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Roadside acoustic sensors to support vulnerable pedestrians via their smartphones

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ABSTRACT: This paper proposes a smartphone-based warning system to evaluate the risk of a motor vehicle for vulnerable pedestrians (VP). The acoustic sensors are embedded in the roadside to receive vehicle sounds and they are classified into heavy vehicles, light vehicles with low speed, light vehicles with high speed, and no vehicle classes. For this aim, we extract new features by Mel-frequency Cepstrum Coefficients (MFCC) and Linear Predictive Coefficients (LPC) algorithms. We use different classification algorithms and show that MLP neural network achieves at least 96.77% accuracy criterion. To install this system, directional microphones are embedded on the roadside and the risk is classified. Then, for every microphone, a danger area is defined and the warning alarms have been sent to every VPs' smartphones covered in this danger area.

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1. Introduction

Smartphones are the best options for safety purposes in the recent years [1, 2, 3, 4, 5, 6, 7]. These instruments are used for pedestrian safety in the current paper. Pedestrian safety is an important challenge in the world, but they like to carry least equipment to protect themselves [3]. Sometimes, infrared sensor, camera, computer vision and wireless networks were used to recognize the environment [3]. Extracted features from sound [8, 9] are also helpful for safety applications. On the other hand, to improve safety, it is necessary to classify risk of different situations. For this aim, different sensors are used to monitor and to classify the roads and vehicles. For example, intrusive sensors such as inductive loops [10], magnetometers, micro loop probes, pneumatic road tubes and piezoelectric cables [11] are commonly used. In[12], the performance of these sensors has been compared. Also as classification perspective, usually, vehicles are classified without pedestrians' properties. For example, Nooralahiyan et al. [13] proposed a vehicle identification method using Linear Predictive Coding (LPC) based on acoustic sound source of moving vehicle. Wavelet packet algorithm for moving vehicle classification has been proposed in [14]. In [11] by using ANN, vehicles are classified into heavy vehicle, medium vehicle, light vehicle, and horns classes with accuracy equal to 67.4%. In addition, in [15], a vehicle sound classification system is presented when low pass filtering was performed that just classifies into six models of cars that is not helpful for VP. In [16], a quadratic discriminant analysis was used to classify audio signals of passing vehicles and its accuracy is 80%. In [17], vehicle sound was classified by using Probabilistic Neural Network (PNN). In [18] an acoustic hazard detection system was developed for pedestrians with obscured hearing that was not mentioned anything about accuracy of classification and vehicle direction detection. Generally, in these works, we face with some drawbacks. They used some unusual and expensive

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equipment for VP. Some extra information from vehicle driver and pedestrian are needed and just a communication between a single car and a single pedestrian is supported. In addition, there is a high cost for installation and maintenance for sensors such as camera. Furthermore, it is not enough clarity to help pedestrians with respect to vehicle direction when we use acoustic sensors.

Based on these works, in this paper we focus on VP including pedestrians who use voice players or work with mobile applications and their attention to risky patterns decreases. In addition, cyclists and wacky pedestrian are considered as VP in this paper. For this kind of VPs, we propose a new warning system based on received sounds in environment. The main contribution of this paper is to use acoustic data with low installation and maintenance costs, light processing, and good performance in different weather conditions such as sunny, rainy and foggy, good performance in the dark and not enough light. To use acoustic sensors for risk evaluation of vehicles in road, we just assume that VP has a smartphone with internet connection and we do not need extra information from vehicle driver such as location and speed and age. We prove that our system provides high accuracy in vehicle sound classification and we consider vehicle direction to reduce false alarms. Furthermore, environment includes many sources of noises and so it is impossible to consider all of the situations. In this paper, we consider some noise effects to improve the system performance.

2. Proposed system

In this section, we propose a warning system for VP when the road is straight without intersection. The system includes two modules: Sensors and Decision-making. Fig. 1 shows the architecture of the proposed system. In what follows, we explain the details.

