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# DigiMesh-based Social Internet of Vehicles (SIoV) for Driver Safety

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***Abstract*— Social Internet of Vehicles (SIoV) represents the next stage in the evolution of Internet of Vehicles (IoV). Vehicles can form potentially short-term and anonymous relationships in an SIoV to address mobility issues. SIoV enables a driver and a vehicle to be aware of their surrounding context and to act accordingly. This paper presents the design and implementation of an SIoV that is local in nature and does not rely on 5G or a similar global network connection. The SIoV is based on the DigiMesh ad-hoc wireless network that dynamically forms an SoIV among vehicles traveling together within a prescribed radius and time. A small on-board microcontroller is used in conjunction with a DigiMesh Radio to transmit and receive bad driving behaviors of surrounding vehicles in the network. Dynamic Time Warping (DTW) is applied to sensor data pulled from the OBD-II interface from each vehicle to create driver alerts. These alerts include, harsh speeding, swerving, sudden braking and tailgating. The system achieved a 98.6 % accuracy in detecting these behaviors and can respond to anomalous events within a time window of 3 seconds in vehicles traveling up to 120 km/hr.**

***Index Terms*— Social Internet of Vehicles, SIoV, DigiMesh, ZigBee, Dynamic Time Warping, Driver safety, Smart cities**

## I. INTRODUCTION

Internet of Vehicles (IoV) has emerged as term to describe vehicles connected through the internet [1]. To realize the IoV, a host of technologies have been proposed to build cyber-physical systems for vehicles [3]. In addition, many communicating technologies have been proposed to connect vehicles in the IoV [4]. In order to solve a number of mobility problems, smart cities are poised to move towards Vehicular Social Networks (VSNs) that combine IoV with social media networks [2]. More recently, social internet of vehicles (SIoV) [5] [6] has been proposed as an extension of the Social Internet of Things (SIoT) to be a network of socially connected vehicles. The SIoV have several unique characteristics like highly dynamic vehicle nodes that can enter and leave the network at any time, rapidly changing network topology, anonymous identity and interaction between vehicles, and message exchange tied to some specific context of use.

Due to the increasingly large number of vehicles, bad driver behavior causes many fatalities. According to a report by National Highway Traffic Safety Administration 37,461 people were killed in crashes on U.S. roadways during 2016 [7]. Therefore, prevention and detection of anomalous driver behavior that may lead to fatalities is an important problem to be addressed by smart cities.

Various technological approaches have been used to address problem of detecting and preventing bad driver behavior. One class of solutions to detecting and preventing anomalous driver behavior relies on sensors attached to the driver. For example, He et al. [8] used google glass worn by drivers to detect sleepy behavior. Hand gestures based on a wrist-worn device have also been used to detect distracted driver behavior [9]. Other similar approaches use strategically placed cameras in the car to detect anomalous driver behavior [10]. Video analytics of street traffic data have also been used to detect anomalous vehicle/driver behavior [11] [12]. Since most drivers carry smart phones, sensors from smartphone in the car have been used to detect anomalous driving behavior. For example, Castignani et al. [13] used data collected using a dash-mounted smart phone to distinguish between calm and aggressive behaviors based on acceleration, braking and steering, slalom maneuvers, and U-turns. Similarly, Singh et al. [14] used sensor data from drivers' mobile phone to detect various types of anomalous behavior like harsh braking, etc. Smart phone Apps have been proposed to provide bad driving feedback, and to exert social pressure on drivers to reduce bad driving behaviors [15]. Finally, Zhang et. al [16] described a system that uses data like speed, RPM, swerve angle, and gear position collected directly from the OBD interface of 29,000 vehicles connected through an IoV to detect anomalous driver behavior.

One key aspect of safe driving is context awareness [17]. Context-awareness is about a vehicle being aware of its surroundings and reacting accordingly. For example, a tail-gating vehicle needs to be recognized and acted upon.

Similarly, a recognition that a vehicle in the near vicinity is accelerating or braking in a reckless manner should alert the driver and the vehicle about a possible collision. In such situations, autonomous vehicles can react automatically while alerts can be issued to drivers of conventional vehicles.

