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A novel method of using sound waves and artificial intelligence for the detection of vehicle's proximity from cyclists and E-scooters

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ABSTRACT

Outdoor air pollution has been found to have a significant adverse effect on health. When the authors attempted to monitor air quality that cyclists or e-scooter users' breath during commuting in different locations for health and safety analysis, it was found that the existence of internal combustion engine (ICE) cars has a significant effect on the pollution levels and the monitoring process. To comprehensively study the effect of cars and traffic on air quality that cyclists and e-scooters users experience, a low-cost and reliable system was needed to detect the proximity of cars that have diesel or petrol engines. Video cameras can be used to visually detect vehicles, but in the modern age with the existence of many electric and hybrid vehicles and the need to reduce the cost of instrumentation, there was a need to determine the passing of vehicles near e-scooter and bike users from the combined engine and tires sounds.

To address this issue, this study suggests a novel approach of using sound waves of internal combustion engines and tire sounds during the passing of cars, combined with AI techniques (neural networks), to detect the proximity of cars from cyclists and e-scooter users. Audio-visual data was collected using Go-Pro cameras in order to combine the data with GPS location and pollution levels. Geographical data maps were produced to demonstrate the density of cars that cyclists encounter when on or near the road. This method will enable air quality monitoring research to detect the existence of ICE cars for future correlation with measured pollution levels. The proposed method allows for:

- The automated selection of sensitive features from sound waves to detect vehicles.
- Low-cost hardware which is independent of orientation that can be integrated with other air quality and GPS sensors.
- The successful application of sensor fusion and neural networks.

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Method details

Introduction

Outdoor air pollution is a vital concern for public health. International regulations have positively influenced the decrease of air pollutants and emission; however, the transportation sector is still a significant contributor its levels [1,2]. Despite many countries working to improving air quality, road traffic is still considered a major cause of air pollution [3], not just through tail pipe emissions but, also brake dust, tyre wear and fuel evaporation [4]. The World Health Organisation (WHO) has reported that many cities do not meet safe levels of pollutants, which it defines as the limit of particles in the air exceeding 10 μg per cubic metre; however, concentrations of 12 μg per cubic metre has been recorded in some UK cities [6], including the city that is the focus of this study [5,6].

Particulate matters as pollutants are complex mixtures of small, solid particles suspended in the air in small droplets of liquid. These pollutants are classified and named according to their size category: PM10 for 10 μm category and PM 2.5 for 2.5 μm category [8]. It has been reported by the European Environmental Agency that the amount of NO2 and PM is above limits in many European cities [9] and many researchers have attributed this to traffic on roads. For example, Shakya et al. [10] stated that there is a clear positive correlation between traffic rush hours and PM2.5 that is released from vehicles; and maximum concentrations of particulate matters are normally recorded during traffic rush hours [11]. The main pollutants that are emitted from traffic are Carbon dioxide (CO2), Hydrocarbons (HCs), Carbon monoxide (CO), and Nitrogen Oxides (NO2) [4]. Other important pollutants include SOx, NOx, NH3, NMOVOC, CO, PM2.5, and PM10 [12].

The audio based vehicle detection using AI has been implemented by [13] to estimate traffic count, with success rate of 92 % to 84 %, but the application was mainly for urban traffic flow rather than proximity to other users. Another paper has used sound waves to detect emergency vehicles on the road [14]. In reference [15], researchers have used sound signals to monitor environmental noise with categorization of cars type. Another paper has used sound waves to identify the speed of cars [16]. Limited research has implemented the sound waves to examine proximity and number of cars passing by e-scooter and bike users.

Previous studies concerning commuters exposure to air pollution have shown that cycling and walking are not risk free [7]. Whilst these studies highlight proximity considerations it was previously difficult to study the relationship between proximity of pedestrians, cyclists, and e-scooter riders to cars and air quality.

