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Original Article

A survey on usage of smartphone accelerometer sensor in intelligent transportation systems

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ABSTRACT: The numerous capabilities of smartphones have made them suitable alternative to expensive tools and methods in intelligent transportation systems. This study surveys the literature on the role of the accelerometer of smartphones in intelligent transportation applications. At first, the opportunities and challenges of using the accelerometer are stated. Then, the architecture of using this sensor including preprocessing, feature extraction, mode detection, reorientation and applications are explained. Finally, different applications that have used the accelerometer of mobile phones in the intelligent transportation systems have been investigated.

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1. Introduction

As much as development of smartphones, various cell phone applications are implemented for different aims in ubiquitous computation [48]. In [36] some smartphones applications in health, environment, social, human behaviors, business and transportation have been discussed. The unique capability of these devices can be summarized in the following attributes:

- The mobility
- The increasing expansion of their usage
- Containing several sensors (e.g. camera, microphone, GPS, gyroscope, accelerometer and magnetometer) which can be used to study the behaviors and actions of their owner and the surrounding environment.
- Their access to different communication networks to send and receive information

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One of the major application domains of cell phones is intelligent transportation systems, such as OD matrix estimation and traffic assignment by processing on stored records in GSM operators [11, 27], traffic monitoring [18, 37] and accident detection [32]. Accelerometers are one of the smartphone sensors, which can be particularly exploited for user behavior analysis and context-awareness in comparison with the other existing sensors. This tool can be used to measure instantaneous acceleration in three coordination axes. Since the accelerometer measures tilt and motion, it can detect rotation and motion gestures such as shaking or swinging. Most smartphones have a relatively large screens (in comparison with the ordinary cell phones) and these screens are used to read or browse internet pages, text files, or possibly various other software. The most common usage of the accelerometer in smartphones and tablets is to activate auto screen rotation on these devices when the user changes their orientation. On the other hand, embedding this sensor in the smartphones allows recording and detecting the smallest cell phone gesture and consequently their users and thus they can be applied to explore performed actions through the instantaneous acceleration analysis.

Research shows that since the late 2000s, when smartphones equipped with context aware sensors, including accelerometers, were introduced to global markets, researches around the use of this sensor have increased. On the other hand, the application of the accelerometer sensor in the field of intelligent transportation system has also been considered. The review of research conducted in Elsevier and Google Scholar databases from 2008 to August 2023 shows the increasing growth of research with related keywords. Figure 1 shows trend chart of the volume of articles published on each of the keywords “accelerometer in smartphone”, “accelerometer in transportation” and “smartphone accelerometer in transportation” in these three databases.

(a) Trend chart in Elsevior

(b) Trend chart in Google scholar

Figure 1: Trend of the volume of articles published

The ability of this sensor to recognize and analyze behaviors can be noted as a fundamental in-vehicle sensor in the vehicle industry. As some instances, in air bag systems, stability control, and also noise, vibration, and harshness (NVH) detection system, this sensor can be used efficiently. Furthermore, this sensor has been used in personal navigation assistant (PNA) to analyze the behavior of the driver and in-vehicle monitoring. In addition to the aforementioned attributes of smartphones, the abilities of this sensor are encouraged the researchers to study the effects of smartphone accelerometers in transportation systems. In this study, first opportunities and challenges of using the smartphone accelerometer with the purpose of transportation are investigated. The architecture model and preparation steps in using this sensor in intelligent transportation system (ITS) is then discussed and finally, the related research is categorized and compared. Thus, this paper provides a framework for the next researches in the following branches:

- The quality of solutions made by the smartphone accelerometers.
- Process architecture models for practical utilization accelerometer
- Overall maturity scores of features, techniques, results of accelerometers in transportation systems

2. Methodology

The literature study methodology of using smartphone accelerometer sensor in intelligent transportation systems is as follows:

At first, the research questions were determined. In this study, the aim was to answer the following questions:

- What are the features, opportunities and challenges of using smartphone accelerometer sensor in intelligent transportation systems?

Figure 2: 3-axis MEMS accelerometer sensor [46]

- According to the researches done, in which of the fields of intelligent transportation systems has this sensor been used?
- In order to use this sensor in studies , what steps and preprocessing are applied on the raw data?

To achieve the objectives of the research, the review was made as comprehensive as possible to ensure that all relevant studies was included.Therefore, with the main related keywords such as “smartphone accelerometer” and “intelligent transportation systems”, the search was conducted during the last decade among the articles presented in reliable scientific databases. Then, for each of the keywords of intelligent transportation systems applications such as “traffic monitoring”, “driving behavior recognition”, “road pavement condition”, “mode detection” and the like, along with the keyword of smartphone accelerometer, it was investigated. The review of survey articles in each field is a priority, and the review of research articles with more citation and papers were published on journals was the next priority. After collecting related studies and categorizing them based on the type of application, the articles were reviewed to study extracted features from the accelerometer and preprocessing techniques on the raw data. Result of this review was the types of preprocessing according to the type of application, which is the basis of The architecture is proposed in this study.

3. Smartphone accelerometer

Accelerometer is a sensor for measuring acceleration and speed changes per unit of time and measuring vibration. This sensor has applications ranging from missile and airplane navigation systems to car airbags, intelligent transportation and medical equipment, and industrial applications. Figure 2 shows a MEMS (Microelectromechanical systems) accelerometer sensor. The sensing range of this sensor are different. Obviously, the accuracy of the accelerometer sensor in an aircraft navigation system or the accelerometer of a car airbag is not needed in smartphones. In a mobile phone, an accelerometer is built into the device for the purpose of screen changes and monitoring changes in the position of the phone, which has an accuracy of about 2 to 4 g, depending on the mobile phone models. The maximun frequency of recording acceleration by this sensor is also different around 100 to 200 Hz depending on the smartphone models. Figure 5 shows an example of acceleration recording on a Samsung n8000 tablet with a recording frequency of 2 Hz by the Androsensor application. The existence of this sensor in the smartphone provides opportunities in intelligent transportation systems, which requires knowing the characteristics and challenges of this sensor to be able to use these opportunities.

