Context Aware Accidents Prediction and Prevention System for VANET

Mussab Aswad
Applied Science University
Computer Science Department
P.O. Box 5055
Musaab@asu.edu.bh

Saif Al-Sultan
Applied Science University
Computer Science Department
P.O. Box 5055
S.j.alsultan@ieee.org

Hussein Zedan
Applied Science University
Computer Science Department
P.O. Box 5055
Hussein.zedan@asu.edu.bh

ABSTRACT
Worldwide, traffic accidents cause over a million fatalities every year. Thus, improving road safety and saving people's lives is an international priority. One major challenge faced by researchers is to design an ideal system that is able to predict road accidents and implement efficient prevention actions. Context-aware systems are those systems that are able to sense, reason and react upon the current contextual information. Utilising those systems in intelligent transportation systems (ITS) might improve road safety and enhance traffic efficiency. This paper introduces a context-aware accidents prediction and prevention system taking into account the most contributory factors that cause road accidents including factors related to the driver, the environment, the vehicle and other vehicles on the road. A context-aware architecture based on VANET's On Board Unit (OBU) is presented. The architecture is divided into three phases: physical phase, thinking phase and application phase, which represent the three main subsystems of context-aware systems: the sensing, the reasoning and the acting subsystem respectively. In the thinking phase, a Dynamic Bayesian Networks (DBN) model has been proposed to predict the accident likelihood and the severity level. The evaluation of the proposed system showed good results in predicting accidents and their levels of severity.

General Terms
Design

Keywords
Context-aware systems, Accidents prediction, Accidents prevention, ITS, VANET, Dynamic Bayesian Network (DBN)

1. INTRODUCTION
Worldwide, traffic accidents involving drivers, motorcyclists and pedestrians cause a million of fatalities every year. According to the UK department for transport (DFT), in the UK in the first quarter of the year 2011, 24770 people were killed or seriously injured [3]. Therefore, there is evidently still an abundant need to improve road safety and efficiency in order to prevent road accidents, reduce the number of fatalities and save people's lives. Accordingly, governments, vehicle manufacturers and researchers are seeking to find and develop new technologies in order to achieve this goal, and therefore several accidents prediction and/or prevention systems have been proposed. However, there is still no comprehensive system that is able to predict the accident by capturing information about the driver, the vehicle, the environment and other vehicles on the road to perform reasoning under uncertainty in order to accurratly predict the accident likelihood and severity. Wireless communication have led to improvement in the ITS that focuses on road safety and traffic efficiency. VANET has emerged as a key application of ITS, each vehicle in VANET is equipped with an OBU that uses the Dedicated Short Range Communication DSRC/WAVE technology to offer two types of communication, vehicle to vehicle (V2V) and vehicle to infrastructure (V2I). These two types of communication enabled a wide range of safety applications, such as intersection avoidance application [4].

Utilising context-aware systems in VANET safety applications might improve road safety by providing the ability to sense information from different sensors, reason about the captured context and perform the appropriate actions in order to avoid or mitigate road accidents without driver interaction. Thus, providing flexible proactive accidents prediction and prevention system. In this paper, we propose a novel five-layer context-aware architecture based on VANET's OBU for predicting and preventing road accidents, it is built upon the five-layer conceptual framework [7]. The operation of the architecture is divided into three phases: physical phase, thinking phase and application phase, which represent the three main subsystems of context-aware system: the sensing, the reasoning and the acting subsystems respectively [15]. The physical phase is responsible for collecting the contextual information and providing it to the thinking phase. The thinking phase is in turn responsible for performing reasoning under uncertainty to predict the accident likelihood and severity, and deciding which application has to be performed in order to prevent the accident. A novel DBN model for inferring the information collected from different sensors and predicting the accident likelihood

ICCASA 2014, October 15-16, Dubai, United Arab Emirates

DOI 10.4108/icst.iccasa.2014.257334

and severity (fatal, serious and serious) has been proposed in the thinking phase. This phase is also responsible for calculating the actions that have to be performed by the application phase in order to avoid or mitigate the accident.

The remainder of the paper is organized as follows. Section 2 introduces the work that have been carried out in the field of accidents detection and prediction. In section 3, the proposed context-aware architecture is presented. Section 4 describes the proposed dynamic Bayesian network (DBN) model for predicting the accidents, which is used to reason about uncertain contextual information. System evaluation is explained in section 5 and the conclusion is given in Section 6.