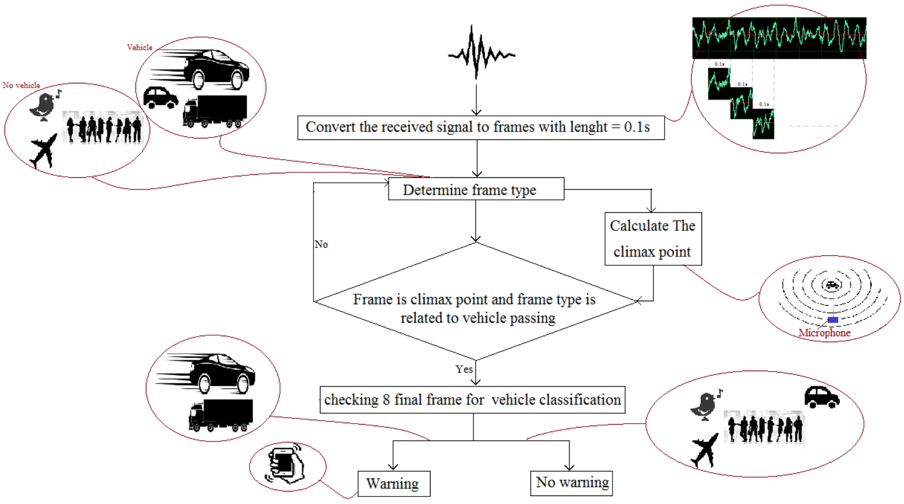


Figure 1: Warning system by using vehicle classification for VPs

2.1. Sensors

Fig. 2 shows the embedded equipment in the roadside and danger area. Distance between two successive processors is 25m. Each processor has a directional microphone (with 3m height) to detect direction in two-way streets when passing a vehicle. Danger area is also defined as a rectangular with 25m length and each processor corresponds to a special danger area that is shown in Fig. 2. These distances are determined experimentally. On the other hand, if the maximum speed to detect is assumed 75 km/h and since we need at least 3 seconds to warn the VP [19, 20], so a vehicle can pass 75m in 3.6 second. Therefore, from 75m ago, we have enough time to warn VP and according to danger area length, the minimum time and the maximum time to warn VP is 3.6 and 4.8 seconds, respectively. subsectionDecision making When a vehicle approaches to a processor, microphone receives the vehicle sound. System detects vehicle direction and classifies the vehicles into in four classes: heavy vehicle (H), light vehicle with low speed (LL), light vehicle with high speed (LH) and no vehicle (NV). NV includes birds' sound, airplanes, and crowds of people. By the aid of directional microphones, vehicle direction can be detected simply. In this research, we use Cardioid directional microphone that provides great sensitivity at the front, only partially at the sides, and little at the back. By using this microphone, the proposed system can detect the right direction of vehicle. In this system, after the sound signal is received, it converts to the frames with 0.1 second length and for each frame; the following phases should be done.

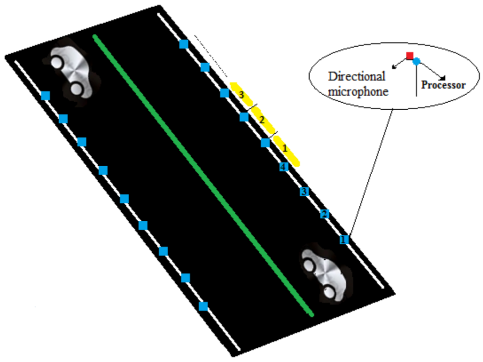


Figure 2: Roadside equipment of the proposed warning system (Blue circle: processor; Red square: directional microphone; Yellow color: danger area;)

Phase 1: Determining the frame type
This phase includes three steps. In the first step, features of Table 1 are extracted.

Table 1: Features of the proposed system

Index	Notation	Feature description
1	P_1	Power of the first half of FFT results
2	P_2	Power of the second half of FFT results
3	F_1	Frequency of the highest power in the first half of the FFT results
4	F_2	Frequency of the highest power in the second half of the FFT results
5	HV	The highest value of the FFT results
6	MFCC	Mel-frequency Cepstrum Coefficients
7	LPC	Linear Predictive Coefficients

To determine the first five features, we use Fast Fourier Transform (FFT). Fig. 3 shows FFT of a vehicle sound. Let $x_1, \ldots, x_{N-1}$ be complex numbers, the following equation shows FFT sequence:

$$x_k = \sum_{n=0}^{N-1} x_n e^{-i2\pi kn/N}, \qquad for\ k = 0, 1, ..., N-1. \tag{1}$$