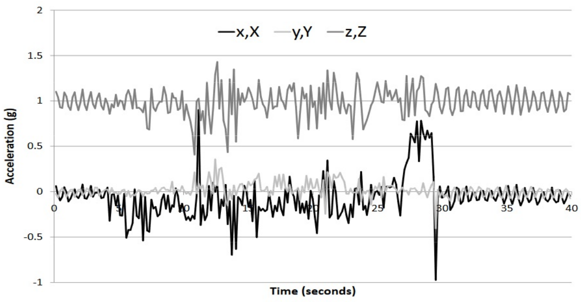
3.1. Smartphone accelerometer opportunities

The cost/extent: In-vehicle sensors usually include sets of monitoring and navigating tools which are connected to other vehicle control systems. These tools are very costly and are mostly used in the new and the top model vehicles, since their installation in all vehicles is not economically justified. On the contrary, the penetration rate of cell phones in most countries is near 100%, while the penetration rate of the smartphones is globally 78% in 2020 which is an increasing number [45].This statistical population is appropriate and adequate for most analysis results of transportation. On the other hand, users do not practically purchase these devices for monitoring or traffic analysis in-vehicle, and so this application is considered as an added value.
The low-energy: In contrast to GPS and Wi-Fi, which consume high energy and require satellite or connection point communication, the accelerometer sensor consumes very low energy (about 1.65 mw).
The possibility of sending and processing data: Today, smartphones have a high processing power, memory, and operating system which provide a framework to install programs and to process data. On the other hand, these devices are accessible to difference communication and telecommunication networks to send the information and results of processing to servers and databases at any time.

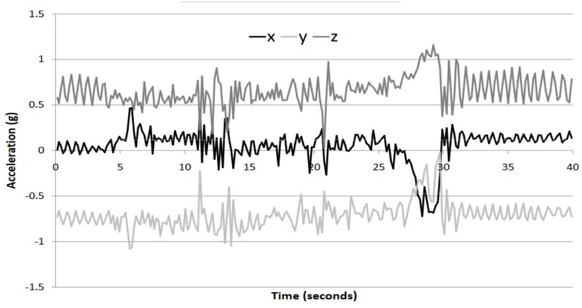
3.2. Smartphone accelerometer challenges

Important challenges of using accelerometer sensor of the smartphones instead of accelerometers embedded in vehicles or PNAs, are described in the following:

Dissimilarity between device and vehicle orientations: Cellphones may be placed differently inside the vehicle or in the driver‘s bag. Therefore, analyzing the vehicle behaviors requires the reorientation of the phone in three axes, Y (the movement direction axis of the vehicle), X (the lateral direction of the vehicle), Z (the axis perpendicular to the vehicle). Inability reorientation causes vehicle‘s movement in one direction to create changes in all three directions of the device‘s acceleration and inability to detect the type of its behavior. (See Fig. 3)



(a) Acceleration in well oriented smartphone



(b) Acceleration in disoriented smartphone

Figure 3: Well oriented and disoriented accelerometer of smartphone in braking act [42].

Therefore, some studies have been considered to investigate the location and orientation of the cell phone, static and in the same direction as the vehicle's movement axis [26, 42]. Moreover, some studies have employed the size of the resultant accelerations which equals the second norm of the acceleration of all 3 axes and it is independent of the orientation of the device [19]. In this case, limited analysis can be provided and fewer applications have been observed [21]. The main approach to reorientation using the following transformation matrix of the two coordination axes with different orientations [6].

$$R(t) = \begin{bmatrix} C_rC_y + S_rS_pS_y & C_pS_y & -S_rC_y + C_rS_pS_y \\ -C_rS_y + S_rS_pC_y & C_pC_y & S_rS_y + C_rS_pC_y \\ S_rC_p & -S_p & C_rC_p \end{bmatrix}$$

With following abbreviations

$$\begin{aligned} S_x &: \sin x \\ C_x &: \cos x \\ r &: \text{Rotation around } Y\text{-axis (Roll)} \\ y &: \text{Rotation around } Z\text{-axis (Yaw)} \\ p &: \text{Rotation around } X\text{-axis (Pitch)} \end{aligned}$$

Therefore, if the three angles between two coordination are specified, reorientation is possible using this matrix. However, computing these angles requires more information for which different methods have been proposed by researchers. One of the information required is the effect of gravity which is needed for reorientation in the z-axis. Vittorio [61] has used this issue to analyze the pavement condition. Others have used GPS information to set and modify the device‘s direction in relation to the vehicle [42]. Furthermore, some studies analyze the forward motion of the vehicle to obtain the angular rotation matrix of the device in relation to the vehicle [12]. Almazan and et al. [6] explain the reorientation and transformation equations and methods in detail. Comprehensive study is represented by carlos [13].

Device movement inside the vehicle: Since cell phone is used to answer calls or send SMS, it is possible that the device is used by the driver or the traveler during driving. Displacing the cell phone, falling from a height (e.g. falling from the seat or the user‘s hand), or generally using it creates a many fluctuations in the accelerometer sensor, none of which are related to the status of the vehicle. Therefore, the source of any change and whether it is related to the behavior inside the vehicle must be detected and eliminated in the preprocessing stage. In order to detect these gestures, other sensors like the proximity sensor can be utilized or the state of using the phone can be checked. Moreover, the behavior of the accelerometer, when the device falls, is another feature which is recognizable in comparison to other behaviors [20, 62].