2. RELATED WORK

Several researchers have examined a wide range of work on predicting road accidents using numerous methods, reflecting the importance of accidents predication systems within the ITS. Some have attempted to focus solely on the driver and others on the vehicle. A summary for the main work that have been carried out in this field is given below.

In [27], a pre-crash safety system utilising adaptive cruise control (ACC) has been proposed. This system aims to enhance the vehicle safety and reduce the injuries caused by collisions by activating pre-crash seat belt and pre-crash brake assist the occurrence of an unavoidable accident. The author has developed millimetre wave radar as well as a new signal-processing algorithm in order to increase the accuracy of the ACC system. When the electronic control unit (ECU) detects an incoming obstacle based on the time to crash (TTC) and detects that a collision is unavoidable, the PCS will activate the seat belt and brake assessment. However, this system acquires information about the vehicle only, leading to inaccurate crash predictions. Moreover, the system works only in the case of unavoidable crashes, which is insufficient, as the aim of this work is to predict the crash early enough to avoid injuries.

Another pre-crash system based on short-range radar was proposed in [25]. The Kalman-Filter approach has been used to fuse information collected by sensors that detect the position of objects using distance and velocity information. A middleware architectural model [24] has been designed to provide safety in high-speed vehicles forming a vehicular ad hoc networks (VANET) network. The Intelligent vehicular ad hoc networks (InVANET) system was analysed for different situations, such as (a) high road traffic intensity; (b) slow-moving vehicles; (c) abnormal vehicle failure; and (d) drunk-driving. Different sensors were used to form a VANET network on top of the vehicle communication structure. An experimental test-drive was carried out on national roads in which nine cars were used for 25 driving hours. It was concluded that the InVANET network had minimal delay in communicating with multiple vehicular nodes compared to other networks.

Yet, [1] has developed multivariate adaptive regression splines (MARS) to predict a vehicle's crash angles. The MARS model is promising in terms of prediction and does not suffer from interpretation complexity. The negative binomial (NB) model was compared with the MARS model using extensive data collected from unsignalised intersections in Florida. Two models for angle crash frequency were estimated, one at three-legged and the other at four-legged unsignalised intersections. The crash frequency as a continuous response variable for fitting a MARS model was examined by considering the natural logarithm of the crash frequency. Finally, the MARS model was combined and examined with other machine learning techniques, such as random forest. It was concluded that the MARS model is considered to be an efficient technique for predicting crashes such as angle crashes at unsignalised intersections.

In [23], a context-aware system for collision warning and avoidance systems was developed using ubiquitous data-mining-based layered agent (UDMLA) model to support vehicle safety. This system may be applied at any type of intersection and integrates multi-agent systems with ubiquitous data mining designs. Sensor technologies were used for environment perception (infrared sensing, video and camera image perception, LIDAR/RADAR sensors, gyro sensors sensing vehicle motion and acceleration, and inertial sensors such as tachometers and speedometers). The XML format was used for context modelling, and processing-sensed data obtained through mathematical algorithms resulted in a virtual understanding of the vehicle environment, such as the path and position of vulnerable road users in relation to other vehicles and road infrastructure.

The aforementioned systems focus on the detection or the prediction of road accidents, they have achieved good results in terms of enhancing road safety and improving traffic efficiency. However, no one of which has taken into account information about the driver, the vehicle, the environment and other vehicles on the road in combination, which reduces their accuracy. Moreover, they have not considered the accident situation as a high-level context (uncertain contex). This paper introduces a comprehensive system that is able predict the accident before it takes place utilising a context-aware system to collect and reason about contextual information about the driver, the vehicle, the environment and other vehicles on the road. In addition, the system is able to perform reasoning about uncertain context (accident situation) utilising the dynamic Bayesian network (DBN). The accident can then be prevented by implementing the appropriate actions.

