S-CarCrash: Real-time Crash Detection Analysis and Emergency Alert using Smartphone

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***Abstract*---Vehicular accidents are one of the leading causes of fatalities across the world. Survival rate depends largely on the time between the accident and when emergency responders arrive or are dispatched to the scene. One way to reduce the delay between accident and emergency response is to use in-vehicle automatic accident detection and notification systems. These in-vehicle accident detection systems are typically available in luxury/expensive vehicles. In several low-end cars especially in developing countries such accident detection systems are not installed by OEMs. In this paper, we attempt to address this problem by proposing an automatic accident detection system based on smartphone. Our algorithm reliably infers an accident based on the data collected through various smartphone sensors in spite of their sensitivity and range limitations. Such a system can prove to be a cheaper alternative to the costly accident detection systems installed in luxury vehicles.**

***Keywords*---Vehicular accidents, collision detection, road crash, emergency accident alert.**

I. Introduction

Road accidents are increasing everyday with increase in number of vehicles on road. Nearly 1.3 million people die in road crashes every year, with over 3000 fatalities in a day on an average [1]. In most of the cases people lose their lives due to the absent or delayed emergency response. Many efforts have been made to propose and develop systems and applications with varied approaches to bring an accident to immediate attention of emergency responders and provide urgent medical assistance. An obvious and effective way to reduce road accident fatalities is to reduce the time delay between the accident and medical help team arrival at the scene [2]. Delay between the actual incident and medical response can be easily reduced by notifying the first responders (medical emergency helplines) as soon as the crash happens. Studies show that reduction in first medical response at the accident location by few minutes or seconds brings about significant increase in number of lives saved [3].

One conventional way of detecting incident in real-time and saving lives of people involved in an accident, is to use in-vehicle automatic accident detection systems, such as *OnStar* (from General Motors), *ACN* (Automatic Crash Notification System by BMW), *ADAS* (Advance Driver Assistance Systems) [4] and *Splitsecnd*, but being expensive they are mostly found in luxurious vehicles. These systems make use of pre-deployed in-vehicle sensors, event monitors and built-in cellular radio to detect accident and communicate further. Hence, installing these available accident detection systems in low-end cars comes with an additional cost of dedicated hardware. This paper proposes an easily accessible and portable automated accident detection system based on smartphone, implemented at low cost, which can serve as a promising alternative to those high-end expensive systems.

Recent smartphones such as *Samsung Galaxy S7*, *Apple iPhone 6*, *Google Nexus 6*, etc. present an appealing platform to develop such solution as they have significantly increased computational abilities and are pre-equipped with multiple MEMS grade sensors like accelerometer, gyroscope, magnetometer, GPS (Location Sensor), etc. With an increase in number of smartphones as per modern trends, a system based on smartphone automatically becomes highly available. Several methods have been proposed in literature towards real-time crash detection, even using smartphones but most of them need a dedicated on-board chip or additional hardware attached to the vehicle. Systems like eCall [5], aims to deploy a dedicated device (equipped with necessary sensors) in vehicles for accident detection and notification to emergency responders. Vehicular crash detection [6] [7] based on Discrete or Hidden Markov Models provide good accuracy but makes use of crash pulse recorded by pre-installed dedicated sensors by OEMs. Automatic collision notification system or *eACN* [8] [9] uses dedicated interior/exterior sensors pre-installed in the vehicle.

Few of the popular crash detection systems are even based on smartphones and make use of MEMS sensor data gathered in real-time during driving. However, data collected from built-in sensors of smartphone are known to have large noise and thus most of the existing solutions suffer with accuracy of detection and false positives. *WreckWatch* [2], a smartphone based collision detection system relies heavily on accelerometer data from smartphone. Some smartphone applications built on the similar approach use smartphone data along with data from pre-installed sensors or device in the vehicle. But due to heavy noise in the sensor stream (can be because of user using the smartphone while driving, or device freely lying in the vehicle getting jerked on road obstacles), many false alarms are raised/noticed. As discussed above, prior work in this field either requires pre-deployment of dedicated sensors or systems in vehicles which are mostly expensive or systems based on smartphones which fail to deliver the expected accuracy of detection and suffer with false alarms. However, an accident

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detection system based on smartphone can be of high value because of its low cost, portability, and potential to cover wide population. This paper proposes a smartphone based automatic accident detection system without compromising on the accuracy and false positive rate. Using smartphone as the data source obviates the need of deploying any dedicated hardware in the vehicle prior to analysis or detection.

