On the Drivers’ Behavior Evaluation using Vehicular Networks

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Abstract

With the emergence of connected and intelligent vehicles, various research projects aiming at reducing traffic accidents by detecting driver behavior have also emerged. These vehicles are generally equipped with cameras and sensors that can be used to detect driver’s fatigue, drowsiness, and distraction using different technologies and a multitude of classification techniques. In this work, we propose a new real-time driver behavior-detection technique based on vehicle-to-vehicle communication (V2V) and by exploiting the information carried by the periodically exchanged messages known as Cooperative Awareness Message (CAM) that are a part of the European ETSI-ITS standard (or Basic safety message BSM in the US standard). These information include the vehicle’s current speed, the average speed, the position, the acceleration, to name a few. In our proposal, each vehicle can classify its neighbors (normal, aggressive) according to its driver’s driving style. An audio or video message can be then generated to warn the driver of any vehicle presenting a danger. Simulations conduct in both rural and urban environments depict that our proposal called "Vehicular Ad-Hoc Network Exchange Message (VanetExM)" can determine the state of the driver with a relatively high success rate and low overhead.

Keywords

VANET, Driver behavior, Safety Message, V2V communication, Road Safety

1. Introduction

According to World Health Organization (WHO), every year the lives of approximately 1.35 million people are lost as a result of a road traffic crash, and between 20 and 50 million more people suffer from non-fatal injuries, with many incurring a disability as a result of these injuries [1]. This means that every 24 second one death is registered on road [2]. furthermore, Road traffic crashes cost to most of the countries more than 3% of their gross domestic product (GDP) [1]. It is estimated that fatal and nonfatal crash injuries will cost the world economy approximately $1.8 trillion dollars from 2015–2030 [3]. One of the most important goals of Intelligent Transport Systems (ITS) is to prevent accidents and improve the safety on roads.

The second International Conference on Computer Science’s Complex Systems and their Applications ICCSA’21, May 25–26, 2021, Oum El Bouaghi, Algeria

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Moreover, The National Highway Transportation Safety Administration (NHTSA) reported that between 94% to 96% of all motor vehicle accidents are the result of human error [4]. That is what made driver behavior detection one of the interesting fields of Intelligent Transport Systems. Many factors can affect the behavior of the driver including the fatigue, alcohol, distraction, reckless or careless, experience, environment and vehicle condition, as well as the physiological and the psychological state of the driver. The real-time capturing of all these data requires various types of sensors which are the key factor of all driver detection systems. The captured information is then passed through computer application models to classify the driver behavior. Several methods have been used to detect the abnormal driver behavior among which: Neural Network [5], Kalmen filter [6], Hidden Markov Model [7], Gaussian Mixture Model [8], Smartphone based [9, 10], Fuzzy Logic [11] and K-means [12]. Recently, with the emergence of Vehicular ad-hoc network (VANET), which characterized by high mobility and permanently changes of network topology and the ability of vehicles to communicate with each other and with infrastructure, the real-time analysis of driver behavior became much more attractive research problem.

In the last years, tremendous efforts have been devoted to the study of driver behavior and various research works have approached the problem of detecting abnormal human driver behavior with the aid of capturing and analyzing the driver's face and the vehicle's dynamics via image and video processing. However, the traditional methods are not capable of capturing complex temporal features of driving behaviors [13]. Other works [14] propose the utilization of accelerometers and gyro-sensors built into smartphones for detecting driving behavior. Yet, the Smartphone-based methods suffer from the inability to detect the aggressive driving cases. The authors of [15] developed non-intrusive driver behavior detection system using a context-aware system in VANET to detect abnormal behaviors exhibited by drivers, and to send warnings to other vehicles on the road so as to prevent accidents from happening. A key limitation of the all above research works is that each vehicle can detect only the abnormal behavior of its driver but not the behaviors of the neighboring vehicles.