Inside or outside the vehicle: In contrast to in-vehicle sensors which are always inside the vehicle, cell phones may be outside the vehicle as well. Therefore, the analysis is valid only when it is assured that the device is inside the vehicle. Thus, one of the initial steps to apply this sensor is to determine the traveling mode (i.e. to distinguish between motorized or non-motorized vehicles). Eftekhari [20] present a new approach to detect intervals which cell phone is inside the vehicle.
Less sensitivity of the cell phone sensors: since embedded accelerometers and PNA devices are connected to the body of the vehicle, their accuracy is high. However, cell phones are not directly in contact with the body of the vehicle and mostly placed in a bag, pocket, or the seat. This prevents proper transference of car momentums to the cell phone and the registered value by the cell phone sensor is relatively lower than the actual value, such that even the location of the device is effective on the quality of the acceleration computed [24]. The sensitivity and the minimum and the maximum measurement interval of the accelerometer sensor inside the cell phone equal 0.018g to 2g and the sampling ratio is usually 20Hz which is mostly adequate for ITS application. Although the acceleration of accidents and sudden brakes are more intense to the vehicle than this value. (E.g., the air bag opens at 5g).
More limited application domain: analysis and detecting behavior using the accelerometers embedded inside the vehicle are effective for making decisions by in-vehicle intelligent systems, e.g. opening air bags or activating the brake systems. However, cell phones can merely perform passive monitoring. Therefore, it indirectly controls the driver.
The accelerometer is not positioning!: we should not forget that accelerometers cannot perform positioning. Therefore, since most transportation tasks required determining the location of the vehicle, in addition to analyzing its behaviors, using accelerometers is mostly coupled with exploiting a location method like GSM, Wi-Fi, GPS, or a combination of these methods

4. Process architecture

Smartphone use is justifiable in identifying behaviors and context awareness because of its advantages, its utilization requires a process whose last step is to analyze the application. This section explains how to become applicable and operable mobile accelerometer data in the transportation field. However, the process architecture is generally usable for other sensors of mobile phones. Fig. 4 shows the process architecture. The steps of this architecture include
Step 1: Preprocessing. Before processing the data, the removal of invalid entries, segmentation, and alignment of sensors are needed. This step, which is also performed on other used sensors, includes:

Removing invalid entries : Values recorded by sensors may be invalid and outside the acceptable range due to various reasons. This data may be the result of random noises or problems caused for the sensor. These noises rarely occur and can be detected and removed by a simple preprocessing.

Segmentation : Data obtained from the sensor is segmented in specified time intervals (e.g., one-minute segments). This segmentation is done for detecting initial behavior and selecting the application sample. Segments without conditions for the application analysis are removed in the second step, and the selected samples are kept.

Alignment: When other sensors are also used, data obtained from the accelerometer and other sensors must be time alignment. This step is a prerequisite for sensor fusion. For example, if a collision is detected by the accelerometer, the GPS data stored in that moment must be extracted.
Step 2: Determining the device status. What is essential in all ITS application is to identify segments where the mobile phone is inside the vehicle. Although in other areas, such as healthcare, it is important to identify the individual's behavior, such as walking, running, climbing or going down the stairs [52], in the ITS domain the sensor data are valid when the mobile phone is inside a motor vehicle whether it is a private vehicle, motorbike or public transport vehicle. Hence, this step is very important. This step requires extracting features that do not need accelerometer reorientation and high processing. Therefore, the term preliminary was selected for extracting its features. This step aims to identify the mode of travel in a general classification of motor and non-motor. This can be done by the second acceleration norm [20] or in combination with other tools, such as GPS and Wi-Fi [35, 44].
Step 3: Device reorientation. accurate study of the vehicle acceleration behavior in 3-Axes directions requires the device reorientation in accordance with the vehicle directions. Reorientation is not needed in some applications, in others it causes a significant increase in detection accuracy and in some application we have to reorient. As mentioned in the section 3, reorientation is done using other sensors and supporting data.
Step 4: Feature extraction. In this step, various features of sensors are extracted based on the application. Some features must also be extracted for determining the behaviors unrelated to the vehicle behavior. These irrelevant behaviors include any use of mobile phones like talking, touching, moving, redirecting or even falling in the vehicle. Particularly, the latter has a serious impact on the accelerometer. Thus, a part of feature extraction must identify these behaviors. After removing their effect, the device reorientation is done, if needed. But the most important part of this step is to extract features used in decision-making and behavior detection of application. Some of these