Vehicular applications based on smartphone are a popular and optimum means to analyze the increasingly complex urban traffic flows and facilitate commuters with smart and intelligent driving solutions including vehicle localization [10], enhancing driving safety [11], driving behavior analysis [12][13] and building intelligent transportation systems [14]. Further, S-Road Assist [15] and Nericell [16] detect road surface and traffic conditions using threshold based heuristics on data gathered from smartphone sensors. One well known challenge to be faced while using smartphone sensors data (for any analysis like driving behavior, collision detection, etc.) captured during driving, is to re-orient smartphone axes w.r.t the vehicle frame of reference or world coordinates. Proposed system addresses similar known challenges, including virtually reorienting the sensors on a phone (which can be in any arbitrary orientation inside vehicle), using filters to reduce noise in data stream, sensor fusion to enhance the accuracy of event detection and heuristics based on patterns obtained after multiple rounds of data analysis, to avoid false positives. Analysis of data involving all these mentioned approaches in the system makes it more accurate than any prior work.

Also, in a practical set up based on NHTSA (National Highway Traffic Safety Administration) crash data [17], vehicle may experience an acceleration up to ~60g (g = 9.8 m/sec^2) during real crash events. However, typical MEMS grade sensor such as accelerometer, found in Samsung Galaxy S7 phone can measure accelerations only up to 16g (due to software/hardware limitations). In this paper we propose an algorithm that reliably infers an accident based on the data collected through various smartphone sensors such as accelerometer, gyroscope, and the phone microphone in spite of the limitations (sensitivity, range, etc.) of the MEMS sensors installed on smartphone.

II. Methodology

Smartphones these days come with variety of in-built sensors like GPS receiver, accelerometer, magnetometer, gyroscope, etc. A rich amount of information can be obtained or deduced from the real-time data collected through multiple sensors present in smartphones. This paper proposes a real-time automated accident detection system using smartphone sensors as the source for input stream, which makes it a cheaper alternative to expensive in-vehicle accident detection systems. Using smartphone for developing such solution gives an easy access to the already established wireless network infrastructure, which can be used to notify emergency responders in case an accident is detected.

To make the system real-time but less intrusive, an application service in the smartphone keeps running in background and tracks user activity context (such as walking, running, driving, etc.). Such a service can be easily developed using mechanisms like *Samsung Motion SDK*, and various other approaches based on monitoring dominant axis acceleration or resultant of linear acceleration on the device [18]. When the driving context is detected, this service launches the ***S-CarCrash*** application. This application collects smartphone built-in sensors data and feeds it to the crash detector. Collected data from multiple sensors is then analyzed for abrupt events (which involve unusual increase or decrease in acceleration on device similar to a crash), by the crash detection algorithm. Crash detection algorithm takes 3-axis accelerometer data after filtering noise to extract change in acceleration on the device in all the three axes. In the event of an accident, if smartphone is in direct contact with the vehicle (docked), it is expected to experience similar forces as the vehicle, if kept in pocket then it experiences a reduced amount of acceleration that is equal to those experienced by the occupant [2]. As mentioned earlier, vehicle may experience up to ~60g acceleration in case of an accident or intense collision. Hence smartphone inside the vehicle experiences significant acceleration, which can be measured using its in-built accelerometer. However, during data analysis it has been observed that a normal drop from even 1m height or above can generate significant acceleration beyond the smartphone accelerometer measuring capability. To reduce false positives in our algorithm we augment the accelerometer readings with readings from other sensors such as gyroscope and microphone.