Limited research has been found that considers the relationship between air quality and the presence of ICE vehicles near other vulnerable road users such as cyclists and e-scooters users. A key limitation to collecting such data is the availability of a low-cost and reliable system to detect vehicles for air quality monitoring. Therefore, this paper suggests a novel method and low-cost system to detect vehicles using sound signals and video camera which captured images for calibration and error detection purposes. This study was carried out by utilising volunteer cyclists who travelled around the city of Nottingham. Their bicycles were fitted with mobile air pollution minoring devices, GPS loggers and Go Pro's for video and sound capture to collect the required data. Artificial intelligence was used for data analysis to confirm the accuracy of the suggested method.

Method

This suggested method uses sound waves to recognize cars with running internal combustion engines. Fig. 1 presents a 1.5 s sample which shows a typical shape of the recorded sound wave of a passing car. Fig. 1 shows how the wave starts to build up while the car is moving towards the cyclist and how the wave is fading out while the car is moving away from the cyclist. The figure has been divided into twelve sections to understand how the wave has been generated. Section 6 and 7 are the sections when the car is in the closest position to the cyclist. The car was seen in picture 6 in the closest position to the cyclist and then passed the cyclists from picture 7 onward.

Fig. 3 presents the sensors used for the full programme of study including this paper, namely the air pollution monitor type Aeroqual 500 (Fig. 2-a), GPS iTrail system (Fig. 2-b) and GoPro for images and sound (Fig. 2-c). For this paper only the GPS and the GoPro data was presented in this paper as the focus was on location and number of cars.

