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Efficient Localization Prediction In Vanet

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ABSTRACT

Identifying the future location of the vehicle in Vehicular Ad Hoc Networks (VANETs) is big challenging task because of its dynamic nature and infrastructure less network and in order to provide reliable communication. Localization prediction plays a most important role in all types of services for VANETs. One of the more attractive issues to be solved in vehicular communication is how to give anywhere and anytime extremely reliable, accurate and efficient localization prediction information in the vehicular environment. Distinctive type properties of VANETs such as mobility, behavior of vehicles provides frequent changes of vehicle location and finding the future location of vehicle is simple. To predict the future location of the vehicle this paper proposes location prediction algorithm called Efficient Dead Reckoning Approach. Proposed system uses current position of the vehicle to find the future position of the vehicle. In this approach, vehicle future position is predicted for a future time and it takes the advantage of a future time-space window. Proposed system is implemented in NS2. Simulation of Proposed system shows dead reckoning approach is better than various prediction algorithms like Map matching, Ad-hoc localization.

Keywords:— *Vehicular Ad Hoc Networks (VANETs), Localization Prediction, Dead Reckoning.*

I. INTRODUCTION

VANETs come into view as the subset of the MANETs applications. It is believed to be a significant approach for the Intelligent Transportation Systems (ITS) [1]. The communication process may occur between the drivers of vehicles and RSU or between vehicles, and that is facilitated by a wireless medium called WAVE (Wireless Access in Vehicular Environment) [2, 3]. This mode of communication is of critical importance in terms of enabling the drivers and passengers to travel safely on roads by means of a safety application fitted into vehicles. The major components of this system include the Application Unit (AU), OBU and RSU. The RSU component provides various sources including safety and non-safety information and internet facility to the road users; therefore it is called the service provider [4, 5, 6]. The vehicle contains an OBU component which receives the services from RSU, and is therefore called the user. It contains applications capable to use the service provided by RSU, which receive the information and messages through an array of sensors in the vehicle. OBUs along with sensors are capable of receiving and processing the information and sending the messages and information to other vehicles through wireless communication. The internet connection is provided by the RSU to multiple vehicles through AUs from multiple vehicles [7, 8].

Most interesting troubles to be solved in vehicular networks is how to give extremely accurate and reliable localization information anywhere and anytime [17]. At this moment, the majority of the manufactured vehicles are coming with a Global Positioning System (GPS). This feature helps us to find location of the vehicle at anytime and anywhere. VANETs' serious applications that depend on extremely accurate and available satellite navigation systems, such as GPS, experience from some undesired harms such as being engaged or not being accurate [18]. For this cause, a number of additional prediction techniques include map matching, dead reckoning, cellular localization, image/video processing is proposed. Addition of these techniques Data fusion techniques also proposed for location prediction. But rapid changes in network topology of VANETs [4] causes these dissemination techniques are outdated for finding localization information of vehicle.

The rest of this paper is organized as follows. In the next section, we discuss the background of VANETs and importance of Localization in it and present different proposals to perform localization prediction in VANETs. In Section III, we highlight potential advantages of using a proposed localization prediction system in several VANET applications. Section IV shows our performance evaluation when solutions are used in realistic VANETs scenario. Finally, Section VI presents our conclusions.

II. VANETs Background

Today's vehicles have become complex electronic networks. Different components constantly exchange the available information and cooperate for the purpose of ensuring driver safety and comfort. Additionally, the vehicle can communicate with the environment by wireless communication. This section provides a systematic classification of the various forms of vehicular communication and gives a brief overview of the state-of-the-art and existing location prediction methods [9-10].

Fundamentals of Vehicular Communications

In-vehicle communication enables the information exchange between different components within a vehicle [14]. Figure 1 show a General VANETs Architecture In general; two application areas for in-vehicle communication can be distinguished V2V and V2I: The first is the in-vehicle network of sensors, actuators and controllers, and the second is high rate multi-media communication for comfort applications, e.g. passenger entertainment. Since in most cases the number of communicating entities will not change over the lifetime of the vehicle, in-vehicle communication networks have a stable topology, a clearly defined limited set of possible communication partners and rely on wire line communication [11, 15]. The term Vehicle-to-Roadside Communication (VRC) with RSU, also known as vehicle-to infrastructure communication, is used for any kind of communication from the vehicle to a fixed infrastructure or vice versa.