As per the prior work in this field, peak impact of an accident stays no longer than half a second or even less (~300ms) [19]. Therefore, sampling rate at which data is collected through smartphone plays an important role in detecting mild, normal and severe accidents. Higher the sample rate, higher is the amount of data collection and it results in higher power consumption. Hence there is a trade-off between sampling rate, computational capability of smartphone, data space available for processing, power consumption and accident detection capability. NHTSA crash data recorded using ADR/EDRs (accident/event data recorders) is generally sampled at 1 kHz; sampling at similar frequency in smartphone is beyond its capabilities. After taking pragmatic considerations into account and smartphone's software & hardware limitations, 100 Hz (sampling frequency) is the best fit to detect false positives and crash events accurately.

An accelerometer is a particularly convenient sensor to evaluate external forces, since it can directly characterize the amplitude and pulse width generated from an impact. But accelerometer data (captured using smartphone) alone is not sufficient to detect accidents as it is not directly attached to the vehicle. Smartphone can be in any arbitrary position inside vehicle, driver's pocket, on dashboard, docked, etc. Hence, even a drop inside moving vehicle or a jerk on the device due to obstacles on the road like bumpers or potholes can produce very high acceleration. To eliminate such cases, sensor data from other sensors can be used. Every accident produces a significant amount of energy which gets converted into g-forces experienced by the vehicle and occupant (results in physical injury and damage) and high amplitude acoustic waves (or sounds), which may or may not catch the attention of people around. A severe accident produces high decibel sound due to the collision and extremely rapid filling of the airbags (if deployed) as compared to normal music, traffic or noise in public places. Sound produced during an accident can be sampled using microphone present in smartphone. Sensor data from both; accelerometer and microphone are recorded at an appropriate sampling frequency and then fed to the crash detector, where algorithm calculates *Collision Index*.

Collision Index (CI) = (MaxAcc / AccThreshold) + (MaxSound / SoundThreshold)

1 < ***CI*** <= 1.5*; implies mild accident*

1.5 < ***CI*** <= 2*; implies medium accident*

2 < ***CI****; implies severe accident*

Here, *MaxAcc* is the maximum linear acceleration (excluding gravity) experienced by the device in a window of 1 second. *AccThreshold* is the average acceleration experienced inside vehicle during an accident. *MaxSound* is the maximum amplitude recorded by microphone in a window. *SoundThreshold* is the average sound amplitude produced during a vehicular accident. Collision index calculation mentioned above considers both the values (acceleration and acoustic amplitude) to classify an event into a crash or accident. It is easy to predict that higher the acceleration produced during a collision, higher should be the amplitude of sound. But, as data is being recorded by a movable device (smartphone) which can be in any arbitrary position inside the vehicle, hence there are possibilities of significant change in the values being recorded in only one type of data, like music in clubs is generally played at very high decibels or during an accident phone might be inside a closed bag or tight pocket. Therefore, the above mentioned formula has been derived in such a way that acceleration can compensate for the sound and vice versa, but both the values are expected to be recorded high enough.

As every sensor data stream is known to have noise involved (can be from external sources or due to hardware limitations), a Butterworth low pass filter is used to remove noise from the signal while keeping the frequency response flat. Later, extended Kalman filter using quaternions is applied to remove irregularities or unusual spikes in the sensor stream emerged due to hardware instability or temporary malfunction. Data collected through smartphone sensors directly affects the accuracy of accident detection as when taken from vehicular systems. One skeptical yet efficient way at times to reduce false positives is to detect frequent or regular false case scenarios and eliminate them before data processing or analysis for event occurrence. So, before collision index calculation, input data stream is checked for false positive cases which may (having a high probability/chance) get mis-classified as crash like device drop inside moving vehicle, drop accompanied by a flip, or a drag due to sudden braking/acceleration, etc., due to the generation of very high acceleration.