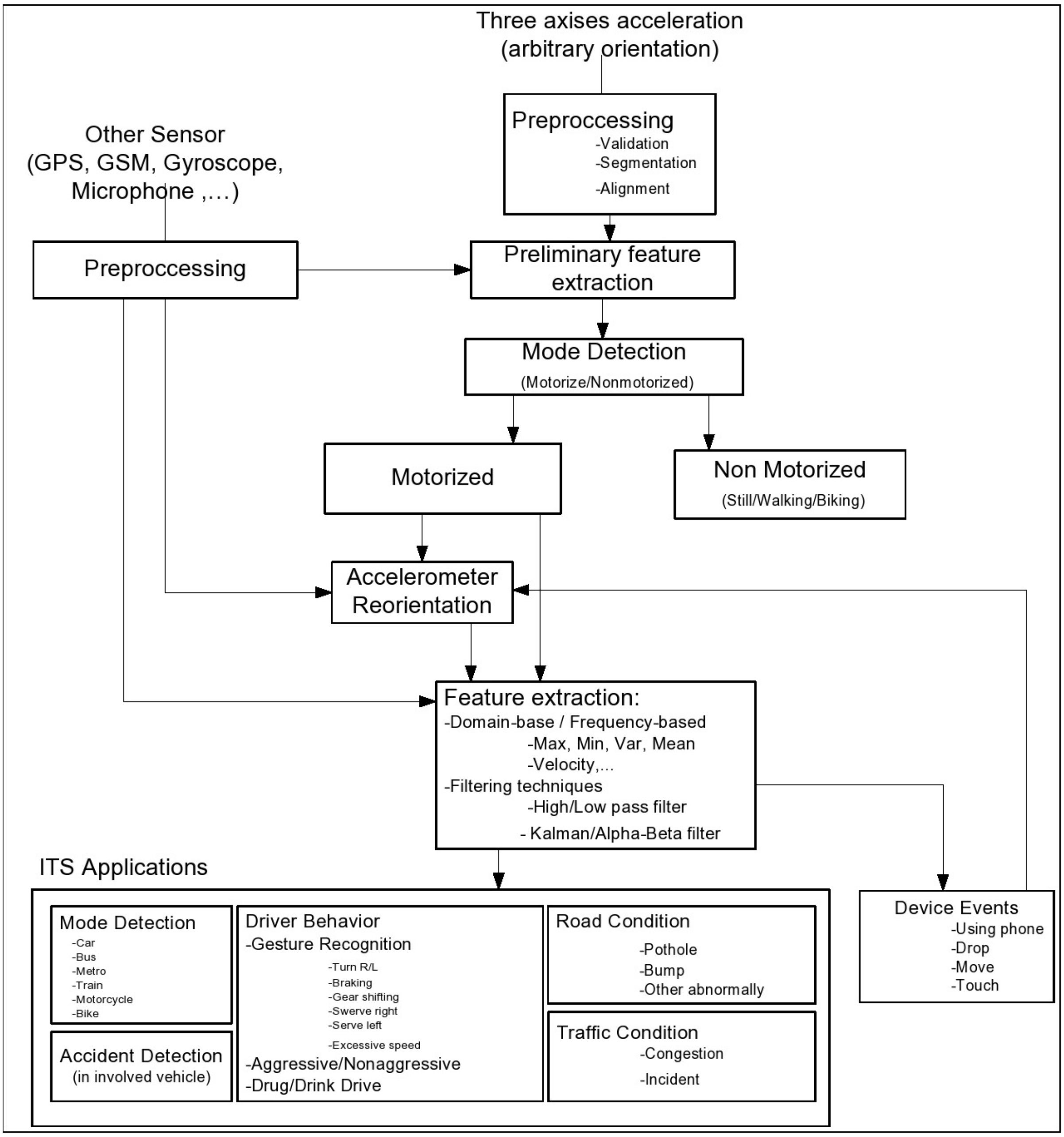


Figure 4: Process architecture to become applicable accelerometer data in the transportation field

features are simply extracted from the accelerometer and some others from other sensors, such as average speed and average acceleration which can also be achieved from GPS. Some features are independent from the accelerometer and are merely extracted from other sensors, such as location or abnormal noises of the accident. Figo and et al. [28] divide the accelerometer features into three general categories: features dependent on domain such as maximum and minimum, variance, mean, and in some articles the stretching and skewness of energy waveform [30]. The second category is time-dependent, mainly derived from Fourier transform of the acceleration energy function, which filtering is also possible. For example, with a suitable low-pass filter, noises and impulses from the vehicle engine can be removed or with a suitable high-pass filter, the effect of gravity on the accelerometer can be removed [24, 34]. The third category of features is seeking to model the acceleration behavior in an alphabetical string format and use algorithms such as SAX [15] or is seeking to evaluate the similarity of two sequences and use algorithms such as DWT [54, 2].

Step 5: Identifying the application using classification. After extracting features, supervised or unsupervised classification techniques are used. According to our research, the accelerometer has been used in five ITS application. These five areas include determining the mode of travel, incident detection, determining the road pavement condition, driving behavior, and traffic and congestion detection. In each application, various classifiers are used, such as Naïve Bayes, decision tree, support vector machines, K-means and other machine learning techniques. Next, works done in each of the five application in the ITS field are explained.

5. Smartphones in ITS applications

5.1. Mode detection

It is common to employ cell phones to determine the mode. The reason for this is that in comparison to other applications, this application is a long term behavior evaluation of the phone owner and an adequate and extended amount of data are exist. On the other hand, there is a significant difference between the accelerometer's data in different modes, e.g. walking, in comparison to driving. This difference makes mode determination possible despite the aforementioned challenges. (See Fig. 5) .

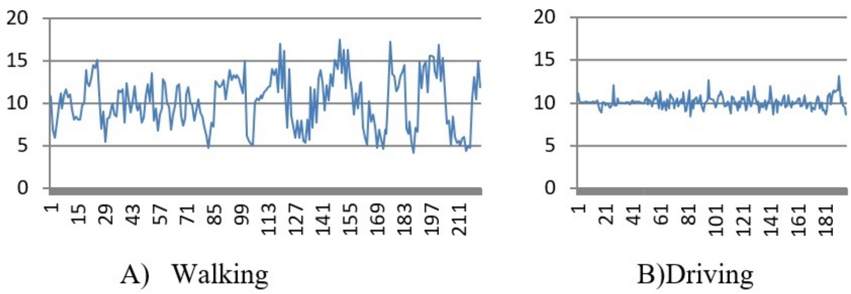


Figure 5: Difference between the accelerometer's data in different modes

Hemminki and et al [30]. have only exploited the accelerometer to determine the mode and extract three feature groups from the energy level of the accelerometer. The first group is related to frames which include means and variance in the vertical and horizontal dimensions. The second group of the features is related to the energy level peak which includes maximum height, density, average length of the peak, Kurtosis, and Skewness. The third group is related to a segment that includes a limited set of frames which determine a mode. Eventually providing 78 dif-ferent features, seven modes (the bus, the vehicle, the subway, the train, the tram, walking, and still) were detected with the accuracy of 84% .

Manzoni and et al. [40] has also distinguished between 8 different modes according to Fast Fourier Transformation (FFT) of the second norm of the acceleration. This method first utilized the piecewise function to break the wave form into pieces and then applies filtering on high frequencies. Eventually, using decision trees and supervised classification, classifies different modes. The resulting accuracy was in average higher than 82%.

