used to measure the interaction between nearby nodesimplicitly.	MAD, MVD	US-101, I-80	In this approach, the test was done on small datasets and for simple scenarios only.
ML based [15]	This approach is designed for both single and multi-users.	Distance Error, sampling time, interval, MSE	Geo-life Project	Semantic context is not focuseddue to lack of data availability.

ADE- Absolute Displacement Error, FDE- Final Displacement Error, MAE- Mean Absolute Error, MRE- Mean Relative Error, RMSE- Root Mean Square Error, MAD- Mean Absolute Deviation, MVVD- Mean Velocity Deviation

Shortcoming/pitfalls

After a detailed study of various techniques, some important points came into existence that can be used for better results. These points guide and inspire every researcher to work on these small issues. Fig. 5 shows a few challenges and modifications for constructing a good model.

Fig 5 Challenges involved in constructing a model



Conclusion and future scope

One major problem of transportation is traffic congestion. To address and overcome this problem, all the relevant information regarding vehicles and traffic is needed, such as type of vehicle, number of cars, number of lanes, the distance between vehicles etc. Traffic prediction is a challenging topic in the road and vehicle environment. After detailed study and analysis, it is noticed that the LSTM model is the most commonly used predicting model that can infer the flow of traffic in case of missing values in data also. This approach is designed to directly learn the user's past trajectories and predict future movements. LSTM has an internal state to serve as a cell's memory that allows a network to learn relations between all features for the long term. For future research, our focus must be on dense road networks. Currently, existing approaches are not suitable for huge data of overlapping trajectories. Hybrid architecture must be designed for short-term and long-term trajectory predictions. Few parameters or performance metrics like accuracy, latitude, longitude, precision value, percentage consistency, yaw angle, latency time, and distance measurements can be considered for designing a novel approach. To simulate a real driving condition in the world, GPS and onboard sensors can be used to locate the actual position of all the neighbouring vehicles. Virtual sensors of CarSim software can be used by importing them into MATLAB or any other Simulink software.

Conflict of interest

The authors declare that they have no conflict of interest.

Declarations

Ethical Approval

There are no human subjects in this article, consent is not applicable.

Competing interests

No competing interest exists.

This paper has been neither published nor submitted for publication.

References

Shirazi, M. S., & Morris, B. T. (January 2017). Looking at intersections: A survey of intersection monitoring, behaviour and safety analysis of recent studies. IEEE Transactions on Intelligent Transportation Systems, 18(1), 4–24. https://doi.org/10.1109/TITS.2016.2568920

Liang, L., Ye, H., & Li, G. Ye. (June 2019). Toward Intelligent Vehicular Networks: A Machine Learning Framework. IEEE Internet of Things Journal, 6(1), 124–135. https://doi.org/10.1109/JIOT.2018.2872122

Wiest, J., Höffken, M., Kresel, U., & Dietmayer, K. (June 2012). Probabilistic trajectory prediction with Gaussian mixture models. In Proceedings of the Intell. Veh. Symp. (pp. 141–146). https://doi.org/10.1109/IVS.2012.6232277

Le Liang, H. P., Li, G. Ye., Shen, X. (S.), Shen, X., . . . Shen, X. (2017). Vehicular communications: A physical layer perspective. IEEE Transactions on Vehicular Technology, 66(12), 10647–10659- 10659, Dec.. https://doi.org/10.1109/TVT.2017.2750903

Wang, Y., Menkovski, V., Ho, I. W., & Pechenizkiy, M. (May 2019). VANET meets deep learning: The effect of packet loss on the object detection performance. In Proceedings of the IEEE 89th Vehicular Technology Conference (VTC) (pp. 1–5). https://doi.org/10.1109/VTCSpring.2019.8746657

Gahlan, D., & Pandove, G. A Review on various issues, challenges and different methodologies in vehicular environment. In. SSRN Electronic Journal. Proceedings of the International Conference on Innovative Computing and Communications (ICICC). http://doi.org/10.2139/ssrn.3606267

Yousefi, S., Mousavi, M. S., & Fathy, M. (June 2006). Vehicular ad hoc Networks (VANETs): Challenges and perspectives. In Proceedings of the 6th International Conference its Telecommunication (pp. 761–766). https://doi.org/10.1109/ITST.2006.289012

Liang, W., Li, Z., Zhang, H., Wang, S., & Bie, R. (2015). Vehicular adhoc networks: Architectures, research issues, methodologies, challenges and trends. International Journal of Distributed Sensor Networks, article in Big Data and Knowledge Extraction for Cyber- Physical Systems,, 11(8, August).

Xue, H., Huynh, D. Q., & Reynolds, M. (March 2018). SSLSTM: A hierarchical LSTM model for pedestrian trajectory prediction. In Proceedings of the IEEE Winter Conference on Applications of Computer Vision (WACV) (pp. 1186–1194).

Park, S. H., Kim, B., Kang, C. M., Chung, C. C., & Choi, J. W. (June 2018). Sequence-to-sequence prediction of vehicle trajectory via LSTM encoder-decoder architecture. In Proceedings of the Intelligent Veh. Symp. (pp. 1672–1678). https://doi.org/10.1109/IVS.2018.8500658

Indrabayu, R. Y., & Bakti, I. S. Areni, and A.A. Prayogi, “Vehicle detection and tracking using Gaussian Mixture Model and Kalman Filter,” in Proc. International Conference on Computational Intelligence and Cybernetics, pp. 115–119. (November 2016).

Ali, S. T., Goyal, K., & Singhai, J. (October 2017). Moving object detection using self adaptive Gaussian mixture model for real time applications. In Proceedings of the International Conference on Recent Innovations Is Signal Processing and Embedded Systems (RISE2017) (pp. 153–156). https://doi.org/10.1109/RISE.2017.8378144

Tian, Y., Zhang, K., Li, J., Lin, X., & Yang, B. (November 2018). LSTM-based traffic flow prediction with missing data. Neurocomputing, 318, 297–305. https://doi.org/10.1016/j.neucom.2018.08.067

Dai, S., Li, L., & Li, Z. (March 2019). Modeling vehicle interactions via modified LSTM models for trajectory prediction. IEEE Access, 7, 38287–38296. https://doi.org/10.1109/ACCESS.2019.2907000

Wang, C., Ma, L., Li, R., Durrani, T. S., & Zhang, H. (June 2019). Exploring trajectory prediction through machine learning methods. IEEE Access, 7, 101441–101452. https://doi.org/10.1109/ACCESS.2019.2929430