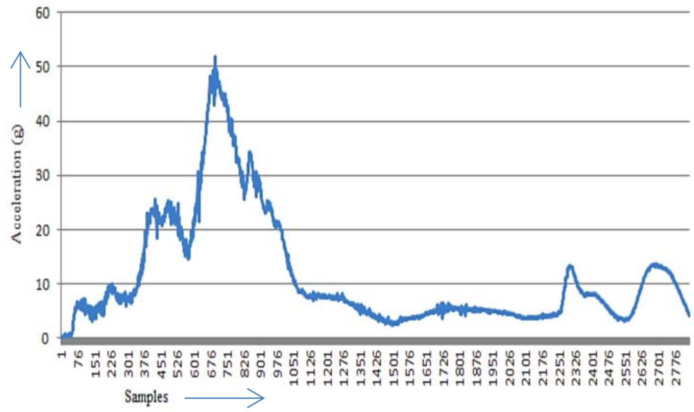

Figure 1. Low Pass Filtered NHTSA Crash

Fig. 1 shows low pass filtered data for a crash event from NHTSA latest crash database [23]. Acceleration peak in the data is noticeable as it has been captured using dedicated sensors inside the vehicle and on occupant. As mentioned above, measuring acceleration of this order (equal or above 60 g) using built-in smartphone sensors is not possible. But in these cases smartphone sensor reports the maximum acceleration up to its capabilities. Therefore, pre-processing of NHTSA crash data is required before feeding it to the crash detection algorithm (designed for detecting crash/collision from data captured via smartphone sensors) to test the accuracy for known crash data set. This NHTSA crash data was down-sampled and trimmed/clipped using the maximum acceleration value which a modern smartphone can measure (16 g in case of Samsung Galaxy S7), as shown in Fig. 2.

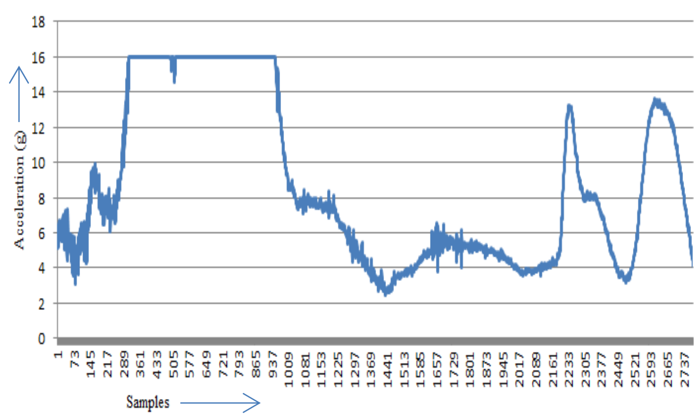

Figure 2. Trimmed/Clipped NHTSA Crash Data

Then this low pass filtered and trimmed amplitude data is fed to crash detection algorithm for further analysis and detection. But, trimming the peaks in acceleration data considering system limitations of smartphone directly affects the selection of features for analysis and detection of event and thus the accuracy. Features like rms (root mean square) acceleration, average acceleration over a window or difference in peaks, etc. become meaningless after input data signal is clipped. Hence, using acceleration on the device with sound level measured using microphone is the way out of the problem with an upper hand to categorize collision into severe, medium and mild based on the difference between magnitude of measured values and thresholds. This coupling of sensor data has proved to be an optimum solution to eliminate false positives and at the same time avoiding any compromise with the system accuracy due to hardware limitations.