In this paper, we propose a novel and efficient method for real-time detection of abnormal driving behavior using the periodically inter-vehicle exchanged messages. The main contributions of this paper are twofold: (1) we propose a method based on exploiting the information included or added to periodically exchanged messages (Cooperative Awareness Message CAM or Basic safety message BSM) like acceleration, location, velocity, braking for detecting the driver behaviors. (2) Alarm the driver or other vehicles by warning messages via wireless communication technology in VANETs.

The rest of this paper is organized as follows. Section II describes the components of the behavior detection system. Section III explain the proposed approach for detecting abnormal driving and alert the driver of vehicle and neighboring vehicles about this dangerous driving which can decrease accident occurring probability. Section IV shows and discusses the experimental results, and finally, Section V concludes the paper.

2. Driver's behavior detection systems

n the last 10 years different commercial and research systems have been proposed to analyze the driver's behavior, to evaluate the driver's performance, and to assist and help drivers during the driving process [16]. All these systems share a common paradigm called "Driving Monitoring System (DMS)". DMSs are generally classified into In-Vehicle Data Recording Systems and Real-time Monitoring Systems [17] where these latter are the most important ones. In this paper, we propose an extension of the classical behavior detection system (c.f, Fig. 1). This system is divided into three units. The first is the Input Unit and is used to capture the different information concerning the driver and the vehicle, this information will then be processed by the second unit called Treatment Unit which also takes the decision according to the degree of risk and transmits it to the third unit called Output Unit as a simple alert or action.

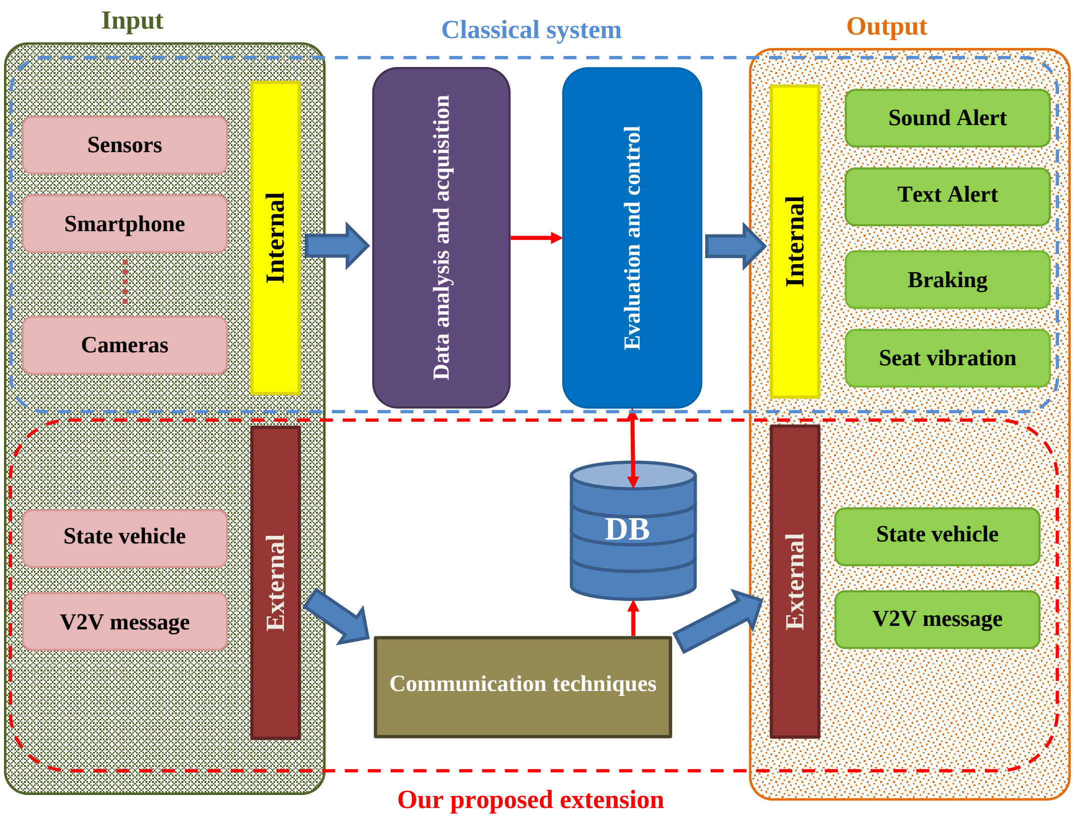

Figure 1: The components of the behavior detection system

2.1. System input

Sensors are the key factor of behavior detecting systems. The information can be captured by:

- *Cameras*: Driver behavior is mainly monitored by a camera, and therefore, this approach is known as video-based measurement. Cameras can be used for detecting driver fatigue and drowsiness by observing abnormal behavior associated with eyes movement, facial expression, and head position.
- *Smartphone*: The development of smartphones over the past decade has provided a permanent and mobile source of computation and processing. Moreover, all new smartphones are equipped with a wide range of sensors such as accelerometer, gyroscope, magnetometer, and many other sensors [14].
- *Physiological sensors:* The driver's physiological signals come from human organs such as the brain, eyes, muscles, and heart [18], which can indicate the level of fatigue and vigilance on real-time. This also includes Brain activity which can be captured by electroencephalography (EEG) or near-infrared spectroscopy (NIRS), Eyes activity, measured by ElectroOculoGraphy (EOG), Muscle activity; by ElectroMyoGraphy (EMG), and heart activity by ElectroCardioGraphy (ECG). The methods which use this type of sensors are known as Bio-signal-based methods [13]
- *Sensors on board of the vehicle*: On-board measurement sensors are used to collect a number of indicators deployed to determine the level of vigilance / drowsiness of the driver, this approach is based on measurement and detection of Steering wheel movement (SWM), Vehicle deviation and position [19] and Vehicle speed and acceleration [20].

2.2. Treatment unit

As shown in Figure 1, internal infrastructure of a behavior detection system is generally composed of two main modules with communication technique to send and receive (to exchange) messages of type V2V or vehicle-to infrastructure. The two modules are:

- *Data analysis and acquisition module*: This module receives data from the different sensors which form a network and communicate with the coordinator network to send the data. The measured signals are then filtered and transformed to eliminate any noise and nuisance that may affect the quality of the sensed data.
- *Evaluation and control module*: The signals are received by the acquisition module undergo in a first step, a noise filtering and unwanted signals discarding phases. In the second step, the signals are processed to extract the main characteristics which reflect the different states of the target application. (e.g. driver's cognitive states). These characteristics can be extracted using learning machine and classification algorithms.

At each identified condition, an appropriate timely action is triggered. This action can be an alarm or a buzz inside the vehicle to alert or wake up the driver. In some cases, the system can take control of the vehicle in order to accelerate or stop the vehicle.

2.3. System output

After the data processing and the risk assessment phases, the results will be either internal or external (sending warning messages to other vehicles) or both at the same time. Internal outputs include alerts that is displayed in the dashboard as text or audible to attract the driver's attention in the event of drowsiness or distraction. Other systems combine the alerts with actions like seat vibration to wake the driver up if he has not responded to an alert or make the decision instead if he is not conscious (drunk driver for instance) by a speed decrease or braking (c.f, Fig. 2).