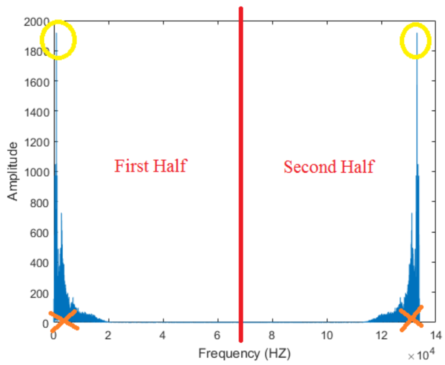
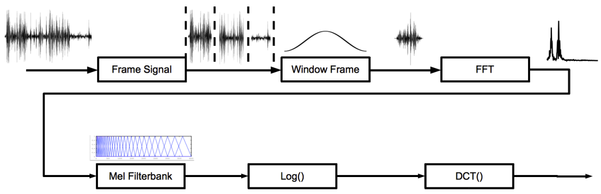
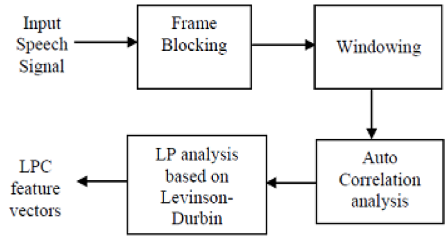


Figure 3: FFT of a vehicle sound.

The first and the second features reach form signal power in the first and the second half, presented in Fig. 3. The third and the fourth features determine as the frequency of the highest value in the first and second half of the FFT. The fifth feature is shown in Fig. 3 with yellow circle as a point that is similar in both sides of half parts of FFT. The sixth and seventh features are corresponded to the outputs of MFCC and LPC algorithms. MFCC is one of the most popular algorithms in speech processing [1]. The details of this algorithm is given in Fig. 4.a. In addition, LPC algorithm provides reliable, robust and accurate estimation of speech parameters. In Fig. 4.b,



(a) MFCC steps adapted from [21]



(b) LPC steps adapted from [8]

Figure 4: Features extraction from sound signals

LPC steps are shown [8]. In the second step of phase 1, we implement a feature selection method namely Principal Component Analysis (PCA) which is a standard tool in modern data analysis for extracting relevant information from confusing data sets. The final step is classification. In this step, we test four classification algorithms including Multi-Layer Perceptron (MLP), K-Nearest Neighbor's algorithm (KNN), Naive Bayes (NB) and Decision Tree (DT). We compared the results of these classification algorithms in the next section. After this step, every frame type is classified.

Phase 2: Calculating the climax point

Climax point is a point that a vehicle is crossing from the nearest point to acoustic sensor that have highest frequency. For finding the climax point, we use Doppler Effect. Doppler Effect is a very important physical phenomenon with a great variety of applications [9]. The Doppler Effect consists of a change in the frequency received by the receptor when the source moves relative to it, that is, the frequency increases when the receptor approaches the source and decreases when the receptor moves away from the source [9]. This means that when a vehicle crosses from the nearest point to a processor, receives the highest frequency.

Phase 3: Checking eight final frames

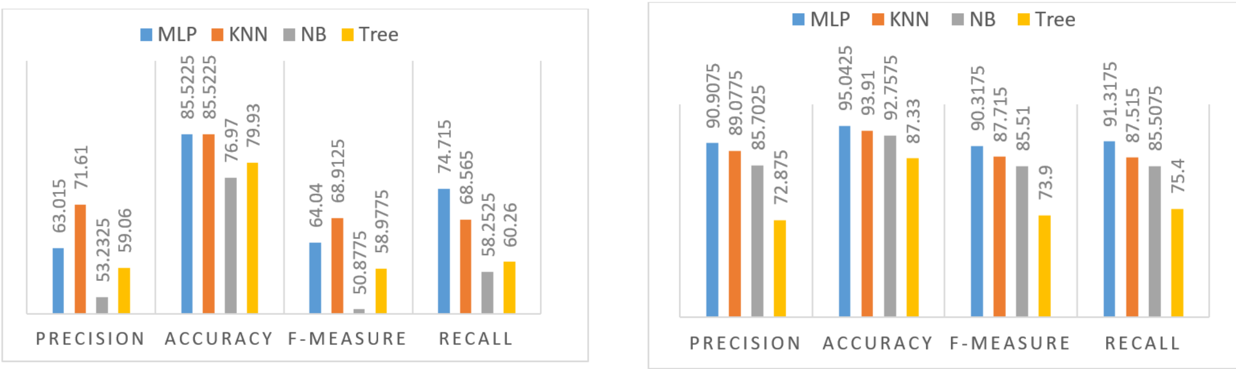
At the end of decision making part, if the climax point is not relevant to frames of NV type, then the third phase begins. In this phase, we use eight last frames up to climax point, to decide about the received sound. We use eight last frames experimentally. If the number of frames with similar type is the greatest, then this frame type is presented as the received sound type.