Localization Strategy for Vehicular Ad hoc Networks

For the location prediction in VANETs, a number of other localization techniques such as Map Matching, Dead Reckoning, Cellular Localization, Image/Video Processing, Localization Services, and Relative Distributed Ad Hoc Localization are usually combined in VANETs to overcome such GPS limitations [1].

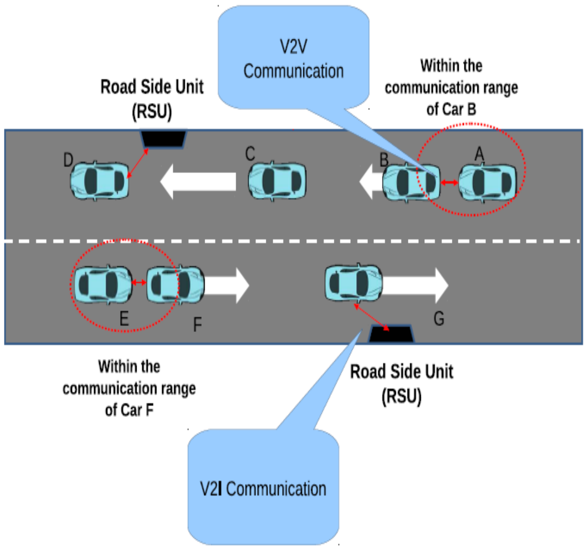


Figure 1: General VANETs Architecture.

Dead Reckoning: Another method of localization, called Dead Reckoning System (DRS), has been adopted in some applications. In this technique, the new location estimation depends on how far an object has moved from a known place given the directions and distances traveled over small periods of time. Since this technique is simple and inexpensive, it is the choice for many applications; however, it has a crucial disadvantage in that the errors in the measurements of the direction and/or the distance affect the final location estimation [5-10]. In other words, the measurement errors accumulate over the total period of time. Thus, the Dead Reckoning technique is recommended for use only over short periods of time [13].

Artificial Neural Networks: Neural networks (NNs) are a well-known option to deal with time series prediction, and for the case of VANETs, are suitable by being able to give solutions to complex problems due to their non-linear processing, parallel distributed architecture, self-organization, capacity of learning and generalization, and efficient hardware implementation [11].Neural Networks has been applied in [4] to estimate the duration of a communication link based on the time series prediction in MANETs. In this approach, a MLP predict the future location of the mobile user based on the time series location observations as the inputs of the NN. Neural Networks also have been applied in VANETs for prediction of future lane change trajectory based in [14]. In this work, a NN was proposed to learn and incorporate the human behavior to predict the lane changing trajectory in the near future.

Filtering: The major objective of target tracking systems is to constantly detect and calculate approximately the state of a target or a set of targets. Moreover the location information, target tracking can be used to detect and forecast future locations of single or multiple targets such as other vehicles. Target tracking can be done by using two filters called Kalman filter (KF) and Particle filter (PF) [1-3].

III. Proposed System

It is well known that the movement of a vehicle in a city is a dynamic process, including static process (traffic light), which is strong nonlinear. These non-linear characteristics of VANETs can severely affect the performance of the predictor algorithm [1-3]. The main advantage of DR relies on its good accuracy for predictions when the vehicles have a linear mobility pattern with a fast initial convergence. DR is able to achieve accurate predictions when computing a position only based on the last known vehicle position.

System Model

The proposed DR localization method is simulated in NS2 with sample simulation parameters considered for simulation is listed in table 1.

Table I: Simulation Parameters.

Simulation Parameters	Sample Values
Simulation Area	1000m X 1000m
Simulation time	300s
Number of node	40
Training Samples	400
Test samples	400
Localization error	0.5m

Proposed Evaluation Technique

In this system, while localization prediction procedure, we assume that each vehicle "i" at regular period observes its current location (V_{it}) at a time "t". Based on the knowledge of the t−1 steps, the vehicle's prediction is known by target state estimate $P_{i(t+1)}$, which will estimate the position ($X_{i(t+1)}$, $Y_{i(t+1)}$, $Z_{i(t+1)}$) for the next time step t + 1 (as shown in Algorithm 1). The future position prediction of each vehicle is made by computing the coordinates $X_{i(t+1)}$, $Y_{i(t+1)}$ and $Z_{i(t+1)}$ and D_r, where D_r is direction of vehicle. The parameters of the engine (machine) learning algorithms have been adjusted through simulation. We intended to get the most excellent accuracy [5,6]. For the ANN and SVR, the input vector is composed of (X_{it}, Y_{it}, Z_{it}, S_t), where X_{it}, Y_{it} and Z_{it} are the coordinates of the vehicle's current location and S_t is its current displacement speed. Therefore, at every time step "t" an input vector (X_{it}, Y_{it}, Z_{it}, S_t, D_r) is added to the set of training data along with the t − 1 inputs. For every vehicle, the training is performed on the last t − 1 training inputs [18].