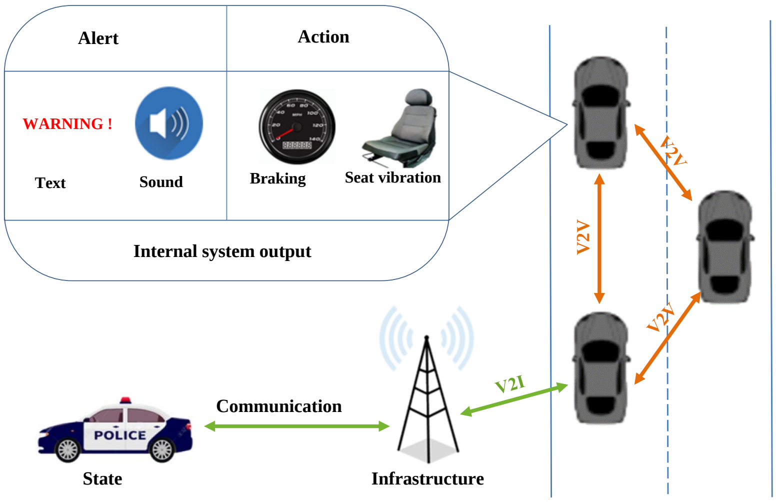

Figure 2: System output

3. Our proposal

Vehicular Networks are deployed primarily to increase the safety of road users. One of the safety aspects is to detect the behavior and state of the driver. Our approach consists of exploiting the inter-vehicular communications and especially the periodically exchanged messages (CAM/BSM) in order to create a state on each vehicle and thus detect the style of driving and dangerous behavior. Thus, by using the information contained in these messages, it is possible to estimate the driver's condition from his speed, acceleration braking, frequent lane change, etc.

3.1. Technique description

We consider that our VANET network consists of nodes which communicate with each other using the V2V type in Ad-hoc mode. Each vehicle periodically sends a CAM type message every Δ milliseconds when $\Delta \in$ [100ms, 1000ms], i.e. with a frequency ranging from 1Hz to 10Hz. This message contains information about the vehicle such as its position and speed. After receiving these messages, a processing is done by each vehicle individually to determine the behavior of each neighboring driver. It should be noted that we have avoided using the judgments of others for security reasons in order to avoid collaborative attacks which will have serious consequences. The basic idea is to calculate the difference between the current speed (SC) and the average speed (SA) of a vehicle. Both information must be included in the CAM message and since the average speed does not exist in the standard message [21], then it is imperative to modify the standard CAM message in order to meet the requirements of the proposal protocol as shown in Fig. 3.

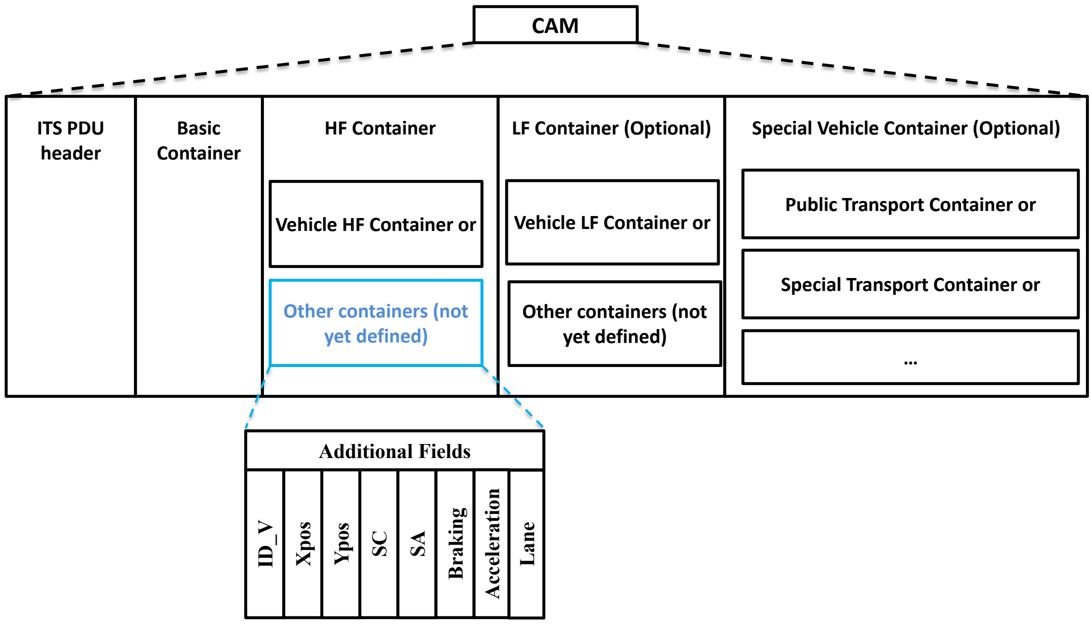

Figure 3: The Modified CAM formats

The additional fields used in our protocol are:

- **ID_V**: Source identity.
- **Xpos**, **Ypos**: Source position.
- **SC**: the current speed of the source.
- **SA**: the average speed of a vehicle on each lane during a period T.
- **Lane**: Lane type (Slow, Medium, Fast, City).
- **Braking**: brake indicator.
- **Acceleration**: acceleration indicator.