3. CONTEXT-AWARE ON BOARD UNIT ARCHITECTURE

This section introduces the proposed context-aware On Board Unit architecture for predicting the accident likelihood and its severity level (fatal, serious and serious). As depicted in Figure 1, the proposed architecture incorporates three main phases: A physical phase, a thinking phase, and an application phase, all of which together represent the three main subsystems of a context-aware systems: sensing, reasoning and acting subsystems [15]. performing the prevention actions in the application phase depends on the output of the

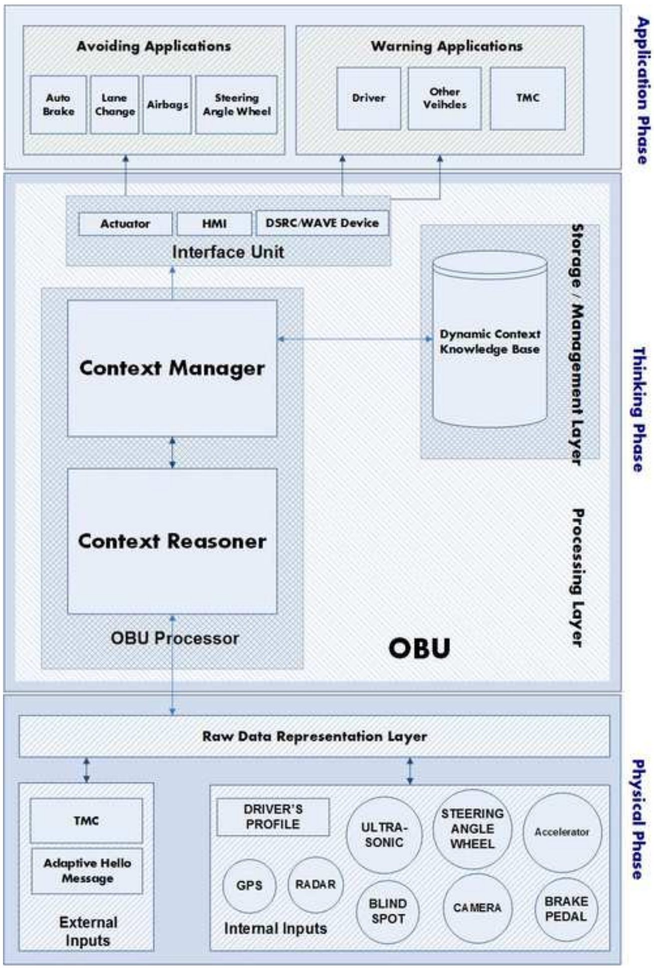

Figure 1: Context-aware On Board Unit Architecture

thinking phase which in turns depends on the contextual information received from the physical phase.

3.1 Physical Phase

The physical phase is responsible for gathering low-level contextual information about the driver, the vehicle, the environment and other vehicles on the road. This phase contains the following two layers: sensing and raw data layers.

3.1.1 Sensing Layer

This layer is responsible for acquiring the context data using different types of sensors. It consists of two types of data sources (sensors) internal data source and external data source integrated into the driving environment in which the system operates. Several types of sensors can be equipped depending on the system needs. The internal data sources represent a set of sensors that are fixed within the vehicle, such as camera, GPS, brake pedal sensor, steering angle Wheel, radar, ultrasonic, blind spot and driver profile, that are responsible for providing information about lane, location, brake status, steering angle, direction, surrounding vehicles and the driver [27, 5, 8, 19, 16, 17, 26, 3]. The external data sources include the traffic management centre and the adaptive hello messages which are periodically disseminated in VANET, those sensors provide information about the traffic and other vehicles' positions, speeds and directions [3, 2].

3.1.2 Raw Data Layer

This layer is responsible for separating the low-level sensing details from the upper layer of the system, as well as for converting the sensed context into a machine-readable form and then provide it to the next phase (the thinking phase). This layer is also responsible for the managing the sensors and provides the reusability of the sensed contextual data.

3.2 Thinking Phase

This phase comprises the management of contextual information. This can vary from a simple mechanism for querying the data to powerful reasoning, including the inference of new context. There are two types of contextual information: certain contextual information, which can be obtained from a single sensor, and uncertain contextual information, which cannot be acquired by a single sensor and which might be incomplete or inexact. The accident likelihood and its severity level is considered as uncertain context, and therefore a reasoning under uncertainty technique is required to accurately predict the accidents and efficiently determine its severity. In this paper, the DBN has been implemented to predict the accident as will be shown in (section 4). This phase consists of two layers as follows: processing layer and storage/management layer.

3.2.1 Processing Layer

This layer is responsible for extracting information about hazardous situations. The processing layer consists the following: the context reasoner, the context manager and the interface unit.

