iBump: Smartphone Application to Detect Car Accidents

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***Abstract*—Traffic accidents are a fact of life. While accidents are sometimes unavoidable, studies show that the long response time required for emergency responders to arrive is a primary reason behind increased fatalities in serious accidents. One way to reduce this response time is to reduce the amount of time it takes to report an accident. Smartphones are ubiquitous and with network connectivity are perfect devices to immediately inform relevant authorities about the occurrence of an accident. This paper presents the development of a system that uses smartphones to automatically detect and report car accidents in a timely manner. Data is continuously collected from the smartphone's accelerometer and analyzed using Dynamic Time Warping (DTW) to determine the severity of the accident, reduce false positives and to notify first responders of the accident location and owner's medical information. In addition, accidents can be viewed on the smartphone over the Internet offering instant and reliable access to the information concerning the accident. By implementing this application and adding a notification system, the response time required to notify emergency responders of traffic accidents can reduce the response time and perhaps help in reducing fatalities.**

Keywords— Smartphone Application; Accident Detection; Dynamic Time Warping (DTW); Pattern Recognition.

I. INTRODUCTION

Smartphones are becoming more advanced and complex, and support a large number of sensors including audio recorders, Global Positioning Systems (GPSs), accelerometers and light and temperature sensors in addition to many others [1]. There are many opportunities of implementing consumer applications that intelligently exploit the built-in sensors of smartphones.

In addition, most smartphones support wireless data services which provides additional opportunities for building consumer applications that exploit the sensors and the network connectivity afforded by the various types of connectivity ranging from SMS, GPRS and 3G/4G.

While there has been consdiertable progress in the use of advanced driver-assistance systems (ADAS), lane departure warning system, and collision avoidance systems, the high cost of these systems has prompted researchers to consider using sensors on smartphones to warn a driver and to prevent unsafe driving behavior [2]. For example, Sathyanarayana *et al* [3] propose the use of a variety of sensors in the car including accelerometers to measure driver distraction. Threshold-based techniques using accelerometer data have also been previously proposed to detect and report accident in motorcycles [4]. However, in a motorcycle accident since the motorcycle typically falls after an accident, it is much easier to use thresholds on acclerometer data to detect an accident. The situation is more complex in a car where the smartphone is typically inside the car and there is a great possibility of false positives while using such a simplified approach. Another closely related problem to detecting an accident is that of fall detection which has attracted signifant research in the past few years [5]. For example, Tamura *et al* [6] used an accelerometer and gyro data to detect falling behavior based on simple thresholding techniques. Similarly, Shi *et al* [7] describe a more advanced system that applied a support vector machine (SVM) classifier to accelerometer data to detect falling behavior. Naïve Bayes classifiers have also been used to detect falling behavior [8]. Similarly, Abbate *et al* [9] describe a system that uses a smartphone based accelerometer data with neural networks to successfully detect falls and reduce false positives. Finally, Kerdegari *et al* [10] conducted a comparative analysis of a variety of pattern classification techniques like Multilayer Perceptron, Naive Bayes, Decisions trees, Support Vector Machine, ZeroR and OneR in conjuntion with accelerometer data to detect falling behavior.

Many built-in systems such as the OnStar AACN, and the ODB-II are used to detect and report car accidents. Built-in sensors in the car can be used to detect changes in acceleration, or even to detect whether an airbag was ejected, which is a clear indication that a car accident has occurred [11]. Use of mobile phones for cars that do not have these expensive built-in sytems has been proposed. For example, WreckWatch is a wireless smartphone-based application that detects and reports traffic accident [11]. The system uses an accelerometer and audio data from the smartphone. The system uses a rule-based approach that combines thresholding on accelerometer with audio data to detect accidents and to reduce false positives. Similarly, Dai *et al* [12] describe a system that uses various types of thresholding on acceleration data to detect several categories of drunk driver behavioar including weaving, drifting, swerving and turning with wide