Other studies have also used the combination of the accelerometers' data and the GPS information. In [50], different smartphone sensors such as Bluetooth, Wi-Fi, GPS, GSM and were investigated and the accelerometer and GPS were evaluated as the most accurate option to analyze the traveling mode determination. The average speed obtained from the GPS, as well as the variance and Discrete Fourier Transform (DFT) of second norm of the accelerations was extracted as features. After that, different classifiers such as Decision Trees, K-Means, Nearest Neighbor were applied to the data. Provided results showed accuracy higher than 93% to distinguish walking, running, stopping, motorized vehicle, and biking modes. These results were obtained using a combination of Hidden Markov Chains and decision trees. In addition to GPS, Stenneth and et al. [56] utilizes the geographic information system (GIS) to increase the accuracy of traveling mode determination. Montoya et al. [43] have proposed a system for detecting multimodal trips. In this system, the fusion of smartphone sensor data, including accelerometer, Wi-Fi, GPS, and urban transportation network information, such as route maps and public transportation scheduling, is used. In the first step, based on these data, a diagnosis has been made between the modes of walking, biking, public transportation and road vehicle through a dynamic Bayesian network. Then, based on the schedule of public transportation, the recognition between subway, bus, and tram has been done.

Using IMU sensors (magnometer, accelerometer, and gyroscope), Sonderen [53] has separated and accurately identified modes of transportation, including walking, running, biking, and driving car. The use of the aforementioned sensors has led to the lowest battery consumption and processing compared to other methods that use GPS or Wi-Fi. After using several learning machine algorithms such Random Forest, Decision Trees and k-Nearest Neighbors, the mentioned research has come to the conclusion that the decision tree algorithm gives the best results. Eftymiou [23] has also presented a similar work using the same IMU sensors. Algorithms random forest and gradient boosting have been used in this research.

Xiao and et al. [63] identified five modes of transportation including walking, bus, car, bicycle and e-bike through hidden Markov model and distinguished between them. The proposed method on GPS data alone has achieved more than 93% accuracy both in training and in testing the learning algorithm. This accuracy has reached more than 95% if other information such as Wi-Fi data and accelerometer are used. The comparison of the previous studies that used the mobile phone accelerometer to detect the mode in intelligent transportation systems is summarized in Table 1

Table 1: Mode Detection studies based on accelerometer

Researches	Sensors	Detected Modes	Results
[30]	accelerometer	bus, vehicle, subway, train, tram, walking, and still	84%
[40]	accelerometer	Bus, Metro, Walk, Bicycle, Train, Car, Still , Motorcycle	82%
[50]	accelerometer, GPS	walking, running, stopping, motorized vehicle, biking	93%
[56]	accelerometer, GPS, GIS	Still, Walk, Run, Bike, Motor	93%
[43]	accelerometer, Wi-Fi, GPS, urban transportation network information	subway, bus, and tram, car, bike, walk	86%
[53]	magnometer, accelerometer, and gyroscope	walking, running, biking, driving car	97%
[23]	magnometer, accelerometer, and gyroscope	Different motorized transportation	86%
[63]	accelerometer, Wi-Fi, GPS	walking, bus, car, bicycle and e-bike	95%

5.2. Accident detection

Early accident detection and in-time notification play an important role in reducing driving fatalities, such that eliminating the time difference between accident occurrences and the first notification or reducing the one-minute duration of reaching the accident location leads to a 6% reduction in human fatalities [49]. Therefore, some automobile manufacturers have embedded the ability to detect accidents and notifying emergency services in their vehicles. The main elements of these systems are the accelerometers to detect the accident, GPS to locate, and communication devices to contact emergency centers. That is why smartphones are a good candidate for this type of issue.

However, the most important relevant challenge is a false accident detection. Since these systems aim to accelerate the notification process, detections are performed without human interaction and verification. Therefore, the ratio of false detections being reported by the system as an accident (false positives) is considerably important. Each detection of the system is an initiative for a rescue operation, thus a false detection will be quite costly.

So, challenges like making sure that the cell phone is in fact inside the vehicle and detecting the difference between accidents happening to the phone (e.g. falling from the seat) and the momentums of the vehicle are even more highlighted. Using other sensors is one of the approaches to detect such difference. The microphone sensor can also be exploited due to the loud and abnormal noises like opening the airbags, sudden brake, or colliding with objects during accidents. It is clear that one of the challenges is detecting the difference between the surrounding sounds like the music players, passenger‘s talking, and street congestion and the sound due to an accident. GPS is not a suitable option to detect accidents due to its low accuracy and updating ratio. Although, White and et al. [62] employs the speed registered by GPS as a trigger for activating the detection system. In that study, two modes were considered for vehicle accidents.

In the first mode, when the vehicle is moving at a pace higher than a threshold, detecting a loud noise simultaneous with high acceleration is an indicator of an accident. Thresholds are also considered for the noise and acceleration. The second mode is when the vehicle is stopped or moves at a low pace; however a sudden movement and acceleration is occurred due to colliding with another vehicle. The movement higher than a threshold, coupled with high acceleration and a loud noise is considered as an accident.

In all conducted studies, the threshold for acceleration plays an essential role. Taking into account the low threshold increases the false positive ratio, and in turn increasing the threshold makes detecting less intense accidents impossible. Moreover, Aldunate [4] detects accidents by assigning weights to the two values from the microphone and the accelerometer.

Amin [8] employs the accelerometer and GPS information fusion to detect the accident, when the velocity of the vehicles is higher than 23km/s and the decelerate is more than 5g. For lower velocities, accidents hardly cause injuries. Aloul [7] uses dynamic time warping (DTW) and hidden Markov models (HMMs) on data collected from a mobile phone placed in an accident car to determine the severity of the accident and provide timely notification. The method used has caused false positive alarms to be reduced to a minimum.