- Context Reasoner (CR): This component is responsible for evaluating the exact situation and reason about uncertain contextual information in order to make decisions about it. The CR's task is to predict the accident likelihood and severity levels as a first step to accidents prevention; the design, implementation and verification for this stage have been achieve using a DBN model.
- Context Manager (CM): This component is responsible for triggering an appropriate application based upon the information being received from the CR. It receives the predicted accident likelihood and the severity level, then it should select the suitable solution in order to either avoid or mitigate the accident severity deploying an algorithm (this algorithm is out of the scope of this paper). This processor is connected to the dynamic data base using bidirectional arrow to store, retrieve and learn different type of data (e.g. historical driver behaviours, road accidents, etc.). It is considered as the next stage after predicting the accident likelihood and severity.
- Interface Unit (IU): This unit receives the final decision from the context manager regarding which application should be used to avoid the accident. This unit contains the actuator which is responsible for carrying out specified control of the vehicle without any

command from the driver, human machine interface (HMI) which is responsible for issuing driver warning and selecting a suitable means of warning the driver (alarms), and the DSRC/WAVE which is a network device based on IEEE 802.11p for communicating the vehicle with other vehicles or with the road side units (RSUs) [142].

3.2.2 Storage/Management Layer

This unit is responsible for storing all the data and information needed to support the context manager. It forms a dynamic context knowledge base, which is extendible and regularly updated; i.e. it can be adjusted to update the stored information, including road maps, driver's historical data and historical accidents data [144].

3.3 Application Phase

This phase represents the acting subsystem in context-aware systems. It is responsible for disseminating warning messages that include corrective actions for the other vehicles on the road. It is also in charge of operating in-vehicle alarms to warn the driver and controlling the vehicle via actuators in order to prevent the occurrence of accidents and to decrease the number of potential fatalities. Two types of applications might be applied in the proposed architecture, as follows (This part is left for the future work):

- Avoiding applications which are responsible for taking the appropriate actions to avoid or mitigate the accidents. This can be achieve by applying a number of applications, such as auto-brake and lane change.
- Warning applications which are responsible for warning drivers via seat vibration, tightening seatbelts, onboard messaging or voice-based alarms. These applications can also warn other vehicles travelling on the road about an abnormal situation using an adaptive HELLO message.

4. DYNAMIC BAYESIAN NETWORK (DBN) ACCIDENTS PREDICTION MODEL

In this section, the proposed DBN for predicting the accidents likelihood and severity has been proposed. As mentioned earlier, the accidents likelihood is considered as uncertain (high-level) context and the status of an accident might change over the course of driving according to several factors (i.e. traffic status). Moreover, the uncertainty might takes place in the physical phase where the captured context that will be inferred to predict the accidents likelihood and severity might be incomplete or inexact [3]. Therefore, a reasoning under uncertainty technique is required to collect and analyse different context that is related to the vehicle, driver, environment and other vehicles on the road. In context-aware systems, there are available different techniques for reasoning under uncertainty, such as Neural Networks, Fuzzy Logic, Bayesian network, Hidden Markov Model and Dynamic Bayesian Network (DBN) [6]. In this paper, the DBN has been justified as the most effective and accurate reasoning technique which can be used to predict the likelihood of an accident due to the following reasons: it is considered as the most reliable method for dealing with inaccurate data and unobservable physical values, it is able to model time series data (the situation that changes over time), it is efficient in combining uncertain contextual information from a wide range of sensors in order to deduce high-level contextual information (it can perform reason under uncertainty) and it is able to combine prior data with the current data [13, 22, 29, 20, 14].

DBN is a directed acyclic graph that represents the conditional independence between a set of random variables, and which deals with uncertain information and probabilistic inference upon receiving evidence. It consists of a set of nodes that represents the random variables and a set of arcs that represents the conditional independences between variables. It is considered as a set of static Bayesian networks interconnected by sequential time slices. The relationship between two neighbouring time slices can be modelled using the first-order Hidden Markov Model, which means that the random variables at time slice (t) are affected by the variables at time slice (t) and the variables at time slice (t-1) only [3, 11]. This is defined as a pair of ($S, \overrightarrow{S}$), where (S) is a BN that defines the prior or initial state distribution of the state variables $P(Z1)$, and $\overrightarrow{S}$ is a two-slice temporal Bayesian network (2TBN) that defines the transition model $P(Z_t \mid Z_{t-1})$, as in the following equation [18]:

$$P(Z_t|Z_{t-1}) = \prod_{i=1}^{N} P(Z_t^i|Pa(Z_t^i)) \quad (1)$$

Where N is the number of nodes in the network, Z_t^i is the ith node at time slice t and $Pa(Z_t^i)$ are the parents of Z_t^i.