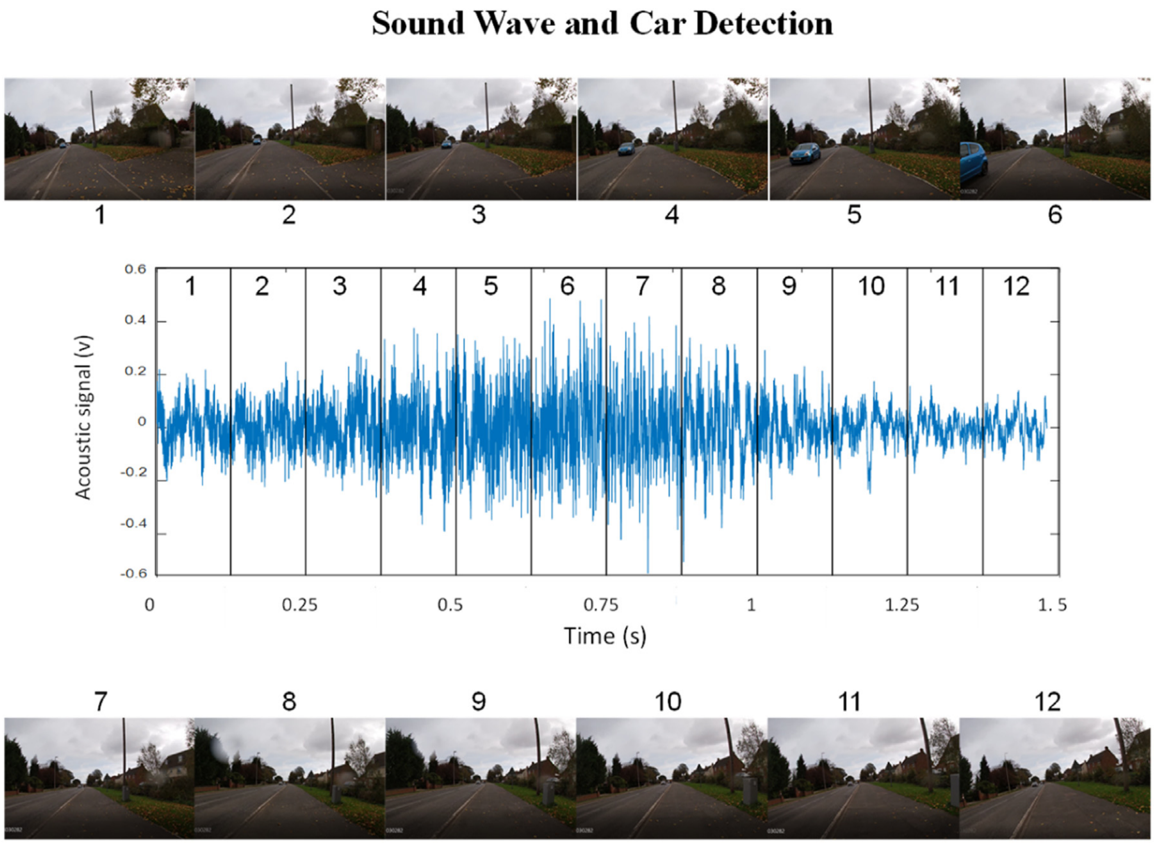

Fig. 1. Image shows the format of the sound wave while the car is moving closer to the cyclist and then when it moves away within 1.5 s period.

Fig. 2. The utilised sensors used: PM10 and PM2.5 (a), GPS iTrail (b) and GoPro (c).

Fig. 2 shows the recorded sound wave when three cars pass by within a five-second interval. The figure shows that there are differences between the waves in each case.

Using these differences in the waves, a useful feature can be extracted to count the number of cars passing nearby the cyclist. The process starts by extracting the sound waves throughout the whole wavelength by taking samples of a length of five seconds with intervals of two seconds. This means that the algorithm will detect cars every two seconds as it has been found that, on average, the car takes about two seconds when passing nearby the cyclist, based on the usual car relative speed in relation to the speed of cyclists. This is assuming a 30mph speed limit in built up areas such as city centre and suburbs.

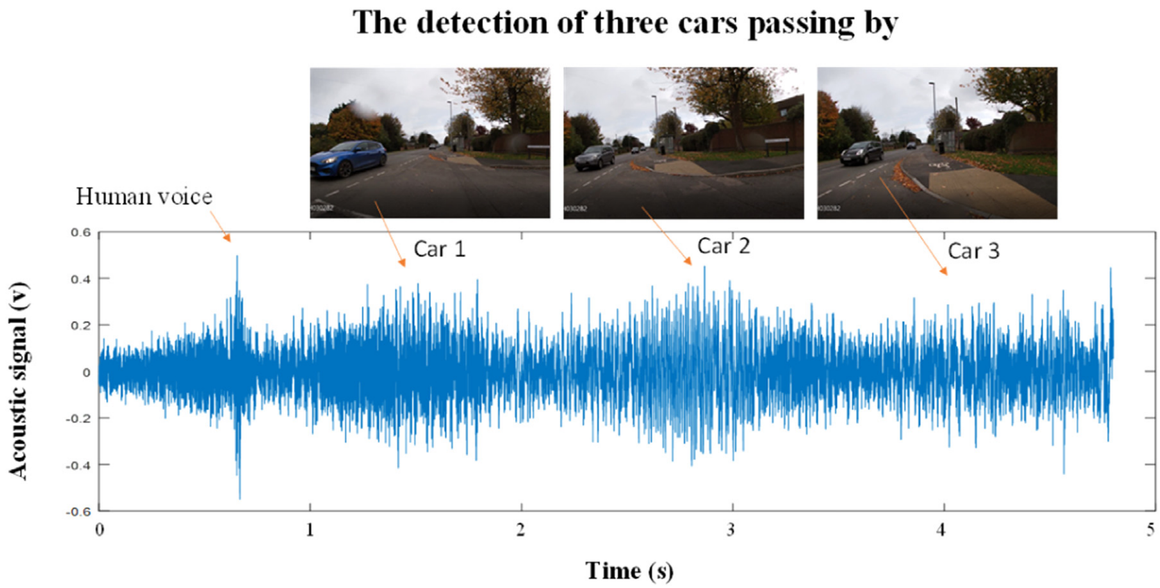

Fig. 3. Three cars passing nearby the cyclist.