To include it in the CAM message, each vehicle calculates its average speed using the following equation for short periods:

$$SA = \frac{1}{N} * \sum_{i=1}^{N} SC_i \tag{1}$$

when N is number of captured speeds in a given interval and SCi is the i $^{\text{th}}$ captured speeds. But in case when the period is large, it is better to use the weighted average using the following equation:

$$SA_{(\Delta t+1)} = \alpha SA_{\Delta t} + (1-\alpha) SC_{(\Delta t+1)} \tag{2}$$

when $\alpha \in [0, 1]$
Knowing that each driver has his own driving style which differs depending on the situation, we have chosen to insert the associated average speed (SA) for each type of lane in both freeway and urban environments. For the sake of simplicity, we have limited the number of lanes to three. Thus, we have four speeds integrated in the message associated with (S (00), M (01), F (10), C (11)) with: 'S' is the slow channel, 'M' is the medium channel, 'F' is the fast lane and C is city. Each node receiving a CAM message executes VanetExM algorithm 1. Therefore, in the case when the current speed is slower or faster than the permissible lane speed, the system sends recommendations to the driver of the concerned vehicle to change the lane or adjust the speed according to each case (see Algorithm. 2). In the other case (when the current speed corresponds to the permissible speed on the lane), the system will try to detect abnormal driver behavior based on braking frequency, acceleration frequency, deviation, and the average speed. If an abnormal behavior of neighboring vehicle detected the system warn the driver (see Algorithm. 3).

Algorithm 1 VanetExM Algorithm

```
VanetExM(_)
Lane: char (S, M, F, C)
ID_V: Integer
SC, SA: Long
Xpos, Ypos: Float
Braking, Acceleration: Boolean
while vehicle receive CAM message from neighbor i Do
if  (Lane = S and SC = 40)or (Lane = M and (SC<40 or SC > 80)) or (Lane = F and (SC <
80or SC > 200)) then
  Warning (ID_V, SC, 'F');
else
  if (Lane = S and SC < 40 ) or (Lane = M and (SC > 40 or SC < 80)) or (Lane = F and (SC
  >80 or SC < 200)) or (Lane = C and SC < 60) then
    Detection (ID_V, SC, SA, Braking,Acceleration, Xpos)
  else if (Lane = C and SC > 60) then
    Warning (ID_V, SC, 'C');
  end if
end if
EndWhile
```

4. Performance evaluation

To evaluate the performance of our proposal with Network Simulator **NS2** we have considered two scenarios where in the first one we use a urban model and a freeway model is used in the second. The simulation parameters are described in the table I:

- **Ratio of abnormal vehicles detected**:

Algorithm 2 Warning

```
Warning(ID_V, SC, Road)
if Road = 'F' then
    if SC > 0 and SC < 40 then
        Send (ID_V, "You must change your lane to the slow");
    else
        if SC > 40 and SC < 80 then
            Send (ID_V, "You must change your lane to the medium");
        else
            Send (ID_V, "You must change your lane to the fast");
        end if
    end if
else
    Send (ID_V, "You are in the city your speed must not exceed");
end if
```

Algorithm 3 Detection

```
Detection(ID_V, SC, SA, Braking, Acceleration, Xpos)
Act_abnormal=(frequency_Braking = high) or (frequency_Acceleration= high)
Dev = (Δx > Deviation_threshold)
if |SC − SA| > Speedthreshold then
    if SC > SA then
        if Dev = True then
            Write ("Vehicle",ID_V," its driver may be drunk");
        else if Act_abnormal= = True then
            Write ("Vehicle",ID_V," its driver behaves aggressively");
        else if Act_abnormal= True then
            Write ("Vehicle",ID_V," its driver may be sleepy or tired");
        end if
    else
        Write ( "Vehicle",ID_V," its driver behaves normally");
    end if
```

Fig. 4 represents the ratio of detected abnormal vehicles in respect of the total number of vehicles, we observe that this ratio increases with the increase in the number of nodes. This can generally be explained by the fact that in a dense network, we have more neighbors and consequently, we receive more messages helping to increase the detection ratio. However, with a density of 25 vehicles, we can see that there is a decrease in this ratio, which is due to packet losses linked to the nature of the wireless medium or to the location of certain isolated nodes .