Algorithm 1: Finding future position of the vehicle.

Input:
Timer (i). timeOut(t); {}
Action:
Measurements = Measurements + 1;
Pr Algo.insert_TrainedData(V_{it}−1, S_{it}−1, V_{it} ,D_r);
if measurements >= 400 then
V_{it}+1 = predictionAlgo.predict(V_{it});
predictionAlgo . compute Results (V_{it}, S_{it}, D_r, laspPredi)
laspPredi = V_{it}+1
end if
$Timer_i$.resched (t + 1);

The NN used in this work is claimed of four layers. The input layer has five neurons to map the input vector of coordinates, direction and speed of vehicles. The output layer has three neurons, consequent to the coordinates of the predicted position in ∈ R. In above algorithm first trained data is submitted. The trained data has five parameters includes X_{it}, Y_{it}, Z_{it}, S_t, D_r. these trained data is submitted to input layer of NN. The output layer has three neurons to predict future position of the vehicle effectively.

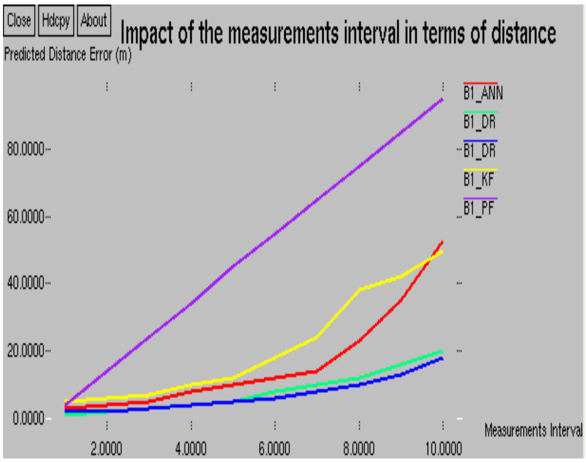
IV. Simulation Results and Discussions

In simulation scenario proposed system is evaluated in terms of Impact of the measurements interval in terms of distance, Energy efficiency and energy management.

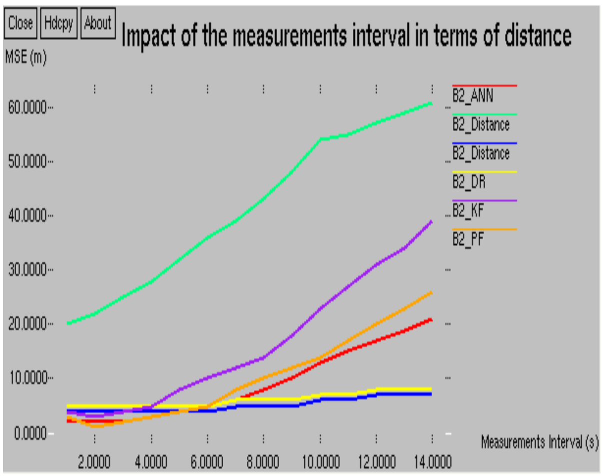
Impact of the measurements interval in terms of distance

To evaluate the impact of the measurements' interval, we increase this parameter from 0.5s to 2s. As depicted in Figure 2(a), DR and KF lead to a small error in the distance between the predicted location and the real future. Figure 2(b), we can notice the disadvantage of NN, SVR, and specially PF with a high increase in the MSE while increasing the measurements' interval [1].

As shown in Figure 3 (a), DR and KF give results closer to the ideal expected time value when the measurements' interval are lower than 0.75 s with a small advantage for the KF algorithm. Figure 3(b) shows that DR, KF and PF lead to a more efficient computational time. Thus, these algorithms can be applied to more restricted computational devices. Also, these algorithms do not require training and DR and KF have a fast initial convergence leading to accurate predictions.