KV [38] developed an application that detects the occurrence of an accident using accelerometer data from a mobile phone located in a car. After confirming the accident, the emergency services are notified through the application. The comparison of the some differnet approaches that used the mobile phone accelerometer to detect the accident in intelligent transportation systems is summarized in Table 2

Table 2: Accident detection studies based on accelerometer

Researches	**Sensors**	**Techniques**
[4]	Accelerometer, microphone	Determining thresholds for each sensor
[8]	Accelerometer, GPS	Activating alarm when deceleration is more than 5g and speed more than 32 km/s
[7]	Accelerometer	Using DTW and HMMs
[38]	Accelerometer	Abnormal deceleration active application untill user response or execution emergency protocol

5.3. Driver behavior

The behavior of the driver plays an important role in accidents, traffic, and fuel consumption. Research shows that alerting the driver about the inappropriate state of driving, e.g. aggressive behavior, sleepiness, etc., reduce almost 20% of the accidents [15]. Moreover, aggressive driving causes 40% more fuel consumption and mitigating the mental convenience of the passengers [5]. Therefore, the managers of insurance companies and transportation fleet seek driver profile and behavior analysis. The research conducted based on the velocity, acceleration, and deceleration analysis have inferred the general behavior of the driver, including being aggressive, sleepiness, using drugs, or alcohol.

Some of these studies like [5], first detect gestures and maneuvers of the driver which includes rotating to left or right, turning, intense line changing, deviating from the path, etc. after that, the general behavior of the driver is obtained by investigating the type of these maneuvers.

Castignani [14] uses fuzzy logic to investigate and grade the driver profile in case of nervousness and recommends employing this grade as a measure to consider discounts or increase the annual insurance payments and rewarding and punishments of the drivers of a fleet. This research exploits four features of the instantaneous acceleration, velocity and linear acceleration obtained from GPS and the steering rate. For each feature, two thresholds (average and aggressive) are considered. The number of times these values exceed the threshold, they are fuzzified in three levels of low, medium, and high, and then using fuzzy rules, the status of the driver is determined based on one Calm, Average, Moderate, Aggressive levels.

In some studies like [59], a simpler method to detect the nervousness of the driver has been employed. This method generally analyzes the acceleration information of the GPS. The acceleration threshold for the normal driving is calculated in the x and y axes. The acceleration values obtained from the driver is then compared with the threshold boundaries. If the distribution of the point outside the threshold boundaries is higher than the points inside this boundary, the aggressive behavior of the driver is reported. Moreover, Dai [16] defines an acceleration threshold boundary in the direction of x and y axes to detect the abnormal behavior of the driver under the influence of alcohol. The perquisite of this method includes reorientation of the phone with the direction of the vehicle which is discussed in the aforementioned research.

Inferring the behavior of the driver based on the vehicle‘s maneuvers is more complicated in comparison to the aforementioned methods, since the driver‘s gestures must be first detected and identified and the general behavior of the driver is then evaluated. With taking into account the threshold of the peak of y axis acceleration (the direction of the vehicle); Fazeen [26] detects the sudden acceleration change. Moreover, in order to detect sudden change of line, the threshold of the x axis acceleration peak (the lateral axis of the vehicle) has been employed. Another extracted feature to determine the sudden change of line is the duration of the acceleration change. Changing the line safely is usually 75% longer than suddenly changing the line.

Chaovali and et al. [15] use SAX algorithm to transform the energy level obtained from the accelerometer to an alphabetic string. A string pattern is then extracted regarding the aggressive behaviors of the driver, including sudden brakes, sudden acceleration, and suddenly turning to left or right. Eventually, these patterns are sought in the driving behavior string of the driver. The section in which there is a high similarity to one of these patterns is detected as an aggressive maneuver.

In addition to utilizing GPS, coupled with the accelerometer, other sensors like the gyroscope have also been employed. This sensor can only show the angular velocity of the device rotation and detect maneuvers and rotations more sustainably than the accelerometer. Johnson [15] has shown that using this sensor, in addition to the accelerometer, leads to good results for detecting different forms of maneuvers. The beginning and the end of a maneuver is obtained by the mean square values of the x-axis gyroscope. In case in an interval, this value is higher than a maximum threshold, it is an indicator of a maneuver. The end of the maneuver is also detected by the reduction of this value lower than the minimum threshold. If only one of the accelerometer or the gyroscope is used to detect the maneuver, the accuracy is about 77 to 79%. However a combination of the two improves the accuracy to 91%. Similar studies can be found in [31].

Eftekhari and Ghatee [22] have analyzed the behavior of drivers using neural fuzzy network. In this research, the fusion of IMU sensors has been used to detect the type of maneuver and the driver behavior in each manuevers. Also, for validation, comparing the results with the driver's anger scale (DAS) questionnaire has been used. In this research, accelerometer data is used without reorientation. Also, in another research [19], by extracting the feature based on the continuous wavelet transformation of the mobile phone accelerometer and using a MLP neural network, the driver's behavior has been divided into three categories: safe, semi-aggressive, and aggressive. Again, the results were compared with the DAS questionnaire, and in 79% of the cases, the proposed model recognized in accordance with the questionnaire results. Using the discrete wavelet transform and ANFIS in a similar study by them, the accuracy of 92% was reported [21].

The comparison of the previous studies that used the mobile phone accelerometer to driver behavior in intelligent transportation systems is summarized in Table 3

Table 3: Driver behavior recognition studies based on accelerometer

Researches	Sensors	Techniques
[5]	Accelerometer	Determining manuevers type, then analysing behavior of driver in each manuevers
[14]	GPS, (Accelerometer)	Creating drive profile based on fuzzy inference
[26]	Accelerometer	Detecting the sudden acceleration based on peak of acceleration curve
[15]	Accelerometer	Using SAX algorithm and alphabetic pattern to detect aggressive driving
[34]	Accelerometer,gyroscope	Detecting the beginning and the end of a maneuver by gyroscope and detecting aggresive driving by accelerometer
[22]	Accelerometer,gyroscope	Detecting maneuvers by gyroscope, fuzzification acceleration in each manuevers and calculating similarity to safe and aggressive driving
[19]	Accelerometer	Detecting class of behavior based on CWT of Acceleration and speed by MLP
[21]	Accelerometer,gyroscope, magenometer	Using DWT and ANFIS, output of six ANFIS fusion to decision of overall driver behavior

5.4. Determining pavement condition

Detecting the condition of roads and streets is one of the requirements of city or sub-urban pavement management. Research shows that abnormal or uneven points like potholes and road bumps along the road can lead to a 2 to 6% increase in fuel consumption [10] and increasing accidents and fatalities [1].