This paper proposes a system based on a dynamic SIoV that allows a vehicle to report its own anomalous driving behavior to other vehicles in the vicinity, and at the same time receive warnings about bad driving behavior of surrounding drivers. The system relies on the DigiMesh ad-hoc wireless technology that allows vehicles to join and leave the network as required without any central coordination. Dynamic time-warping (DTW) is used to classify drivers' behavior data collected from the OBD-II interface of each vehicle.

The rest of the paper is organized as follows. Architecture of the proposed system is presented next. This is followed by a description of the data collection activities. Justification of the algorithm, and the algorithm used to build a behavior classifier based on this data is presented next. The paper ends with an evaluation and a conclusion.

## II. THE PROPOSED SYSTEM

Fig. 1 shows the architecture of the system. As the Figure shows, an OBD-II adapter is used to collect data from the vehicle. This data is serially transmitted to the Raspberry PI 3 which is a small microcontroller. The Raspberry PI has an attached ultrasonic sensor for tailgating and has an LCD screen attached to it. The ultrasound sensor has a range of 4 meters. Raspberry PI 3 is connected to an XBEE Pro 900HP Radio that is a node in the DigiMesh ad-hoc wireless network [18]. DigiMesh is like the ZigBee network except that it does not require a coordinator for a PAN.

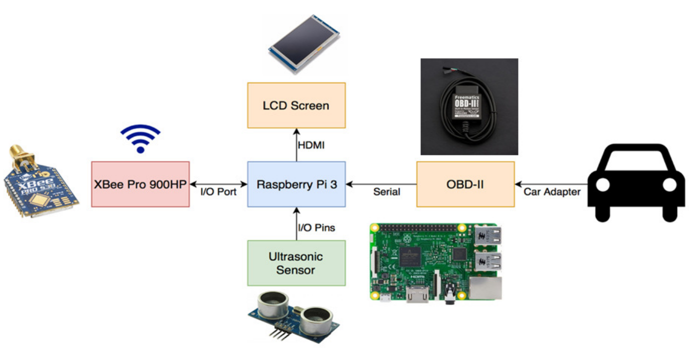


Fig. 1 Architecture of SIoV for anomalous driver behavior

In a DigiMesh ad-hoc network, all nodes can operate on a battery and can sleep at will. Most importantly, this network does not rely on a coordinator or a gateway to maintain time synchronization, and therefore, has no single point of failure. This also means that nearby vehicles can dynamically enter or exit the neighborhood network of a vehicle. This wireless network can have a range of up to 60+ kilometers for each hop which is more than sufficient for the proposed system. In most cases, the nearby vehicles being entertained can be restricted based on the strength of the RSSI signal to determine an operative radius of SIoV neighborhood. DigiMesh network supports bandwidth of up to 256 Kbps which is appropriate for sending various types of sensor data and messages from each vehicle. The network is secure because it supports both 128 and 256-bit AES encryption. Finally, the network is resilient against interference because it supports either Frequency-Hopping Spread Spectrum (FHSS) or Direct-Sequence Spread Spectrum (DSSS) depending on the frequency being used.

The driver interacts with the system through the simple LCD screen as shown in Fig 3. The system presents the driver with four options each indicating dangerous drivers' behavior in vehicle's surrounding context. For example, if another vehicle within the determined radius of the vehicle is speeding, the speeding button in the screen lights up warning the driver that someone in the vicinity is speeding and to be cautious.

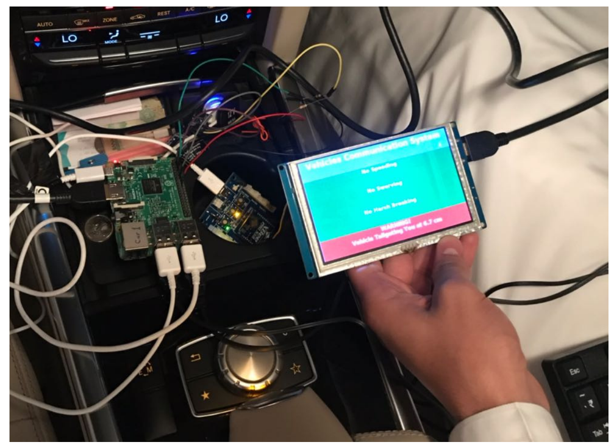

Fig. 2 Using OBD-II to collect and transmit data

Note that the system is not able to indicate who is speeding but only that one vehicle in the surrounding context is speeding. The ultrasonic detector mounted in the rear of the car simply indicates the approximated distance of the tailgating car.