2.2. *Warning*

When the direction is detected and the vehicles are classified, if there is a risk made by a heavy vehicle or light vehicle with high speed, then the proposed system sends a warning massage on VPs' smartphones that are located in the corresponding danger area. In this system, we need to find the location of VP by the aid of Global Positioning System (GPS). When VP need to became aware of a risky vehicle, which is approaching, it is necessary to turn on GPS of her/his smartphone. Then the roadside processor can send warning to VP through an application installed on smartphone. In addition, the roadside processor just sends the messages to smartphones located in its danger area. According to [22], the maximum acceptable error in warning systems is one meter and in [23], the best error of GPS was reported between 0.01 and 1 meter. Thus, the usage of GPS for positioning is acceptable in the proposed system.

3. Experimental results

In Table 2 the best results about the assistant systems for pedestrians are presented. In the final column of this table, the preferences of our proposed system compared with the previous systems are presented. Also in Table 3, the best results on vehicles sound classification is shown. In addition, we present the advantages of the proposed system compared with these vehicles sound classification is shown. In addition, we present systems. However, to compare the numerical results of the proposed system, we need some benchmarks. Based on our best knowledge, there is not any standard benchmark for VP safety problems; therefore, we provide a set of sound recordings in traffic roads. These data are collected from different type of traffic roads and at the different times of day and night. The number of our collected data is 210 sample that 70, 50, 44, and 46 samples related LH, LL, H, and NV, respectively. Training process was done based on cross-validation (6-fold). To show the effectiveness of the proposed system, we use different feature extraction and classification algorithms. In the first, we express results related to frames then express the results of the received sound. In Fig. 5.a, the performance of the different classifiers by considering the first five features of Table 1, are presented. This figure shows that KNN and MLP on the first five features of Table 1 provides the best results; but the accuracy in this case is 85.5%. Fig. 5.b studies



(a) Using the first five features of Table 1

(b) Using MFCC and LPC features

Figure 5: Comparison between different classification algorithms

on the effects of MFCC and LPC features. As one can see, the most accuracy corresponds to MLP, which is 95%. Finally, Fig. 6 illustrates the effects of all of the features of Table 1. Again, MLP with 97.8% accuracy is the best classifier. Therefore, using all features of Table 1, is the best choice in the proposed warning system. According to the different measures including Precision, Recall, Accuracy, and F-measure, one can understand that using MLP classifier algorithm has the best result compared to the other algorithms. After determining the type of each frame, the proposed system uses eight final frames (unit climax point) for making final decision regarding to the warning. Table 4 shows the results of warning with respect to H, LL, LH, and NV classes. These results are reached by voting between in eight final frames. Results given in Table 4, show that the proposed system can classify the different situations between 93.47% and 99.35% that shows that the proposed system is reliable.

Table 2: The works on pedestrian assistant systems

Ref.	Approaches and Tools	Weakness	Preferences of our proposed system
[24]	Using infrared sensors that installing on glasses	• Use of additional equipment for pedestrian • Infrared sensors cannot detect differences in the objects which have a very similar temperature range • Infrared sensors are extremely expensive	VP does not need to carry extra equipment. Acoustic sensor has a lower price.
[25]	Using camera that installing on bicycle helmet	• Use of additional equipment for pedestrian • Expensive for pedestrian • High cost in process • Lack of privacy	• VP does not need to carry extra and expensive equipment. • The processing of acoustic data has a lower cost than image data. • Preserve privacy.
[26]	Using a walking assistant robotic based on computer vision and tactile perception	• Use of additional and very big equipment for pedestrian • High cost in process • Expensive for pedestrian	• VP does not need to carry extra and expensive equipment. • Preserve privacy. • Low cost in processing.
[27, 28, 3]	Using vehicle to pedestrian connection	• Get extra information from vehicle driver such as Exact location, speed, and age • Some of this article connect only one car and one pedestrian Don't need extra information.	• Only give pedestrian location. • Risky vehicle alert send to all of people that placed in danger area (not one person).