There are several operations that can be performed using DBN including filtering, predicting, smoothing and viterbi decoding. We will use the prediction operation in our proposed model in order to predict the future likelihood of an accidents and its severity. The prediction process takes place by providing the current and the past sensors readings, and then calculating the future likelihood of an event [11]. There are several steps that have to be followed in order to construct a DBN for predicting the likelihood and the severity. The first step is to identify the hypothesis variables (nodes). The second step is to identify the information variables that denote somthing about the hypothesis nodes. After defining the hypothesis variable and the information variables, the next step is to create the directed links between the variables in the networks which represent the conditional independences between the identified variables. Finally, the prior probability tables for the root nodes, the conditional probability tables for the leaves nodes and the conditional probability over time in the network have to be created [12]. In our proposed system the DBN is treated as a singly connected static Bayesian networks in which the hypothesis node at time slice (t) depends on the observations at time slice (t) and the hypothesis node at time slice (t-1) only, where the prediction of the accident likelihood and severity will be calculated in time slice (t+1).

4.1 Identifying the DBN Variables (Nodes)

The hypothesis node in this network is the (crash) node, which includes four mutually exclusive states: fatal, serious, slight and no crash. The rest of the nodes are divided into two groups: information factors and observable factors. The first group (the information nodes) represents the variables that may affect the state node, such as age, gender, driver, day of the week, time, traffic status, weather condition, road surface conditions, light status, speed limit and road type. The second group (the observable nodes) corresponds to the information that results from the state node, such as brake pedal, distance, speed, lane, steering angle and blind spot. All the nodes in our network have been identified based on the UK department for transport dataset which provides information about 60000 records (50000 records were used for parametrising the DBN and the other 10000 records were used for system evaluation) for accidents with different levels of severity [9]. In addition, several published papers and researches have been used to effectively chose the nodes (factors) in our proposed model [10, 28]. Each node in our proposed model has a set of mutually exclusive states, during the system operation each node will be in one of its states.

4.2 Dynamic Bayesian Network Graph

In this step, the conditional independence between the DBN nodes is decided after the variables have been chosen; this step consists of drawing the directed acyclic graph. Figure 2 depicts the DBN structure at time (*t-1*),(*t*) and (*t+1*) and the conditional independence between the variables. The hypothesis node at time slice (*t+1*) is affected by the information variables at time slice (*t*) and the hypothesis node at time slice (*t-1*).

As shown in Figure 2, the higher nodes represent the information factors, the node in the middle, which is the crash node, represents the hypothesis node (unobservable node), and the nodes below represent the observable nodes. The network consists of different time slices, all of which contain an identical Bayesian network. The nodes between the time slices are connected with arrows to represent dependencies among these time slices. The proposed DBN is unrolled to represent a static Bayesian network that consisting of three time slices (*t-1*),(*t*) and (*t+1*) in order to infer it using the clustering inference (prediction) algorithm.

4.3 Specifying the Conditional Probability Table

After choosing the DBN nodes, drawing its graph by specifying the relations between the nodes, the next step is to fill in the conditional probability table (CPT) values with the prior probability of the root nodes and the conditional probabilities of the links in the network. Deciding the value for each node is the main key to enable the network to infer the network and obtain the likelihood of accident and its severitys. The following two methods may be used to obtain the probabilities of the states for each node in the network [3]:

- Obtaining the values by performing statistical analysis of a huge amount of training data. Training data is obtained by performing several tests in a test-bed specifically designed for the system and collecting the output for each test.
- Parametrising the network can be done using syntactical data from several published papers that are related or similar to the system, accidents reports and transportation standards.

Our proposed network has been Parametrised applying a combination of both of the above methods. The dataset that is published by the UK department for transport has been used to learn the majority of the nodes. While, some of the nodes have been learned depending on published work that are similar (related) to our model [30, 14, 13, 21, 9]. After determining the parameters of the DBN, the network at this stage is ready to collect and analyse contextual information and predict the probability of accidents and the different levels of severity in the future time slice (*t+1*) given sensors readings of the current and the previous time slice (*t*) and (*t-1*) respectively.