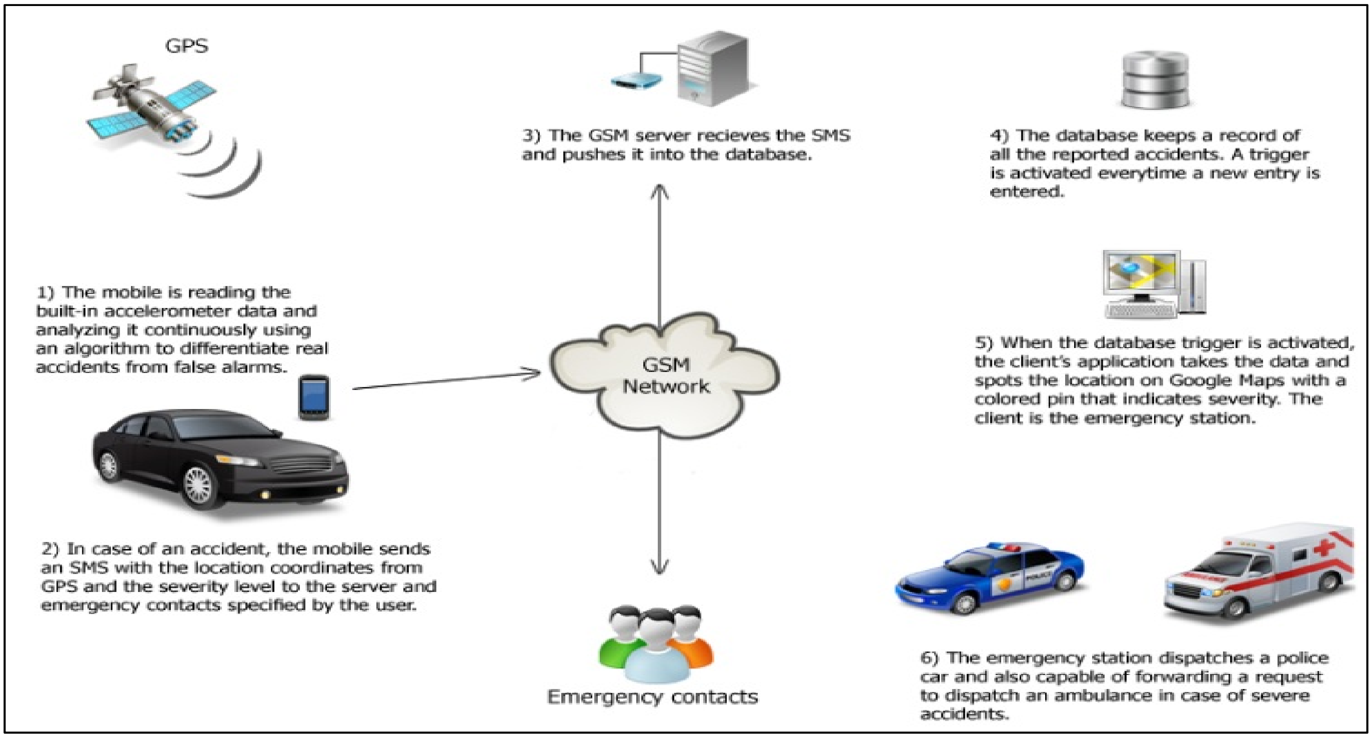


Fig. 1. Overview of the proposed system.

radius. Another approach has been to combine data from car's OBD-II networks with those from smartphones [13].

This paper considers the use of a smartphone to detect and report a car accident based on using pattern classification techniques.

The remainder of this paper is organized as follows: Section II describes the components of the proposed system. Section III describes the system implementation. Section IV presents experimental results. Finally, Section V concludes the paper.

