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Early Alarm for Emergency Response Based on the Priority Associated with the Cooperative Awareness Messages in Vehicular Ad-hoc Network

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Abstract: Vehicular Ad hoc Network (VANET) is a promising technology for future smart vehicles systems and an essential component of Intelligent Emergency System (IES). The IES includes a wide range of modern technologies such as Global Positioning System (GPS), digital maps, video cameras, sensing devices and the wireless communication devices. It provides necessary information about the condition of the roads in time for drivers and traffic management systems to improve traffic efficiency, reduce traffic congestion, waiting times and fuel consumptions. Design and implement an IES which automatically controls the encryption of the Cooperative Awareness Messages (CAMs) according to the priority associated with CAMs exchanged between emergency vehicles and Road Side Units (RSUs). The CAMs sent from the emergency vehicles to RSUs be signing using a Secure Hash Algorithm (SHA-2) to distinguish them from normal messages issued from other vehicles. The IES uses the features extracted from the trace file that describes the normal and urgent behavior in the VANETs. The type and the number of features have an important role in increasing the classification accuracy rate and decreasing false alarms, especially False Negative Rate (FNR). In this study, the process of classification of urgent records by using (self-organizing map, feed-forward neural network and Elman neural network). The proposed system is based on a program written by MATLAB R2015a. Our selection used for design and programming the proposed system. These algorithms have already been employed to solve the problem because of its importance in saving time and effort as well as providing high results accuracy in quick time unlike other programming languages. The result is clear in overall system in each technique in SOM accuracy degree 99.5% and FNR 0% while FFNN accuracy degree 99.3% and FNR 0.84211% for number of features 16.

Key words: VANET, routing protocol, intelligent emergency system, secure hash function, RSU, employed

INTRODUCTION

Recent advances in wireless networks have led to introducing a new technology called Vehicular Ad hoc Networks (VANETs) that combines different types of networks such as Ad hoc network, cellular technology and wireless LAN (WLAN). VANET is an extension of Mobile Ad hoc Networks (MANETs) which can enhance road safety, essential emergency alerts, traffic management and infotainment facilities for drivers and passengers with increased efficiency of the transportation systems (Anonymous, 2009). VANETs communications can be provide three techniques; They are Inter-Vehicle Communication (IVC), Inter-Roadside Communication (IRC) and/or communication between Vehicles and fixed Roadside equipment (V2R) communication (Dass *et al*., 2012). In VANETs, each vehicle acts as a communication node (sender and/or receiver) to exchange the information either directly between vehicles as single-hop communication or vehicles be capable of retransmit messages in that way enabling multi-hop communication (Karagiannis *et al*., 2011).

The technology that has been standardized for communication in VANET is DSRC (dedicated short-range communications) that includes wireless technologies like WiFi, IEEE 802.11, WIMAX, IEEE 802.15, Bluetooth, IRA and Zig Bee. In VANET environment, each vehicle has its built in device called On Board Unit (OBU)/radio interface that facilitates them to communicate with other vehicles and RSUs and also enabling short-range wireless ad hoc networks which receives safety messages such as sudden break warning from other vehicles, essential emergency alerts, etc. and non-safety message such as comforts and entertainment related information (Yang *et al*., 2014). Figure 1 shows vehicles, RSUs and the occurrence of an accident. Once

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Fig. 1: An example of the process of responding to cases of emergency on the road

an accident has occurred, CAMs and control data generated and communicated to the RSUs and other vehicles in that zone.

In our research, we designed a new emergency detection system by adding a sign to emergency messages to give priority for urgent case which allow the emergency vehicle to get to the incident scene faster and more safely. The EDS utilizes trace files generated from the Network simulator Version 2 (NS2).

Literature review: Traffic jams and controlling flow of vehicles are one of the most major problems in modern urban area which caused multiple road accidents in the city and loss of life due to the delay in the arrival of the ambulance to the accident site in time (Assila *et al*., 2012). The above problems can be solved by taking advantages of recent advances in the field of wireless networks. Vehicles and equipment manufacturers have the opportunity of enhancing the surface transportation via. using the communication capabilities of the VANET to support Vehicle-to-Vehicle (V2V) communication and Vehicle-to-Road Side Unit (V2RSU) communication and offer an Intelligent Transportation System (ITS) to the drivers (Hung *et al*., 2008; Gaur *et al*., 2013). In real-time applications, emergency vehicles need access to important information such as warning messages and CAMs between vehicles and RSUs. Therefore, security and privacy becomes a very important issue in VANETs developments (Alheeti *et al*., 2015).