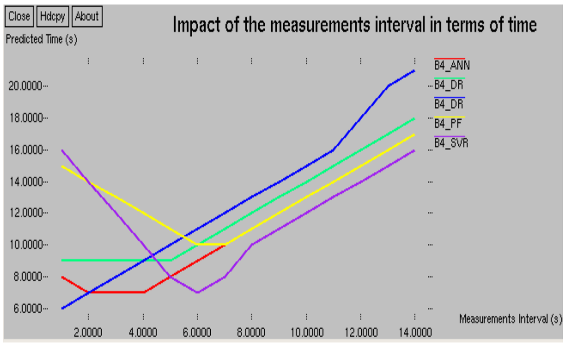


2(a)

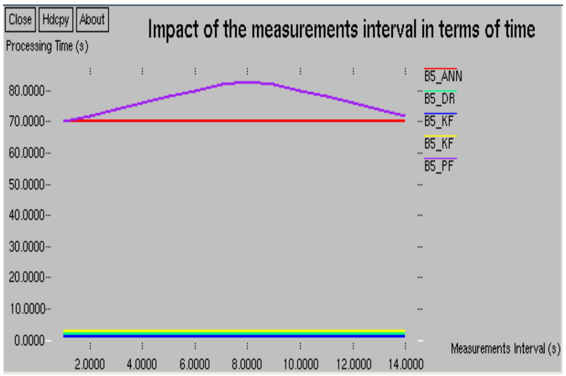


2(b)

Figure 2: Impact of the measurements' interval in terms of distance



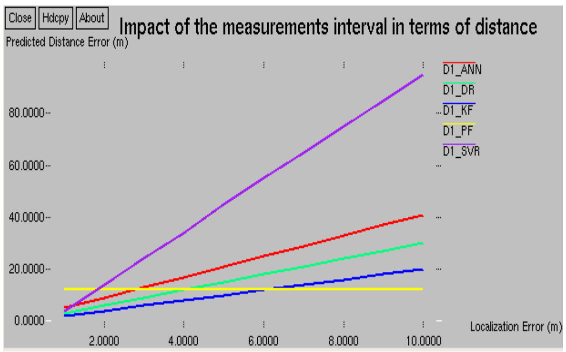
3 (a)



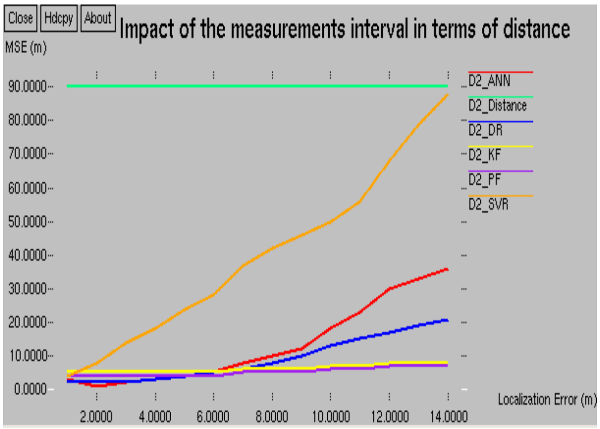
3 (b)

Figure 3: Impact of the measurements' interval in terms of time

Figure 4 (a) the prediction accuracy of PF is almost constant while increasing the errors in the computed positions of the vehicles and leading to the best prediction accuracy for localization errors greater than 8m. in terms of the MSE, we can also notice in Figure 4(b) that when the localization errors are greater than 10m, the PF algorithm presents the best results on average and is the best option for the localization prediction.



4(a)



4(b)

Figure 4: Impact of the localization errors in terms of distance

V. CONCLUSION AND FUTURE WORK

In this paper, In proposed system, we studied localization prediction technique with respect to Vehicular Ad Hoc Networks (VANETs). We surveyed various approaches for localization prediction techniques used to estimate the future position of a vehicle. In this work we illustrated how localization prediction techniques can be used to predict accurate positions based on current position of vehicle. Technique studied in this paper called dead reckoning, presents the best computational performance in terms of response time. In dead reckoning method future position of the vehicle is identified with respect to its current position in the form of various parameters called X_{it}, Y_{it}, Z_{it}, S_t, D_r. Along with current position direction and speed of the vehicles is considered. Simulation results of proposed system shows that Efficient Dead Reckoning Approach for Localization Prediction has small error in the distance between the predicted location and the real future location and high accuracy. While other prediction techniques called PF and NN has low accuracy in the form of predictions. Addition of this proposed system has low MSE while comparing with PF and NN.

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