II. The Proposed System

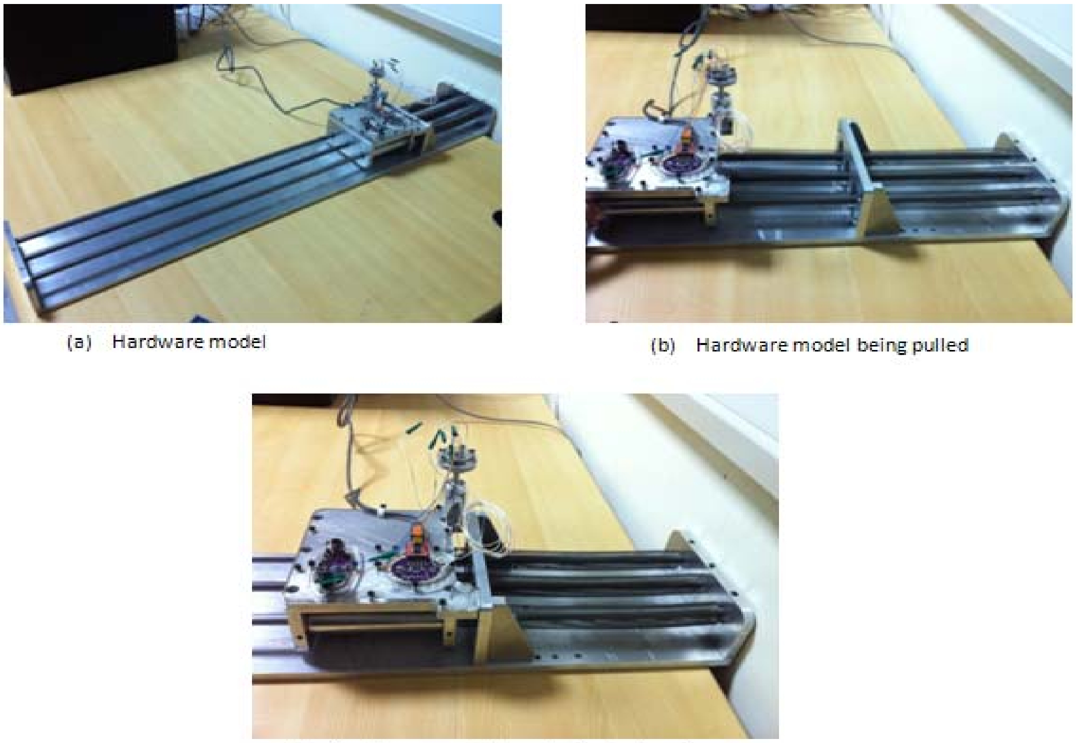
Figure 1 shows the architecture of the proposed system. The system is based on a smartphone application that continuously detects if there is an accident using the built-in accelerometer. In the case of an accident, the severity of the accident is detected and the location is identified using the built-in Global Positioning System (GPS). The system then sends an SMS to emergency services and registered emergency contacts notifying them of the user's information, accident, its severity, and its location.

The system consists of two main components: an Android application to be downloaded and an application server. Each is described below.

A. Android Application

An Android application, as shown in Figure 2(a), is downloaded on to a smartphone with a built-in accelerometer and supporting smartphone location services like a built-in GPS and/or GSM triangulation. As Figure 2(b) shows, the application allows a user to enter their personal information including name, ID, blood type, and phone numbers of individuals to inform in case of an accident. The application runs in the background and if an accident occurs, the application immediately sends an SMS to the police, emergency services, and registered emergency contacts with user's information and geo-location. After sending SMSes, the application alerts the user of the sent SMS message by beeping for a minute and displaying a message on the smartphone screen. The application also gives the user an option to register a false alarm which if done, sends SMSes to the various parties indicating that the previous SMS was a false alarm (Figure 2(c)).

Fig. 2. Screen shots of the accident detection smartphone application.



(a) Hardware model

(b) Hardware model being pulled

(c) Hardware model after hitting the barrier

Fig. 4. Screen shots from the accident simulator apparatus.

B. *Application Server*

The application server is a web-based application built using Apache, PHP, MySQL and JQuery. The application server provides the following services.

- Real-time reporting of accidents with geolocation
- Various report showing current accidents and their location and trends
- User registration and tracking

A screen shot of the application server is shown in Figure 3.

Fig. 3. Screen shot from the application web server.

III. System Implementation

The system was developed based on crash data generated using a physical apparatus as shown in Figure 4. A 3-axis accelerometer interfaced to a microcontroller was mounted on a metal surface of the testing model. Various severity of crashes were simulated by extending the spring to various lengths and by letting the accelerometer crash into the fixed surface. Accelerometer data during this movement was stored and retrieved for later analysis. Accelerometers embedded in current generation of smartphone typically have a range of +/-3Gs which is sufficient for monitoring daily user activities, such as running or walking. However, a car typically produced values much higher than 3G. Therefore, the appratus used accelerometers with a range of +/-16Gs, and this data was clipped to a threshold of 3Gs in order to verify that the proposed algorithm would work accurately in detecting car accidents on the smartphone.

The data retrieved from the appartus was used to construct the Dynamic time warping (DTW) algorithm for crash detection. The development of the DTW algorithm is described next.

Dynamic time warping (DTW) is a time series alignment algorithm developed originally for speech recognition. It align's two sequences of feature vectors by warping the time axis iteratively until an optimal match (according to a suitable metrics) between the two sequences is found [14]. The standard DTW has a time and space complexity of $O(n^2)$ where n is the length of the sequences being compared [15].