Athavan *et al*. (2012) designed an intelligent transportation system for the ambulance which is controlled automatically the traffic signals based on the accident site and the hospital site according to the information stored for each node in VANETs to cross ambulance smoothly traffic junctions to reach the hospital in time when an accident on the road. Buchenscheit *et al*. (2009) designed an emergency vehicle warning system that is using wireless communication to warn other vehicles or to preempt traffic lights for the purpose of the arrival of the emergency vehicle to the intended destination in the fastest time and reduce accident risks during emergency reaction trips. Alarm system in emergency vehicles gets detailed information from roadside infrastructure like a traffic light about congestion, speed and ambulance site to take the appropriate action and timing. Kabiri and Aghaei (2011) suggested a new approach of extracting suitable and static features from the trace files which describe the type of vehicles in the network. This approach is based on feature selection method and it applies PCA theory to determine network operating conditions. The different numbers and types of features had a direct impact on the accuracy of the IES. Raut *et al*. (2014) proposed an early alert system of dedicated vehicles based on the great circle algorithm and RSU deployment in vehicular networks to receive early alert messaging and identify the vehicles existing in the dangerous zone via. relative positioning. Discussion a set of security issues and challenges that threaten Vehicular Ad hoc Networks (VANETs) and focus on attacks that get the message itself rather than the car such that attacker dropping packets and it may contain important information for the recipient, attacker may send wrong information in the network. Samara *et al*. (2010) proposed suitable solutions for these challenges and problems to reach a satisfactory level for the driver and manufacturer to achieve safety of life and infotainment. Doijad *et al*. (2015) proposed a new security and safety system based on wireless technology to secure the communication between Vehicle-to-Vehicle (V-to-V) in VANETs. The proposed system is the development of communication module by using ATmega with transceiver and LCD.

MATERIALS AND METHODS

In our study, we propose an IES that is based on a dataset which was collected from a trace file that was generated utilizing NS2 to identify behavior of vehicles, whether normal or urgent case. The steps below explain the methodology:

Mobility model: We used two tools to create a real scenario of normal and/or urgent behavior in VANETs. These are Simulation of Urban Mobility Model (SUMO) and MObilty VEhicles (MOVE). The SUMO is widely known in the field of VANET simulations, it purveys

Fig. 2: Interconnection of MOVE, SUMO and NS2

efficient computation even in various sizes of scenarios and purvey a better way to effectively plan. Also, support operates and design intelligent transportation systems. The move generator is designed on SUMO (CCC., 2011). The output file of these tools represents a mobility file for normal and emergency vehicles in VANETs. These files are used as input to NS2 (Danquah and Altilar, 2014). Below is the logical flow and interconnection between the above three simulators that we based on to simulate vehicles, road network and finally the wireless sensor network as shown in Fig. 2.

In this study, we used the Manhattan urban mobility model to create a mobility and traffic scenario for vehicles. The reasons for selecting this type of mobility is flexibility and easily is selection of direction for vehicles which may be vertical or horizontal direction and is widely used in this research field.

Simulation environmental and parameters: We selected an efficient network simulator NS2 to evaluate and measure the performance of the proposed IES. The NS2 is designed to simulate different networks such as wired and wireless networks. A common problem that is exposed when simulating the VANETs with NS2 is a realistic mobility model and traffic modelbecause the simulator is not designed specifically for VANETs. To overcome this problem, we used the SUMO and MOVE tools to create realistic mobility and traffic model for VANETs. A screenshot of NS-2 utilizing Network the Animator (NAM) trace file is shown in Fig. 3. Figure 3 shows Manhattan mobility model that consists of 9 RSUs and 140 vehicles (136 normal vehicles and 4 emergency vehicles).

One of the important issues in the simulation system is the initial parameters. Some parameters used in simulating the VANETs are: Constant Bit Rate (CBR) application that sends constant packets through the transport protocol such as (UDP), mobility model (Manhattan) and radio propagation model (two ray ground) in Table 1 (Samara *et al.*, 2010).

Fig. 3: Screenshot of Simulation in NS2 NAM

Table 1: Simulator environmental and parameters

Parameters	Values
Simulation time	1000 (sec)
Number of nodes	140 vehicle
Number of traffic lights	5 signal
Number of edges	24 street
Number of RSUs	9 RSU
Type of traffic	Constant Bit Rate (CBR)
Topology	552×452 (m)
Transport protocol	UDP
Packet size	1000
Routing protocol	AODV
Channel type	Wireless
Queue length	50 packets
Number of road lanes	2
Radio propagation model	Two ray ground
MAC protocol	IEEE 802.11
Speed	60 (m/sec)
Interface queue type	Priority queue
Network interface type	Physical wireless
Mobility models	Manhattan mobility model