- **Number of generated warning messages**:

Fig. 5 illustrates the performance of the number of generated warning messages compared to the number of vehicles. It can be observed for the two models (Urban and Freeway) that the

Table 1
Simulation parameters

Parameter	Scenario 1	Scenario 2
Channel type	Channel / WirelessChannel	Channel / WirelessChannel
Protocol	Mac/802.11p	Mac/802.11p
Transmission range	250 m	250 m
Mobility model	Freeway	Manhattan
Number of nodes	[5 – 40]	[5 – 40]
Road length	1.1 Km	–
Packet length	512 Bytes	512 Bytes
Simulation time	100 seconds	100 seconds
Number of intersections	–	3x3

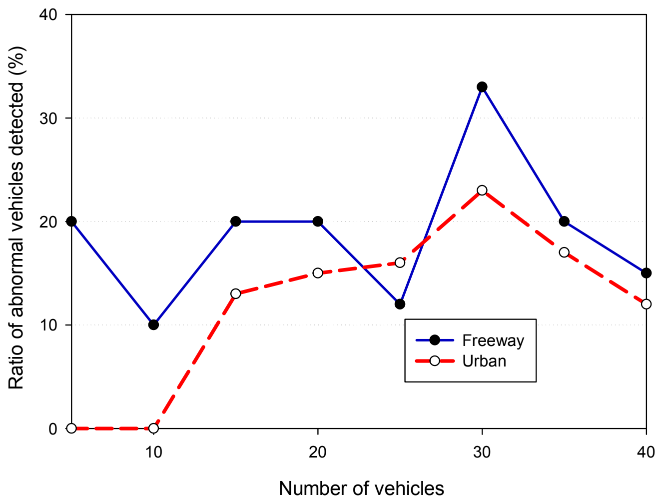

Figure 4: Ratio of abnormal vehicles detected with respect to the total number of vehicles

number of generated warning messages increases with the increase in the number of nodes. The number of warning messages reaches a maximum of 125 in the freeway. On the other hand, it reaches 27 warning messages for the urban scenario. We attribute this increase to the fact that with the increase in the number of nodes in the network, there will be more neighbors. Therefore, each node will detect, in the normal case, all the normal vehicles within its range, and this explains the increase in the number of warning messages. In addition, we notice that the number of warning messages increases more on the freeway than in the city, because in an urban environment, the disconnection is frequent since there are more obstacles and changes of direction (lane), something which decreases the ratio of correctly received messages.

- **Number of vehicles that reacted**:

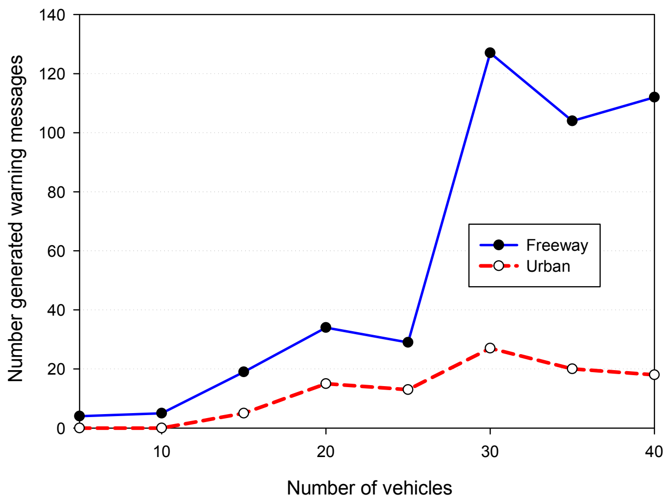

Figure 5: Number of generated warning messages with respect to the total number of vehicles

The generation of a warning messages in the normal case should be followed by corrective action of the situation. Fig. 6 represents the number of vehicles which reacted after warning messages according to the number of vehicles.