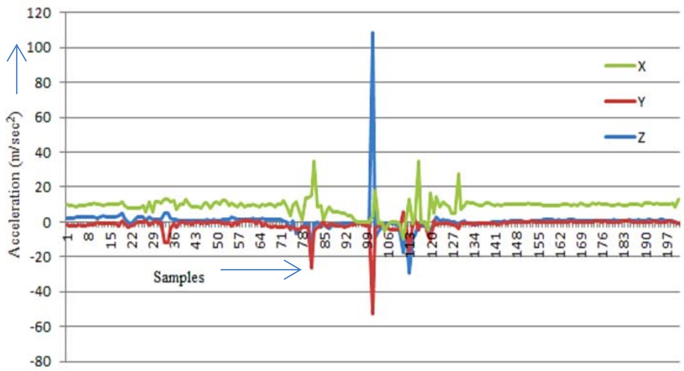

Figure 3 (a). Smartphone drop inside moving Vehicle - acceleration

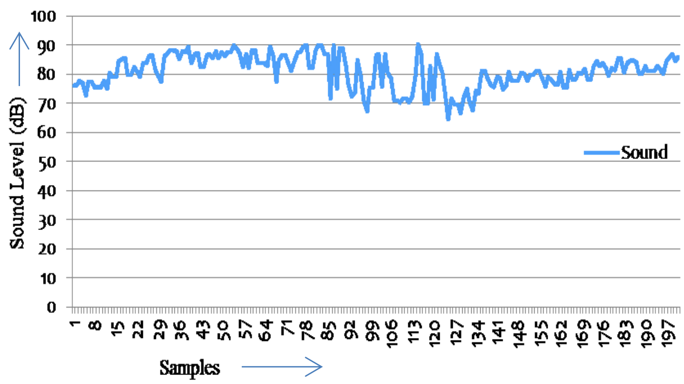

Figure 3 (b). Smartphone drop inside moving Vehicle - sound

Fig. 3 (a & b) shows collected data through smartphone application for a drop inside a moving vehicle. A drop is a free fall state where force due to gravity is cancelled out by weight of the object (smartphone in this case). During data analysis, it has been observed that similar frequently occurring scenarios inside vehicle having a high probability of being classified as collision can be a flip, drag or even a spin event. In case of flip, smartphone changes its orientation along its horizontal plane, which can be easily detected using the combination of gyroscope and accelerometer pattern as shown in Fig. 4 (a & b).

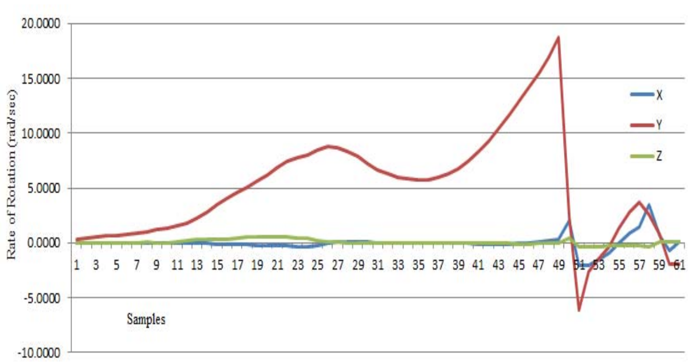

Figure 4 (a). Flip event - Gyroscope

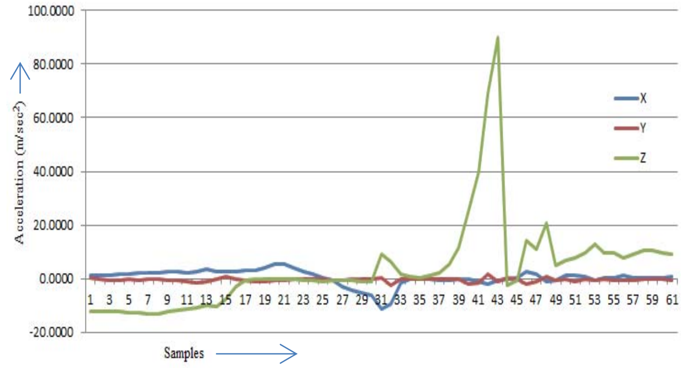

Figure 4 (b). Flip event - Acceleration

Sudden brakes or acceleration when smartphone is not docked or lying free inside a vehicle either on dashboard or a seat results into a drag producing high acceleration due to collision in the end. However, prior to collision device experiences frictional force due to gravity and surface it lies on, in opposite direction of the movement (shown in Fig. 5). Hence, resultant acceleration goes below g for all 3-axis of device.