The ASPS approach

The ASPS approach refers to the Automated Sensory and Signal Processing Selection System. It searches automatically for the most sensitive features to be used to detect specific phenomena using a 'black box' approach. The ASPS Approach has been proposed, designed and confirmed for different applications by Al-Habaibeh [13–15]. The approach employs the acquiring of data (e.g., signals and/or images and/or together) and processing them to extract the most useful information, or sensory characteristic features (SFCs) (or simply features). The approach is based on collecting the necessary data from the available standard sensors and subjecting them to a systemic processing method to extract the most sensitive features. The ASPS approach also supports sensor fusion, where the features from more than one sensor and signal processing method can be used and integrated. It is an automated self-learning method to detect sensitive data for the design of condition monitoring by implementing a systematic application of design and analysis in order to produce high quality and low-cost monitoring systems. The ASPS approach will be used in this novel application to detect cars with internal combustion engines based on sound as shown in Fig. 3.

Fig. 4 presents a simplified block diagram of the proposed ASPS approach. The ASPS approach starts by extracting SCFs from a wide range of sensors using a wide range of signal processing methods (Fig. 4-a, b). The SCFs are then arranged in a 3D matrix, namely SFM (Sensory Feature Matrix), Fig. 4-c. Then the dependency (sensitivity) of the SCFs is assessed using different methods such as the relative change in value or the slope of the linear regression line, where the sensitivity values for each sensor and signal processing method are arranged in an Association Matrix (ASM) as shown in Fig. 4-d. The values of the SCFs are arranged based on their sensitivity, as high sensitivity features are then selected to design the condition monitoring system. The less significant SCFs are discarded from the designed condition monitoring system, keeping the sensitive SCFs for the monitoring process. As shown in Fig. 4, neural networks will then be used to implement and test the designed system for accuracy. The ASPS approach can have the capability to transfer the design of a condition monitoring from being a specific problem for a specific application to a more general problem that can be described in generic terms and the solution might be provided for different groups of processes that have specific criteria in common [13–15].

To find the relationship between the number of cars and the pollution levels, a smart algorithm has been created to extract the necessary information (features) from sound signals to count the number of cars passing nearby cyclists or e-scooter users. Hence, the ASPS approach will be used to extract the best features that will be used later to recognise the cars by using the sound signals and compare that with the obtained images for validation. All this information will be fed to a neural network as an input in order to automate the process of counting the number of ICE cars passing nearby the cyclists.

As shown in Fig. 5, the method starts by a preparation step in which the region of interest (ROI) in the signals are identified. The signals are then subjected to a wide range of signal processing methods within the time domain and frequency domain such as statistical analysis, Fast Fourier Transform (FFT) and Discrete Wavelet Transform (DWT). This is because the time-domain data might not produce clear information while the frequency domain form (FFT) and the frequency/time domain form (DWT) have vital hidden information significantly assists in extracting the useful features.

According to the ASPS approach, the data should be subjected to an extensive processing method to ease the extraction of useful information. Once the required data is collected and prepared, the ASPS approach extracts the most sensitive sensory character-