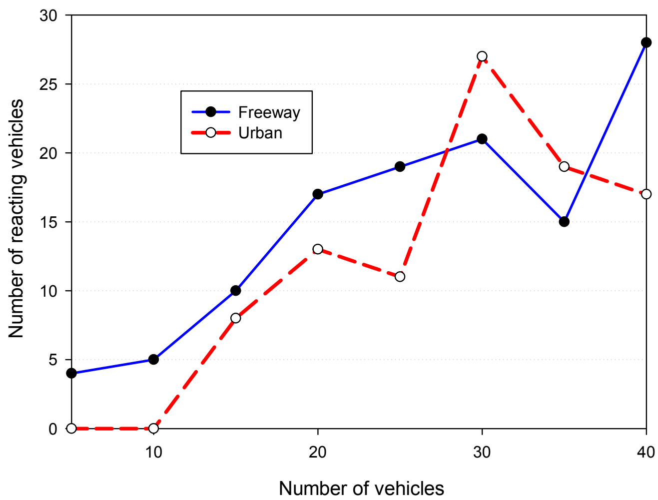

Figure 6: Number of reacting vehicles with respect to the total number of vehicles

The shape of the curve can have the same explanation of the above curves. Thus, the number of abnormal nodes and the number of reactions increase proportionally with the number of nodes in the network. On the other hand, we justify the decrease for a density of 25 and 35 by the decrease of the abnormal nodes in the network which reacted after warning messages during the simulation time.

- **Ratio of positive faults**:

The ratio of positive faults represents the number of false generated warning messages.

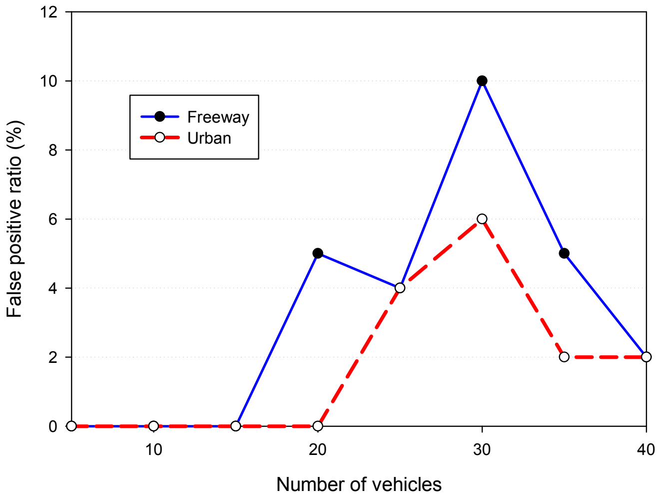

Figure 7: False positive ration with respect to the total number of vehicles

Fig. 7 shows that this rate is between 0% and 10% of all the abnormal nodes reported. The rate of positive faults reaches its maximum of 10% when the abnormal nodes present more than 20% in our network, which represents 2% of the density. So, the algorithm is overall very reliable.

5. Conclusion

Monitoring and detecting abnormal driver behavior is an important task for improving road safety and preventing accidents. In this context, we presented in this paper our driver behavior detection protocol which uses inter-vehicle communications. This approach made it possible to detect two "normal or abnormal" behaviors while driving and to classify the abnormal behavior as drowsy, drunk, or aggressive drivers on the fly. In the case of abnormal behavior, the vehicle generates a warning message to reduce the potential undesired damages. The performance evaluation results of our approach called Vehicular Ad-Hoc Network Exchange Message "VanetExM" in both urban and freeway environments demonstrated the ability of the proposed algorithm to infer driver behavior using readings from different sensors over time and messages received from other vehicles.

As a future work, we plan to run realtime testbeds using smartphones as a mean of inter-vehicles communications to further asses and improve our proposal.

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