Feature sets and extraction a trace file and a network animator represent output files of the NS2. These two files are used for analyze and viewing network simulation of the behavior in VANETs. The trace file generated in NS2 is divided into three parts. These are basic trace, internet protocol trace and AODV (CCC., 2011). The type of event taking place at the node and can be one of the five types: Send (s), Receive (r), Drop (D), Forward (f) and Movement (M) (Zhou and Hass, 1999). The events of VANETs are described using trace file, it contains many different data features which are used for analysis. These features describe normal and urgent behavior in the VANETs. To increase the efficiency and the accuracy of the proposed system, the most effective features are extracted from the trace file. Many methods used in the field of VANETs to extracted effective features. We used the AWK language

Table 2: Features selection

Basic trace	IP trace	AODV trace
Packet ID payload size and type, source and destination MAC and ethernet	IP source and destination	Packet tagged, hop, counts, boardcast ID, destination IP with sequence number source IP with sequence number and priority

Table 3: FFNN parameters

Parameters	Values	Description
TrainParam.epochs	1000	Maximum number of epochs to train
TrainParam.goal	0	Performance goal
TrainParam.max_fail	6	Maximum validation failures
TrainParam.min_grad	1×10^{-6}	Minimum performance gradient
TrainParam.sigma	5×10^{-5}	Determine change in weight for second derivative approximation
TrainParam.lambda	5×10^{-7}	Parameter for regulatng the indefiniteness of the Hessian

Fig. 4: SOM structure

to extract features that capture the events of vehicles (Alheeti *et al*., 2015). In this study, a new field (the priority) is added to the trace file to give a higher priority to emergency vehicles to navigate and smooth access to the intended destination in a timely manner. Priority value (0) given for emergency vehicles and (1) for normal vehicles. Table 2 shows the 16 selected features from whole features that were used in the proposed emergency system.

Intelligent emergency system: In our research, we designed an IES based on SOMs (unsupervised nets) and FFNN (supervised nets) to detect emergency vehicles in VANETs. SOM network consisting of input layer, the hidden layer and output layer, the hidden layer and output layer are compatible. An input layer consists of 16 neurons with the actual data and both hidden layer and output layer consists of 4 neurons as shown in Fig. 4. SOM trains a network with weight and bias learning rules with batch updates. Weights and biases updates occur at the end of an entire pass through the input data.

In our study, we used trial-and-error to select the best structure of FFNN employed in the proposed emergency system. The best structure of the FFNN is consist of three layers, the input layer consists of sixteen neurons, the hidden layer consists of two neuron and the output layer consists of three neurons as shown in Fig. 5.

The initial parameters play an important role in the performance of the FFNN that have a direct impact on the performance of detection. Table 3 shows the parameters of the training phase used in the FFNN. We design the simulation on system with an Intel core i5 processor (2.40 GHZ) and RAM memory (4GB).

Fig. 5: FFNN structure

Fig. 6: Architecture of IES

The proposed model of IES: The proposed system has five stages; Fig. 6 shows the overall architecture of the proposed IES, namely:

The first stage (Generate the mobility and the traffic model): At this step, we used two software programs to generate the realistic scenarios that reflect vehicles behavior on roads. NS2 used the output files from SUMO and MOVE as input to generate a trace file that describes the normal and urgent behavior for vehicles in VANETs.

The second stage (data collection and pre-processing): The features are extracted from the data in the trace file were generated in the previous step. The selected features were pre-processed to convert some letters and symbols to numeric values and to generate a uniform distribution to balance the different types of classes in collecting the data to increase the efficiency of the classification rate and normalization process to convert all the values of the features between zero and one.

The third stage (training and testing phase-SOM): We trained and tested the SOM with the extracted features that describe normal and urgent behavior. In this stage, we obtained the detection rate, the error rate and we calculated four types of alarm.

The fourth stage (training and testing phase-FFNN): We trained and tested the FFNN with significant data that was extracted in the second stage to check the efficiency of the proposed security system in the detection of emergency vehicles in comparison to normal vehicles.

The five stage (comparison): In this stage, we compared the two proposed intelligent detection systems based on the three criteria, detection rate, the number of false alarms and error rate.