As Figure 4 shows, the apparatus described earlier was used to collect 30 samples for each of the three severity states of low, medium and high by varying the displacement of the spring. Figure 5 shows sample accident data from the apparatus. The no-accident state data was collected by including actual data from a car including cases of sudden acceleration, sudden brake, and uneven road. Figure 6 shows actual no-accident data reflecting a car driving on an uneven road.

The raw data thus collected from the accelerometer consisted of a_x, a_y, and a_z as the acceleration on x-axis, y-axis and z-axis, respectively, and was transformed into a single magnitude of acceleration (MA) as shown in equation (1).

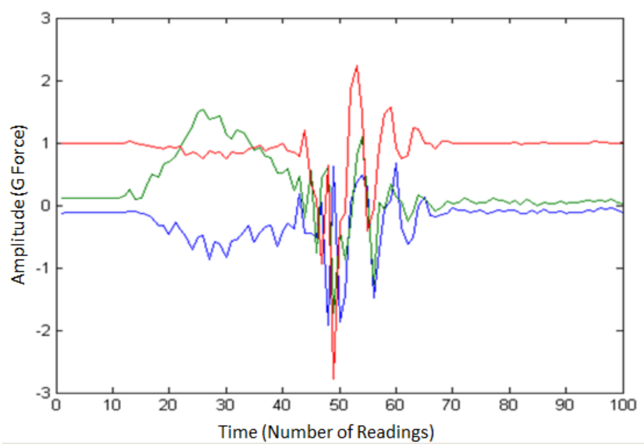


Fig. 5. Sample data readings reflecting an accident from the apparatus. Different colors represent the *x*, *y*, and *z*-axis readings.

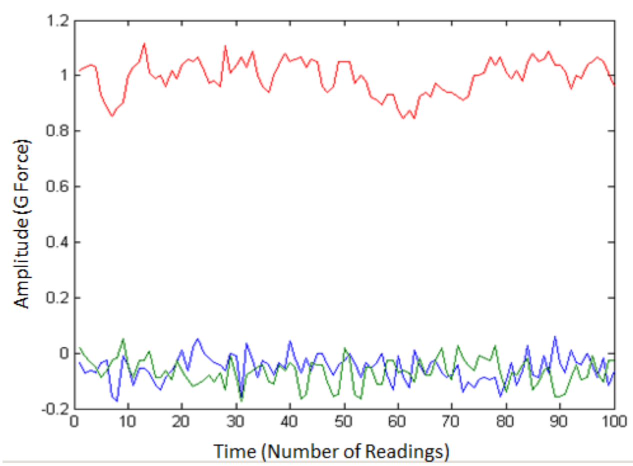


Fig. 6. Sample data readings reflecting a no-accident from an actual car driving on an uneven road. Different colors represent the *x*, *y*, and *z*-axis readings.

$$\mathrm{MA} = \sqrt{a_x^2 + a_y^2 + a_z^2} \tag{1}$$

In order to apply this technique, it was assumed that a vehicle can be in one of four states; no-accident, low severity, medium severity and high severity accidents. Training data was collected for each of the four states using and appratus an susequently, DTW was then used to distinguish between the four states [16].

IV. Experimental Results

In order to test the Dynamic time warping (DTW) algorithm, 25 additional test cases were developed for each of the states for a total of 100 test cases. The algorithm was executed on each of the test cases to make a prediction about the actual state. The results are shown in the from of a confusion matrix in Table 1. The confusion matrix shows the comparison of predicted vs. actual results. For example, in Table 1, out of 25 no-accident cases, 23 were predicted correctly by DTW and only 2 cases were false positives. Furthermore, all 75 accident cases were predicted correctly as accident cases.

The accident condition shown in Table 1 includes all three severity levels using DTW. As the Table shows, the DTW method was able to achieve an overall performance of (23+75)/100 = 98% accuracy in distinguising between a no-accident and an accident state.

TABLE I. Confusion Matrix for DTW

Actual / Predicted	No-Accident	Accident
No-Accident	23	0
Accident	2	75

V. Conclusions

In this paper an intelligent approach using Dynamic Time Warping (DTW) has been implemented and tested to detect and report car accidents using smartphones. Even though the approach seems promising, it needs to be tested in the field using automative crash simulation and detection systems. One key advantage of this approach is that it only requires the user to download and run the application on their smartphone without any extra equipment or cost. This system can be used in any moving vehicle without the need for expensive car built-in accident detection systems.

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