5. EVALUATION

This section introduces the evaluation of the proposed accidents prediction and prevention system. The proposed system has been implemented and tested using the GeNIe version 2.0 software [11], as it provides powerful tools, graphical user interface and it is reliable and freely available software. Different scenarios have been performed in order to challenge the system and to verify its validity and effectiveness in predicting different types of accidents with different levels of severity. In each scenario, the network has been enrolled for three time slices representing the past, current and the future time slice. Sensors readings were provided for the past (*t-1*) and the current (*t*) time slices, the system was able to accurately predict the probability of accidents in the future (*t+1*) time slice. It is impossible to include all the scenarios here, we will explain the evaluation of the system using the 10000 records obtained from the UK department for transport to show the accuracy of the proposed DBN model. As mentioned earlier, the UK department for transport has provided a dataset for accidents occurred in the Great Britain in year 2011 [9]. The dataset includes 60000 records, 50000 of which have been used for learning the system. While, the other 10000 records have been used here for system accuracy verification. The GeNIe 2.0 software has the ability to validate the Dynamic Bayesian Network accuracy using real datasets. The evaluation using 10000 records for accidents showed good results for the crash node with different levels of severity at all time slices, (*t-1, t, t+1*).

Figure 3 depicts the system evaluation using the data provided by the UK department for transport. It can be seen from the figure that, there are two curves representing the the total number of records for each severity category and the number of situations that are correctly predicted by our propose system. The evaluation records include the total of 919 fatal accidents, the system was able to accurately predict 624 fatal accidents with accuracy degree of 0.68. As for the serious accidents, the total number of serious accidents included in the evaluation records was 2253, the system was able to predict 1260 serious accidents with the accuracy degree of about 0.56. For the situation of slight accidents, 3054 records were reported, the system has detected the amount of 2513 slight accidents with the accuracy degree of 0.82. Finally, for the no_crash state, the the system was able to accurately predict 3703 situations out of 3774 situations. The evaluation results showed the validity and the effectiveness of our proposed model in predicting different accidents

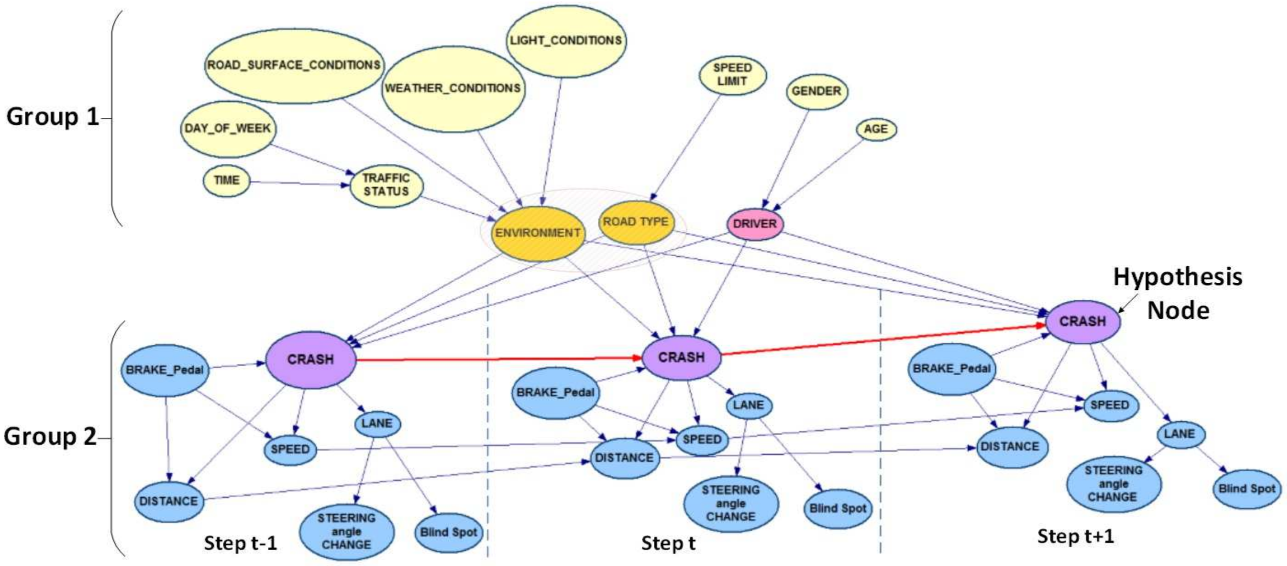

Figure 2: Dynamic Bayesian Network Graph

Figure 3: System Evaluation

with their levels of severity, which will provide the ability to perform set of action in order to mitigate or prevent road accidents, and hence enhancing road safety, increasing traffic efficiency and saving people'e lives.