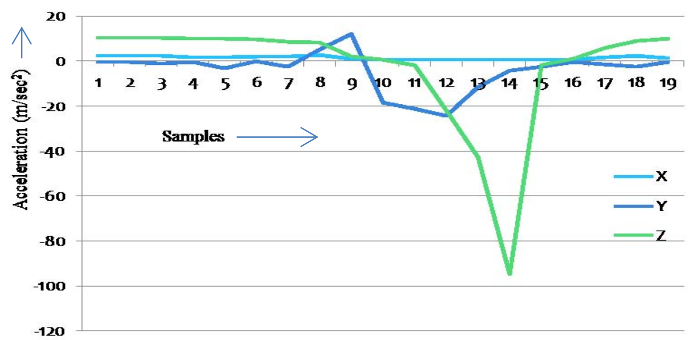

Figure 5. Smartphone drag followed by a collision

Similarly every false positive possesses a pattern before smartphone receives the impact. Note that, in the case of an accident *impact precedes other events*. Moreover, the sound decibel values generated during a crash event are much more than a drop or flip or drag events inside a moving vehicle. Also the duration of impact is higher in case of an actual accident than any false case scenario, which is visible from Fig. 2 and Fig. 3 (a). Additionally, the GPS location data from smartphone is used to calculate change in velocity of vehicle during an impact. In case of an accident velocity of vehicle changes significantly, based on the initial state of the vehicle and severity of accident (intensity or extent of collision). Vehicle at stationary or moving slowly on being hit by another running vehicle will result in instant increase in the velocity of first vehicle, whereas a vehicle running at very high speed meeting a collision will result in an immediate abrupt deceleration and decrease in velocity. It is noticeable that in both the cases change in velocity of vehicle is significant. But this abrupt increase or decrease in velocity can also be a result of sudden acceleration or deceleration due to aggressive driving [19]. Hence, GPS velocity information is used only to confirm what collision index calculation gives as the output.

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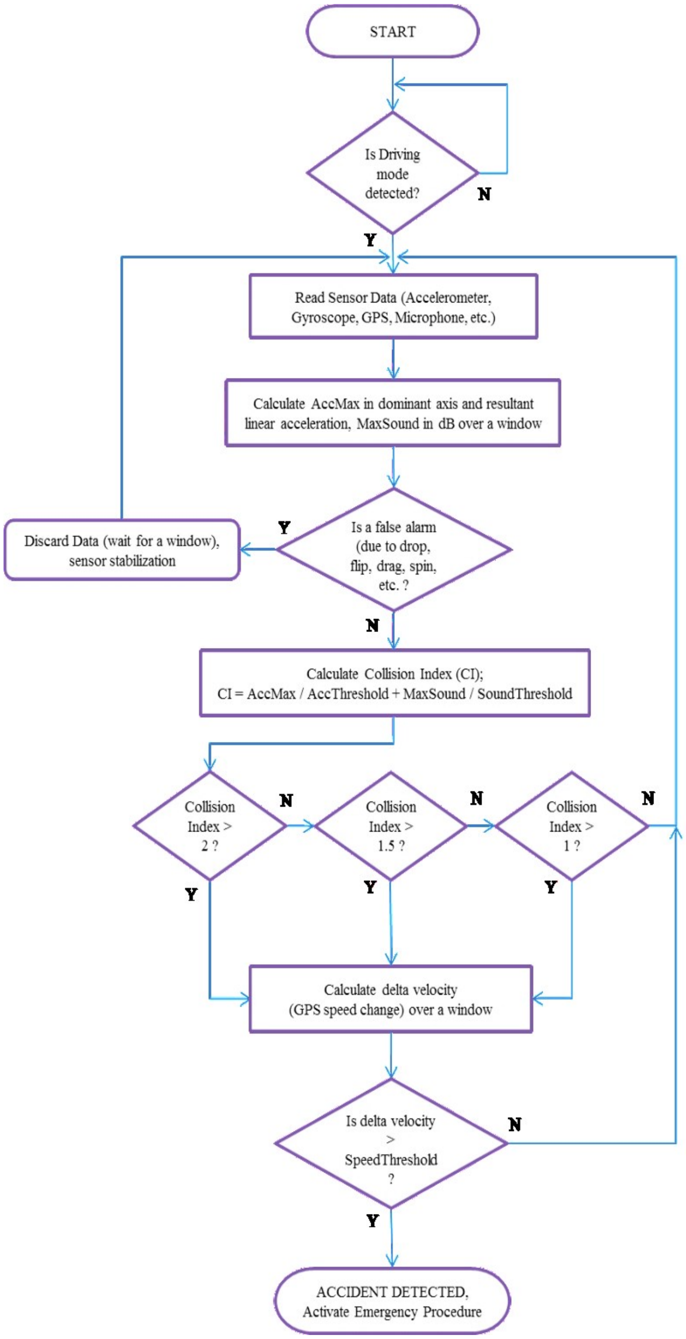