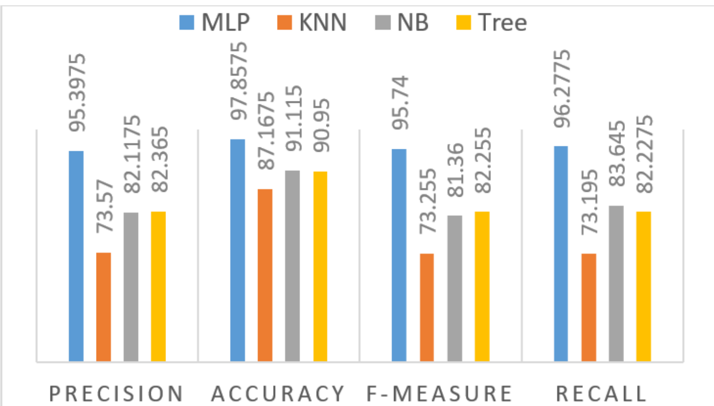


Figure 6: Comparison between different classification algorithms using all features of Table 1

Table 3: The works on pedestrian assistant systems

<table>
<tr><th>Ref.</th><th>Classes</th><th>Accuracy and weakness</th><th>Preference of our proposed system</th></tr>
<tr><td>[29]</td><td>Car, Bike, Lorry, Truck</td><td>• Low accuracy 86.86% in classification
• Lack of direction detection
• Don’t attention to environment sound.</td><td>• Accuracy is between (93.93%, 96.77%)
• Direction detection by directional microphone.
• No vehicle classification includes some of environment.</td></tr>
<tr><td>[17]</td><td>Car, Bike, Lorry, Truck</td><td>• Maximum of neural network training results for the classification of the type of vehicle is 94.5
• Not mentioned accuracy of test in neural network
• Lack of direction detection</td><td rowspan="3">Test accuracy between (93.93%, 96.77%).
Direction detection by directional microphone.</td></tr>
<tr><td>[11]</td><td>Heavy, Medium, Light, Horn</td><td>• Low accuracy 67.4% in classification.
• Lack of direction detection.</td></tr>
<tr><td>[16]</td><td>Bus, Car, Motor, Truck</td><td>• Low accuracy 83% in classification.
• Lack of direction detection</td></tr>
<tr><td>[18]</td><td>Bus, Truck, 4-wheel drive, sedan</td><td>• Without presenting the classification accuracy.
• Lack of direction detection.
• Lack of clarity in helping pedestrians.</td><td>• Helping pedestrian express in detail.
• Test accuracy between (93.93%, 96.77%).
• Direction detection by directional microphone.</td></tr>
<tr><td>[30]</td><td>Two type of car, and Large trucks</td><td>• Don’t express the classification accuracy.
• Classification with a limited number</td><td>• Test accuracy between (93.93%, 96.77%).
• 3 classes of vehicle and 1class of no vehicle.</td></tr>
</table>

Table 4: Sensitivity analysis for 8 final frames

Measure	H class	LL class	LH class	NV class
Precision	98.30	95.87	98.38	93.47
Recall	93.54	93.93	98.38	98.85
Accuracy	98.38	96.77	99.35	97.74
f-measure	95.86	94.89	98.38	96.08

4. Conclusion

In this paper, we proposed a new warning system based on acoustic sensors to warn VP with respect to the risk of vehicles that approach from the behind. The proposed system has the following advantages:

- Only using the acoustic sensors
- Low cost in installing equipment and maintenance in roadside.

- Without necessary to carry extra equipment by VP.
- Efficiency of the system in both of the sunny and the foggy conditions.

In this paper, to help VP in risky conditions, we define some features based on the vehicles sound and we classify them efficiently. We express the new features associate with MFCC and LPC to classifiers to increase the system accuracy. The proposed system can be used efficiency in rainy air if we use a Proper filter. In this paper, the proposed system classifies the received sound in four classes: heavy vehicle, light vehicle with low speed, light vehicle with high speed, and no vehicle with classification accuracy between 93.47% and 98.38%, which shows the applicability of the proposed system in real situations.

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