In comparison with traditional methods of collecting data by deploying scanners with special equipment, this domain can also benefit from the idea of utilizing smartphone sensors to collect pavement information and detecting abnormal points. The general approach to exploiting smartphones is detecting abnormal points using the changes in acceleration, particularly along the Z axis (the perpendicular axis of the vehicle). Abnormal point location is then performed by GPS and the candidate points are sent to the analysis center using cell phone communication networks. Eventually, the analysis center makes a decision based on the frequency of the announced points. Abnormality can be a result of speed bumps, at the cross section of urban train rails, or small or big holes. Detecting the difference between different abnormalities is the challenge of this mechanism.

Another challenge of this mechanism is that any abnormality announced by one vehicle crossing a street may not be detected by other vehicles, since the second vehicle does not necessarily cross the same section of the street as the first one. On the other hand, the announced abnormality may be a false positive due to reasons other than the pavement. Another issue is related to the speed of the vehicles. The behavior of the accelerometer in detecting the axes accelerations (especially the Z axis) is directly related to the speed of the car. In other words, when the speed of the vehicle is high, an abnormality at the surface of the road creates a stronger momentum along the Z axis and it is more likely to detect it. While when the speed is low, the momentum is also less intense and its distinction with the normal momentums of the vehicle will be more difficult. Therefore, some studies define two or more threshold for different velocities.

A well-known relevant research was conducted by Eriksson [25]. The advantage of this research is the possibility of detecting the abnormal points based on their type, including potholes, manhole caps, railroad crossing, and bumps. This is performed through machine learning. After manual sampling, the acceleration behavior is trained for each type of abnormality and the acceleration behavior for a smooth road. The data collected from the vehicles is then filtered in a five-stage process. The threshold boundaries of the filters are determined according the initial training sample and the best one is selected. One these thresholds are the peak of the z axis. If the acceleration exceeds this threshold, it can be considered as an abnormality. In other articles, this feature is referred to as the z-peak. According to the five-stage filtering, 7 taxies navigated 5 streets. The points close to each other were interpreted as one point using clustering. Results indicated that in all but in one of the streets, the false positive ratio was very low and insignificant (less than 0.5Another research distinguishing between different abnormality types was performed by Fazeen [26], in which detects the road condition, potholes, and speed bumps based on merging and analysis of the acceleration along x and z axes. This study introduces the velocity of 20 m/h as an appropriate speed to detect the abnormalities with high accuracy. The height of the speed bump is also estimated in this research. Although there is not much detail regarding the methodology and we are referred to (Eriksson), results are acceptable and in all case, accuracy was reported higher than 70

In [42], another feature is provided to detect abnormalities at velocities lower than 40 km/h. this feature, which is called z-sus, takes into account the continuing low energy levels of the z axis acceleration (sustained dip lasting for 20 milliseconds). Since abnormality at low paces involves a longer duration along the z axis, it can be a more suitable alternative to z-peak at low paces. However, for velocities higher than 40 km/h, z-peak is employed. Moreover, it is also confirmed by the results and the false positive/negative ratios. Mednis [41] introduces sudden changes of the z axis acceleration as a feature called z-diff. If during a short interval, this change is higher than a threshold, an abnormality is identified.

In addition to reorient the device differently, Bhoraskar and et al. [12] which follow the notion of [42], exploit machine learning techniques including k-mean and SVM, instead of defining a threshold to detect the abnormal points. Using 2-mean, the z axis acceleration is classified into two distinct classes by training bumpy and smooth roads and provides an unsupervised learning to detect to abnormal behavior. Results are then trained to a SVM. In [47], abnormal behaviors along the z axis are divided into two classes. The first class includes small bumps, small road unevenness, and railroad crossings. The second class consists of speed bumps and big potholes which makes the driver to brake. For feature extraction, mean, standard deviation, the distance peak to peak distance, and the FFT frequency domains are employed. This research also investigates the effect of speed on detecting abnormalities and shows a linear relationship between the vehicle speed and the extracted features. Furthermore, SVM has been used as a classifier. However, as the article states, results are not fully satisfactory. There are several studies evaluating the abnormalities without reorientation. For instance, Jain [33] aims to find intense abnormalities which significantly reduce the driver‘s speed and are not detectable due to foggy weather or the unclear state of the road. The proposed idea detects these points through the crossing drivers and inform the drivers adjacent to these points. Since the second norm of the acceleration is used, reorientation or related challenged are eliminated. Results indicate that 80% of the abnormalities are detected and the driver is falsely informed for 20% of the cases.

Astarita and et al. [9] detect and distinguish rubber and stone speed bumps with a particular form using reorientation along the z axis. This reorientation is possible based on the gravity. Therefore, no complicated computations or additional lateral information is necessary. A similar work can be found in [60]. In addition to detecting road abnormalities, the smartphone accelerometer is used to collect the road gradient and its turn to provide geographical information of the roads [17]. Tian [57] shows that IMU sensors embedded in smartphones have been the most popular data source. They introduce the procedure of recognition pavement anomalies based on inertial data in three phase, including preparatory phase, data collection phase, and data processing phase. Sandamel [51] proposes the application of smartphone-based roughness data to evaluate the condition of rural road pavements and compares it with results obtained from roughness measurement equipment. The results show that it has a good correlation, which shows that it has sufficient accuracy compared to conventional roughness measurement methods.

Based on the International Roughness Index, Alatoom [3] has provided a low-cost method to evaluate the roughness of urban street pavements by using smartphone accelerometer signal processing and using different filters. In this research, the effect of vehicle speed, sampling rate, mobile phone position has been investigated in order to achieve higher accuracy.