Figure 6. Flow chart explaining Crash Detection

Fig. 6 shows the complete flow and structure of crash detection algorithm. Driving mode detection is the trigger for sensing and recording data from sensors present in smartphones, as fetching data from sensors consumes power. Then, parameters to be used in known false alarm scenarios detection and collision index calculation are calculated over a window of 1 second. As mentioned earlier, peak impact of collision during an accident can be felt for around half a second or even less (~300 ms) [20]. Input data stream is then analyzed for known false positive cases like drop, flip, drag, etc. which are capable of producing very high acceleration, high enough for a smartphone sensor to measure. During data analysis it was observed that the effect of a false scenario like drop remains on the sensors for few hundred milliseconds, which corrupts the window data and derived values from it. Hence, after a false case is detected it is important to discard data for some time as big as 1 window (1 second). Discarding data after a false case allows the window to be cleared properly for the analysis of data being captured in next time frame. If the reported event does not match one of the known false cases, then collision index is evaluated for severity of accident. Collision Index (CI) greater than “2” in ideal case can be inferred as both the data values acceleration and sound crossing (or exceeding) the thresholds. In general, recorded sensor values for acceleration and sound get affected by the position of phone inside vehicle. In these cases, one of the values will have to cross the threshold by a larger magnitude to compensate the difference between the threshold and max value captured for other parameter. Hence, setting the thresholds very high will tune the algorithm for severe accident detection but will miss mild or medium accidents, where either of the parameters may not cross the thresholds. Similarly, lowering the thresholds for detecting mild accidents will result in additional false alarms.

Thresholds are to be chosen so that algorithm should detect severe and medium accidents without missing mild accidents and raising almost no false alarms (or negligible). Hence, a comprehensive analysis of data is required before drawing out any conclusion on the thresholds. After analyzing NHTSA data for various crash events and data captured using the prototyped application for various false cases like drop, average threshold for acceleration, sound and change in velocity is calculated. *AccThreshold* (15 g), *SoundThreshold* (110 dB) and *SpeedThreshold* (5 m/sec) are within the capability of smartphone sensor to measure and are high enough for a normal event to produce such figures. It is observed that almost all the severe and medium accidents data from NHTSA are crossing the set thresholds. False positive detection and elimination before the analysis helps in reducing false alarms, while keeping the same thresholds but with lowered collision index for mild accidents. Furthermore, evaluating change in velocity of vehicle after collision index calculation is the key to overcome the compromise made with thresholds to identify mild or medium accidents and with smartphone sensors capabilities. It also takes care of any unknown or un-expected false alarm scenarios. Once the accident is detected, application raises an alarm in form of a notification, with an option to cancel. Either by user approval through voice or smartphone interaction, a pre-designed SOS message containing the geo-map link to accident location with street address is sent to pre-identified emergency contacts for help. Here, approval by user for SOS message can suppress the warning if generated by any false positive which system hasn’t identified and eliminated itself. Emergency SOS will also be sent in case of an auto-timer countdown gets expired, where user is not in a position to interact with smartphone after the accident. Manual SOS facility is also present in the application where due to any reason be hardware malfunction or severity of accident being too mild or crash detector fails to report any event, user can send a pre-configured SOS message to emergency contacts for immediate help.

III. Results

Proposed solution makes use of collision index calculation coupled with known false positive detection and elimination further confirmation with location data from smartphone to overcome limitations of using smartphone as the source for capturing data. Crash detection algorithm discussed in the paper is able to classify all the crash events in the NHTSA latest crash data set [23] accurately with a perfect recall score of 1.0, as shown in Table 1.

Table 1. NHTSA Test Data Result

Test Reference No.	Test Configuration	Barrier Information	Result (S-CarCrash)
CV1601.0008	Vehicle into Pole	Side Pole Barrier	**Detected**
CV1601.0007	Vehicle into Barrier	Frontal Flat Barrier	**Detected**
CV1601.0009	Impactor into Vehicle	-	**Detected**
BT16063011	Vehicle into Barrier	Load Cell Barrier	**Detected**
BT16070111	Vehicle into Pole	Side Pole Barrier	**Detected**
BT16071211	Vehicle into Barrier	Load Cell Barrier	**Detected**
BT16071311	Vehicle into Pole	Side Pole Barrier	**Detected**
BT16071312	Impactor into Vehicle	-	**Detected**
BT16072811	Impactor into Vehicle	-	**Detected**
BT16082311	Vehicle into Barrier	Load Cell Barrier	**Detected**