RESULTS AND DISCUSSION

The emergency system may be installed in three configurations: emergency vehicles, RSU or both on the emergency vehicles and RSU. In our study, we selected to install the system in RSU. The evaluation of implemented approaches and comparative results are based mainly on calculating the accuracy rate, the error rate as well as we need to calculate four types of alarms: True Positive Rate (TPR), False Positive Rate (FPR), True Negative Rate (TNR) and False Negative Rate (FNR). The most important factor is to measure the alarm rates, since, the issue is to find out the false alarms (especially false negative the most dangerous alarm). The accuracy and error rate are used as a performance metric to evaluate the proposed an IES. The accuracy and error rate of the system result should be calculated as follows:

$$\text{Accuracy rate}(\%) = \frac{N_T}{N_P}\times 100 \quad (1)$$

$$\text{Error rate}(\%) = \frac{N_F}{N_P}\times 100 \quad (2)$$

In addition, the measures will be calculated as follows:

$$\text{True positive rate}(\%) = \frac{TP}{TP+FN}\times 100 \quad (3)$$

$$\text{True negative rate}(\%) = \frac{TN}{TN+FP}\times 100 \quad (4)$$

$$\text{False negative rate}(\%) = \frac{FN}{FN+TP}\times 100 \quad (5)$$

$$\text{False positive rate}(\%) = \frac{FP}{FP+TN}\times 100 \quad (6)$$

In these equations, NP is the total number of patterns, NT is the number of correctly classified patterns, NF is the number of patterns classified as unknown, TP is the number of normal connection record classified as normal, TN is the number of urgent connection record classified as urgent, FP is the number of normal connection record classified as urgent, FN is the number of urgent connection record classified as normal.

Result of training and testing SOM neural network: During the training and testing phase, we used the same dataset in both phases that was generated from the trace file to detect emergency vehicle in VANET. During the testing phase, calculate the total accuracy of an IES and error rate of the system. In this SOM neural network the accuracy obtained is (99.5%) and the error rate obtained is (0.5%). The experimental results obtained for TPR, FPR, TNR and FNR were explained in Table 4.

Train and test FFNN neural network: During the training and testing phase, we used the same dataset in both phases to calculate the total accuracy of the EDS, true positive, false positive, true negative, false negative. The total accuracy of the training classification was (99.3%) and the error rate was (0.7%). The experimental results obtained for TPR, FPR, TNR and FNR were explained in Table 5.

The motivation of this research is to provide an intelligent security system that creates a safe environment for emergency vehicles. The methodology of the proposed IES was implemented in five phases: generating the mobility and traffic model, data collection and preprocessing phase, training and testing for the SOM, training and testing for the FFNN and comparing the results that were generated in the two types of IES. When we compare the two types of IES, we can observe that the IES was based on the SOM was more effective and efficient in detecting emergency vehicles with a low false negative alarm rate than the IES based on the FFNN. The comparison performance between the SOM and FFNN is as shown in Fig. 7.

Table 4: Alarms rate

Alarm types	Accuracy (%)
True positive	100
True negative	84
False negative	0
False positive	16

Table 5: Alarms rate

Alarm types	Accuracy (%)
True positive	99.1579
True negative	100
False negative	0.84211
False positive	0

Fig. 7: Performance comparison

The error rate for the IES based on the SOM was 0.5%. In this system, the alarm rate fluctuated between 84 and 100% with good and efficient accuracy. On the other hand, the average false negative alarm rate was 0% which is an excellent indicator of the results. At the same time, the error rate for the IES based on the FFNN was 0.7%. The alarm rate fluctuated between 100% and 99.1579% with excellent and efficient accuracy. On the other hand, the average false negative alarm rate was low at about 0.84211% which is a good indicator of the results.

We could improve the emergency system by using SHA-2 to encrypt the messages exchanged between emergency vehicles and RSUs as shown in Fig. 8.

We could improve the detection rate by adding priority feature to the trace file that creates flexibility in selecting the system that is more efficiently with different conditions. In addition, in our proposal, we selected the significant features based on the previous study (Alheeti *et al*., 2015). All these factors make the proposed security system more efficient in securing the external communication systems for emergency vehicles.

Fig. 8: Sign the CAM using SHA-2

CONCLUSION

Security and safety are a serious issue and a crucial requirement for emergency vehicles. The network is exposed to various types of attacks that have a direct impact on the development and deployment of emergency vehicles in that zone. Our proposed IES can provide reliability for drivers by encrypting CAMs sent from the emergency vehicles to RSUs using a hash function to distinguish them from normal messages issued from other vehicles in order to ensure the protection of the network from any breach or fraud by normal vehicles to be emergency vehicles so we have achieved security and authentication. In other words, emergency vehicles without security cannot achieve their task in providing comfort and safety while in operation. In our study, we designed an intelligent security system to secure external communication and ease of movement for emergency vehicles in VANETs environment to reach the accident site in time to save lives. The IES has been designed for training and testing with important features by using SOM and FFNN. This system deals with two system scenarios: emergency and normal that have been created on the NS2. Our system is to analysis the behavior of each mobility vehicle in the VANETs to identify if it is an emergency vehicle or normal vehicle. The number and the type of features have a vital direct role to increase the efficiency and the accuracy of the detection system. Further attentions should be given to use a fuzzy data set to reduce the rate of error, the number of false alarms and may be used to represent integrity to dataset with fuzzy concepts.

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