In [55] the location and accelerometer data of smartphones are sent directly to the center without any processing. In the central servers, the data collected from all smartphones is aggregated based on time and place. Then it estimates the condition of the pavement of each 10-meter section of the road. The results were compared with a set of reference data of the road infrastructure administration, and a binary classifier was trained based on target data, and the results obtained from these results had high accuracy. The comparison of the previous researches that used the mobile phone accelerometer to detect pavement condition is summarized in Table 4

Table 4: Pavement abnormality detection studies based on accelerometer

Researches	**Type of abnormality**	**Accuracy**
[25]	Potholes, manhole caps, railroad crossing, and bumps	False positive less than 0.5
[26]	Potholes, and speed bumps	higher than 70%
[42]	Potholes, and speed bumps	In the best case study FN=23%, FP=5%
[41]	Large and small potholes, pothole clusters, gaps and drain pits	92%
[47]	Small bumps, small road unevenness, and railroad crossings	Not reported
[33]	Abnormalities which significantly reduce the driver‘s speed	80%
[9]	Distinguish rubber and stone speed bumps	93%
[55]	Assigning four class for road pavement	90%

5.5. Detecting traffic conditions and congestions

Another domains employing the accelerometer is traffic monitoring. Since traffic monitoring is highly dependent to location and the velocity of the vehicle, such research has mostly utilized GPS. On the other hand, the acceleration obtained from the speeds difference of GPS is adequate for analyzing the status of the traffic. Therefore, these studies less frequently use accelerometers and mostly exploit it as a complementary to detection. Due to high energy consumption of GPS, Mohan and et al. [42] uses this sensor only at certain times. Thus, most of its analysis is based on the accelerometer. This study first reorients the device and then finds the difference between the stop-and-go traffic and walking. Since the acceleration fluctuations in the consecutive stop-and-go are similar to walking, their difference is detected by defining a threshold and investigating the difference between their acceleration peaks. Location is also performed based on GSM and if necessary, GPS is used to enhance accuracy.

Another related research is [29] which utilizes the existing sensors in smartphones like GPS, accelerometer, gyroscope, and digital compass to analyze the velocity and acceleration. This article features traffic monitoring in different modes including cars, bikes, tricycles, and public transportation. This study has showed that for each mode, the velocity and acceleration in crowded and non-crowded traffic is different. Moreover, features were extracted to detect traffic lights, as well as the accidents. This research utilizes different methods including SVM, decision trees, and Markov hidden chain to classify the traffic behavior and the compares their results. Decision trees obtained the best results with an accuracy of 85%. Of course, the difference between the walking behavior and the stop-and-go traffic behavior was not investigated.

Wenwen Tu and et.al. [58] using nonlinear classification such as deep neural network proposes a framework to classify traffic flow states based on accelerometer, gyroscope and GPS speed data of smartphone. he study found that acceleration and angular acceleration data can increase the accuracy of traffic flow classification significantly. 24 feature are extracted from three dimensions of accelerometer and gyroscope, such as mean, variance and other statistical expression and are used in this study. Mandal [39] has detected the traffic flow using smartphone accelerometer data of two-wheelers with an accuracy of more than 83%. This recognition is based on characteristics such as the location of speed bumps detected by the accelerometer or the density of Wi-Fi hotspot on the route.

6. Discussion

The literature review on studies reports that mobile phone sensors, especially the accelerometer, have good capacities to be used in intelligent transportation systems, although the reliability of this sensor and the accuracy of the applications that use this sensor, it is not very high. Therefore, this sensor can be a candidate for use in decision support systems, and the possibility of using this sensor in decision-making systems is doubtful; especially in applications such as accident detection.

The results show that great research has been done in mode detection by accelerometer alone or by fusion with other smartphone sensors, and the performance of this sensor has been acceptable. Also, the results obtained in the analysis of driving behavior show that this sensor reflects well the aggressive or abnormal behavior of the driver. One of the reasons that has caused the smartphone accelerometer to perform well in the analysis of the driving style is the continuous monitoring of the driver's behavior in different positions and maneuvers in time and during the trip (or different trips) which includes dozens of maneuvers.

An application such as the detection of abnormality in road pavement, if reported by a large number of mobile phones, can be reliable and can be used for deciding on repairing pavement. In other words, the detection false positive or negative report of a mobile phone can be reduced to a minimum through the aggregation on reports and decision fusion on results.

Regarding the application of detecting the traffic condition, the fusion of other sensors has a decisive role, and actually the detection of the traffic condition is highly dependent on speed and position which cannot be extracted by the accelerometer. Therefore, the role of the accelerometer is as a guide for activating the positioning systems or helping to better detection traffic congestion.

7. Conclusion

Since smartphones can access various communication and telecommunication networks and they are equipped with different sensors like the accelerometer, gyroscope, microphone, and positioning, e.g. GPS and GSM, they have become a suitable candidate for different behavior recognition, including traffic and transportation. Nevertheless, these sensors and capabilities of smartphones are not designed and customized for such purposes and thus their operation in ITS poses many challenges. This study discussed the research conducted regarding the using of the accelerometer sensor of smartphones in transportation systems. This sensor, which aims to detect the direction changes of the cell phone‘s screen, is able to accurately record different gestures and momentums of the device. This feature allows it to be utilized in various application of the transportation domain, including mode detection, accident detection, traffic monitoring and the behavior of the driver, and the road pavement condition detection. However, using this sensor poses challenges like requiring device reorientation, the sensitivity of the sensor, and detecting the source of the gesture. On the other hand, the cost of the built-in equipment for intelligent transportation installed in vehicles has caused the use of the capabilities of mobile phones, to be considered in intelligent transportation systems. In this study, an architectural model of preparation of smartphone accelerometer is provided to utilize it in the ITS applications and the techniques employed are discussed. Finally, a survey of researches related to each application, as well as methods, features, and complementary sensors are investigated and compared.

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