Algorithm is also thoroughly tested for false case scenarios like drop, flip, drag, spin, etc., and is able to detect and eliminate all of the general and similar known scenarios from the input data stream, thereby making the F_1 score close to its best value (i.e. 1) for all test results.

$$F_1 = 2 \cdot \frac{\text{precision} \cdot \text{recall}}{\text{precision} + \text{recall}}$$

$F_1 = 2 * (1 * 1) / (1 + 1);$

$F_1 = 1$ (for test results)

After detecting and eliminating all known false case scenarios, precision for test results came out to be 1. However, it may vary for real crashes as every accident or collision is different from the other in terms of speed of vehicles involved, vehicle designs, center of gravity, acceleration produced, road infrastructure, weather conditions, etc. And it is not feasible to simulate all possible false case scenarios which may have a potential to raise a false alarm. But, algorithm is designed in such a way that it promises to not to have any false negatives and still be able to return all the relevant results.

Table 2. Comparison with existing work

	In-vehicle Accident Detection Systems	Acceleration based Smartphone Apps	S-CarCrash
Severe Accident Detection	Yes	Yes	**Yes**
Medium or Mild Accident Detection	Sometimes[21]	Sometimes (unclear accuracy)	**Yes**
False Alarms	No	Yes	**No** (eliminated)
Pre-deployed Hardware	Required	Sometimes (acc. monitors)	**Not required**
Cost of Deployment	Highly expensive	Free (sometimes paid)	**Free**
Availability	Only in luxury vehicles	Readily available	**Readily available**

Table 2, shows the comparison of proposed solution with existing systems based on smartphone acceleration measurement (either using in-built sensors or dedicated hardware) and pre-installed vehicular systems by OEMs for crash/collision detection.

IV. Conclusion

Automated accident detection systems help in reducing fatalities emanating from vehicular accidents by decreasing the emergency response time. Real-time accident detection and emergency alert can save lives. In this work we have presented a smartphone based accident detection system which augments data from sensors such as accelerometer, gyroscope and microphone to reliably detect a vehicular crash. Proposed models based only on acceleration thresholds have false positives in absence of GPS. In-vehicle airbag deployment is triggered at acceleration above or equal to 60g [2] whereas mild or medium accidents produce acceleration only up to 40g [22] which may result in serious injury to the driver or passenger on-board. Hence, keeping the thresholds high will definitely reduce false positives but it will introduce false negatives, and keeping it low will bring false positives along with actual true positives (crash events). Therefore, using microphone data with acceleration and false positive elimination strengthens the proposed work against existing solutions. An accident detection application based on smartphone provides several advantages over conventional in-vehicle accident detection systems, as they are independent of vehicle they are carried in, increasingly pervasive and incur low implementation cost. Additionally, smartphones are capable of providing rich amount of data for accident analysis, like data from multiple sensors, including pictures and videos, etc.

In accidents where smartphone itself is completely damaged, this solution may not be able to deliver what it promises to. Hence, it may not be possible to beat the accuracy of expensive in-vehicle systems equipped with high-end accident detection technologies with a smartphone sensor based application, as they have the obvious advantage of direct access to the vehicle. However, there might be several scenarios where the smartphone is actually not damaged wherein such a solution can result into life-savings. Especially in developing countries where people in general cannot afford those pre-installed vehicle accident detection systems because of the cost involved, this solution becomes even more important and will have a significant impact on first emergency/medical response team reaching the accident location on time and thus saving lives. Therefore, having a solution with similar level of accuracy which can make a difference as big as saving lives of people is better than having no other alternative at all [9].

As a part of future work we are investigating whether pictures/videos from smartphone and data from multiple mobile gadgets like smartwatch, heart rate monitor or other smart wearables can be used to identify and improve the accuracy of analyzing severity of an accident. This data captured during an accident or at the location can help emergency responders to better analyze the accident and situation of injured people or victims and act accordingly. Moreover, this solution can be integrated with traffic congestion monitoring solutions to divert traffic from accident location.

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