6. CONCLUSION

VANET safety applications are attracting the attention of researchers due to their potential in preventing road accidents, and hence enhancing road safety and improving traffic efficiency. There are many factors that contribute to road accidents including factors related to the driver, the vehicle, the environment and the other vehicles on the road. Therefore, it is important to capture all the above factors in order to perform accurate reasoning (prediction) using the DBN model. In this paper, we introduced a context-aware accidents prediction and prevention system for VANET, the system is able to accurately predict road accidents by collecting information about the driver, the vehicle, the environment and the other vehicles on the road. Our contribution can be summarised as follows. An On-board unit architecture based on context-aware system is presented to predict the accident and its severity (fatal, serious or slight), and to prevent or mitigate the accident by applying the appropriate actions. The architecture is divided into three phases and contains five layers . Moreover, a Dynamic Bayesian Network (DBN) model that is able to predict the accident likelihood and severity by collecting information from different sensors under uncertainty is introduced. Our future work comprises the design of accidents prevention model and the addition of more contextual information to the proposed DBN model in order to increase its prediction accuracy.

7. REFERENCES

[1] M. Abdel-Aty and K. Haleem. Analyzing angle crashes at unsignalized intersections using machine learning techniques. *Accident Analysis & Prevention*, 43(1):461 – 470, 2011.

[2] M. Al-Doori, A. H. Al-Bayatti, and H. Zedan. Context aware architecture for sending adaptive hello messages in vanet. In *Proceedings of the 4th ACM International Workshop on Context-Awareness for Self-Managing Systems*, page 10. ACM, 2010.

[3] S. Al-Sultan, A. Al-Bayatti, and H. Zedan. Context-aware driver behavior detection system in intelligent transportation systems. *Vehicular Technology, IEEE Transactions on*, 62(9):4264–4275, Nov 2013.

[4] S. Al-Sultan, M. M. Al-Doori, A. H. Al-Bayatti, and H. Zedan. A comprehensive survey on vehicular ad hoc network. *Journal of Network and Computer Applications*, 37(0):380 – 392, 2014.

[5] M. Baldauf, S. Dustdar, and F. Rosenberg. A survey on context-aware systems. *International Journal of Ad Hoc and Ubiquitous Computing*, 2(4):263–277, 2007.

[6] C. Bettini, O. Brdiczka, K. Henricksen, J. Indulska,

D. Nicklas, A. Ranganathan, and D. Riboni. A survey of context modelling and reasoning techniques. *Pervasive and Mobile Computing*, 6(2):161–180, 2010.

[7] A. K. Dey, G. D. Abowd, and D. Salber. A conceptual framework and a toolkit for supporting the rapid prototyping of context-aware applications. *Hum.-Comput. Interact.*, 16(2):97–166, Dec. 2001.

[8] E. Dilge, M. Gulbins, T. Ohnesorge, and B. Straube. On a redundant diversified steering angle sensor. In *On-Line Testing Symposium, 2003. IOLTS 2003.9th IEEE*, pages 191–196. IEEE, 2003.

[9] U. D. for Transport. Road casualties in great britain, road accidents and safety data 2011. `https://www.esds.ac.uk/newRegistration/UKDSshowProjectDataset.asp?pn=63946`. [Online; accessed 10-august-2014].

[10] T. Hofer, W. Schwinger, M. Pichler, G. Leonhartsberger, J. Altmann, and W. Retschitzegger. Context-awareness on mobile devices - the hydrogen approach. In *Proceedings of the 36th Annual Hawaii International Conference on System Sciences*, pages 10 pp.+, 2003.

[11] J. Hulst. Modeling physiological processes with dynamic Bayesian networks. Master's thesis, Delft University of Technology, 2006.