Fig. 3 LCD screen showing driver safety interface

## III. DATA COLLECTION

To train the system to recognize anomalous driver behaviors, various types of bad driving behavioral data like harsh acceleration, harsh breaking, etc. were collected using the Raspberry PI using the OBD-II interface. Python language was used to program the Raspberry PI microcontroller.

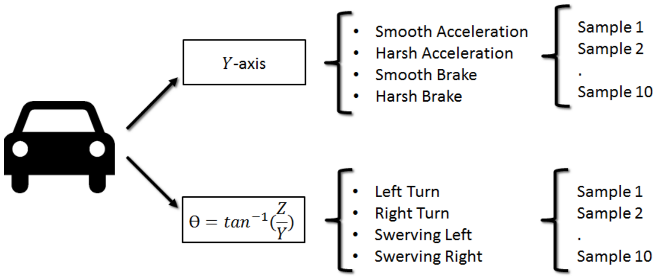


Fig 4. Data collection using OBD-II interface

As Fig. 4 shows, the Y-axis of the accelerometer data was used to detect acceleration and breaking behavior while Y and Z-axes were used to detect turning and swerving behaviors. Many samples were collected for each behavior (e.g., harsh breaking), and ten representative samples each were selected to represent variations of each behavior. Each representative sample consisted of a sequence of accelerometer data for 3 seconds sampled every 0.2 seconds. Hence each sample had 15 accelerometer data points in time. Fig. 5 shows sample data for Y-axis acceleration with the OBD-II device mounted in-line with the vehicle's direction of movement for continuous soft braking. Each data point was taken with a 0.2 seconds interval. For training purpose, windows of 15 points (3 seconds) were used.

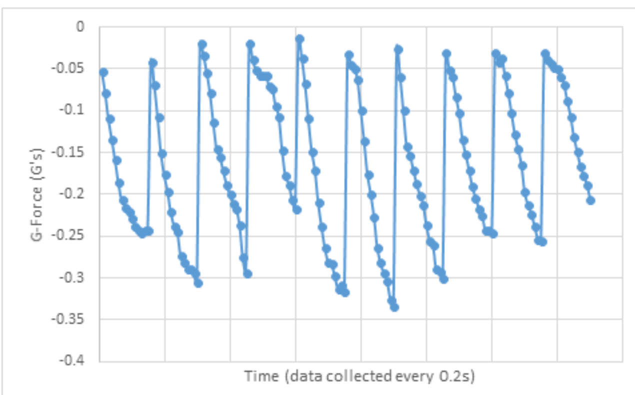


Fig. 5 Sample of data collected for soft braking

Fig. 6 shows sample data for harsh braking behavior that needs to be distinguished from soft braking behavior. As the Figure shows, the form of the curve is like soft braking, but the magnitude is different with harsh braking having much higher deceleration as expected.

Based on this data thus collected, one key problem was to build a classifier that could distinguish between situations of normal behavior like left turn, right turn, soft braking and soft acceleration, and abnormal behavior like harsh acceleration, harsh braking, and swerving.

## IV. Anomaly Detection Algorithm

For this system the anomaly detection algorithm is a classifier that would observe a window of accelerometer data from the OBD-II interface and classify the vehicle's current behavior into one of the seven classes (e.g., harsh barking) described earlier. Several techniques have been used in the past to build classifiers based on accelerometer data. First, Hidden Markov Machines (HMM) have been used to successfully classify 2-D gestures based on accelerometer data [19]. HMMs also generalize to handle data with larger dimensions. For example, HMMs have been used with very high dimensioned joint data from camera-based sensors [20].