[12] F. V. Jensen and T. D. Nielsen. *Bayesian Networks and Decision Graphs*. Springer Publishing Company, 2nd edition, 2007.

[13] Q. Ji, P. Lan, and C. Looney. A probabilistic framework for modeling and real-time monitoring human fatigue. *IEEE Transactions on Systems, Man and Cybernetics - Part A: Systems and Humans*, 36(5):862 –875, sept. 2006.

[14] X. Li and Q. Ji. Active affective state detection and user assistance with dynamic bayesian networks. *IEEE Transactions on Systems, Man and Cybernetics, Part A: Systems and Humans*, 35(1):93 – 105, jan. 2005.

[15] S. Loke. *Context-Aware Pervasive Systems: Architectures for a New Breed of Applications*. Auerbach Publications, 2006.

[16] S. Loke. *Context-aware pervasive systems: architectures for a new breed of applications*. CRC Press, 2006.

[17] J. A. Misener, R. Sengupta, and H. Krishnan. Cooperative collision warning: Enabling crash avoidance with wireless technology. In *12th World Congress on ITS*, volume 3. Citeseer, 2005.

[18] K. Murphy. *Dynamic bayesian networks: representation, inference and learning*. PhD thesis, University of California, 2002.

[19] S. Olariu and M. C. Weigle. *Vehicular Networks: From Theory to Practice*. Chapman & Hall/CRC, 2009.

[20] V. Pavlovic, J. Rehg, T.-J. Cham, and K. Murphy. A dynamic bayesian network approach to figure tracking using learned dynamic models. In *Proceedings of the Seventh IEEE International Conference on Computer Vision*, volume 1, pages 94 –101 vol.1, 1999.

[21] G. Rigas, C. Katsis, P. Bougia, and D. Fotiadis. A reasoning-based framework for car driver #x2019;s stress prediction. In *Control and Automation, 2008 16th Mediterranean Conference on*, pages 627–632, June 2008.

[22] G. Rigas, C. Katsis, P. Bougia, and D. Fotiadis. A reasoning-based framework for car driver's stress prediction. In *Proceedings of the 16th Mediterranean Conference on Control and Automation*, pages 627 –632, june 2008.

[23] F. D. Salim, S. Krishnaswamy, S. W. Loke, and A. Rakotonirainy. Context-aware ubiquitous data mining based agent model for intersection safety. In *EUC Workshops*, volume 3823 of *Lecture Notes in Computer Science*, pages 61–70. Springer, 2005.

[24] K. Saravanan, A. Thangavelu, and K. Rameshbabu. A middleware architectural framework for vehicular safety over vanet (invanet). In *Networks and Communications, 2009. NETCOM '09. First International Conference on*, pages 277–282, Dec 2009.

[25] M. Skutek, M. Mekhaiel, and G. Wanielik. A precrash system based on radar for automotive applications. In *Intelligent Vehicles Symposium, 2003. Proceedings. IEEE*, pages 37–41, June 2003.

[26] V. Stavroulaki, Y. Kritikou, and P. Demestichas. Introducing cognition in the management of equipment in the future wireless world. In *Personal, Indoor and Mobile Radio Communications, 2008. PIMRC 2008. IEEE 19th International Symposium on*, pages 1–5. IEEE, 2008.

[27] S. Tokoro, K. Kuroda, A. Kawakubo, K. Fujita, and H. Fujinami. Electronically scanned millimeter-wave radar for pre-crash safety and adaptive cruise control system. In *Intelligent Vehicles Symposium, 2003. Proceedings. IEEE*, pages 304–309. IEEE, June 2003.

[28] H. Wu, M. Siegel, R. Stiefelhagen, and L. Yang. Sensor fusion using dempster-shafer theory [for context-aware hci]. In *Instrumentation and Measurement Technology Conference, 2002. IMTC/2002. Proceedings of the 19th IEEE*, volume 1, pages 7–12. IEEE, 2002.

[29] G. Yang, Y. Lin, and P. Bhattacharya. A driver fatigue recognition model based on information fusion and dynamic bayesian network. *Information Sciences*, 180(10):1942–1954, May 2010.

[30] Y. Zhang, Q. Ji, and C. Looney. Active information fusion for decision making under uncertainty. In *Information Fusion, 2002. Proceedings of the Fifth International Conference on*, volume 1, pages 643–650 vol.1, July 2002.