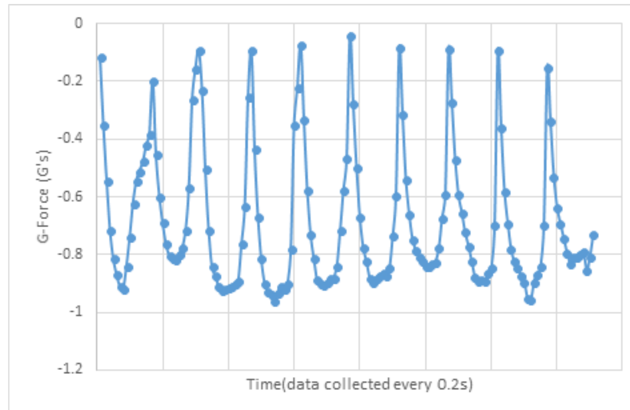


Fig. 6 Sample data for harsh braking behavior

A second approach is to use neural networks to build classifiers from accelerometer data. For example, Xie and Cao [21] used a Feed Forward Neural Network (FFNN) and Similarity Matching (SM) to build a classifier based on accelerometer data from a pen. More recently, deep learning has also been used for activity detection and classification from triaxial accelerometer data [22].

A third approach to classifying accelerometer-based activity is to use Dynamic Time Warping (DTW) [23]. For example, Wang and Lee [24] used DTW to build a gesture classifier based on accelerometer data from a smart phone.

It is interesting to note that the three approaches discussed earlier have resulted in similar performance in terms of accuracy and precision of classification. Therefore, any of these techniques could be used in our case. One consideration, however, is the size of the training data set. Calin [25] has shown that HMM tends to perform better than DTW as the size of the training data increases. Similarly, neural networks are also data hungry. Since at this stage, we had limited data available, as a first step, we decided to use DTW for classifying driver's behavior. Because the time complexity of DTW is $O(N^2)$ where N is the length of the sequences being compared (e.g., N =15 in our case), one key potential issue will be the ability of the onboard microcontroller to keep up with processing the real-time accelerometer data. In the future, as more data is acquired, we intend to experiment with using HMM's or deep neural networks for building classifiers.

Fig. 7 shows the anomaly detection algorithm based on DTW. As Fig. 7 shows, accelerometer data is collected from the OBD-II interface every 3 seconds with a sampling frequency of 0.2 seconds. A low-pass filter is applied to smooth the data. This distance of the collected data with each representative sample of each behavior is then calculated using the DTW algorithm. For example, for each driving behavior like smooth braking, ten representative samples were used, and therefore, the average distance for smooth braking is the average distance of the data collected from all ten samples. In the end, the algorithm selects the behavior whose average distance from the collected data is the smallest for all behaviors. The system broadcasts a warning to all vehicles in vicinity if the deduced behavior is anomalous (e.g., hard braking). All drivers participating in the SIoV are consequently alerted about the anomalous behavior of one or more drivers in the group with minimum time lag of 3 seconds.

```
Behaviors = {smooth acc., harsh acc., smooth brake, harsh brake,
left turn, right turn, swerving}

Do every 3 seconds {
  data = collect ACC data from OBD-II
  data = Low-Pass-Filter(data)
  For each b in Behaviors
    For each s in sample[b] calculate dist[s]= DTW(s,data)
    avg_dist[b] = mean(dist[s])

  Select behavior b' such that avg_dist[b'] = min (avg_dist[b])

  If b' is an anomalous behavior and transmit to all vehicles
  in the vicinity
}
```

Fig. 7 Algorithm for data collection and transmission

## V. Evaluation

The code shown in Fig. 7 took 1.6 seconds on average to run on the microcontroller which is fast enough because the data is sampled for a 3-second time window. To evaluate the algorithm, 10 newly collected independent samples each of the 7 behaviors (i.e., 70 samples in total) were used to calculate the predicted value based on the algorithm. The algorithm achieved an accuracy of 98.6% accuracy in distinguishing between the test scenarios. In addition, the wireless system performed well in practical driving tests with participating vehicles traveling at speeds of up to 120 km/hr.

## VI. Conclusion

While the proposed system works well, each vehicle will have to be equipped with our system to work. This limitation can be overcome only if major manufacturers agree on a standard. In addition to forming a local SIoV, however, a 5G or a narrow-band IoT (NB-IoT) network card can be added to the system to transmit each car's location based on a GPS to a central server. Such a configuration can allow for additional modalities like knowing the approximate location of the vehicle which is speeding nearby. However, the proposed system will continue to work even when the 5G coverage is not available. The proposed SIoV can also be enriched by adding social media data for each driver through their smart phone. Finally, the current system only used accelerometer data from the OBD-II interface. However, additional data like RPM, engine temperature etc. can be used to further refine the classification process.

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