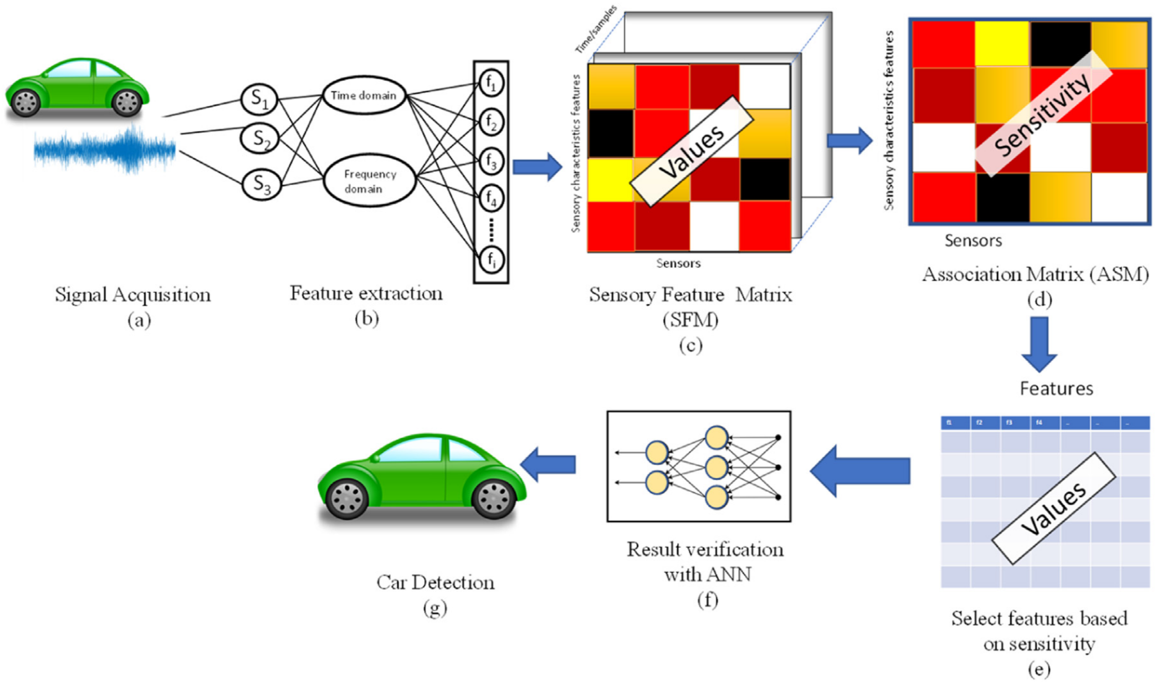

Fig. 4. The ASPS approach that has been implemented to detect passing internal combustion engine cars using sound waves.

istic features to build the high sensitivity monitoring system. The extraction process is carried out by applying multiple statistical/mathematical equations such as (but not limited to) the equations shown in Table 1 which have been used in this paper.

Car sound wave processing

In order to identify the sound wave of the cars and consequently count them or identify their proximity from cyclists, the most sensitive features (SCFs) require extraction and multiple mathematical functions are applied as per the suggested ASPS approach. The ASPS approach uses the 'black box' concept [17–19] where the dependency of any feature on the existence of a car's sound is automatically detected. As shown in Fig. 4, the sound signals are processed using Discrete Wavelet Transformation (DWT), Fast Fourier Transformation (FFT) and statistical analysis in the time domain, the functions for which are presented in Table 1. The sound waves are transformed to Discreet wavelet transform and Fast Fourier Transformation, so that the functions have to be applied to more signals in different forms of the same wave, rather than processing one wave with fewer details (raw signal). This transformation means greater details will appear on the surface and consequently afford more precision in extracting the most useful features.

Fig. 4 shows the raw wave and its transformation to the DWT which produces two forms of the signals (cA and Cd for low and high frequency respectively) and the FFT signal. The FFT wave is then subjected to further processing to search useful features in different frequency segments. The FFT signal is divided into several sections and each section is dealt with as a separate wave and processed like the other waves. The very low frequency of the FFT signal is ignored as it is believed to carry no useful information.

As well as the FFT wave, Log (FFT) is also used as shown in Fig. 4. The FFT and the Log (FFT) waves are divided into 6 segments, the low frequency segment is ignored due to the low frequency content; with only the other 5 segments being used. The number of segments is case dependent; but for most applications having between 5 and 20 segments is be sufficient. In total, as shown in Fig. 4 and Table 1, there will be 18 sub-signals × 16 signal processing methods to produce 288 SCFs in total for each sound wave from which the most useful SCFs will be selected to build the required monitoring system. The sensitivity, or dependency, of the features (SCFs) will be evaluated based on the slope of the best fit line between 'no car' status and 'the existence of car' status. The higher the slope of the line, the better the sensitivity of the feature. The slope of the line is then used as a sensitivity to rank the features and use the most sensitive ones (i.e., with most dependence on the existence of vehicles). The most sensitive SCFs are utilised to design the system as an input for the neural networks to identify the existence of cars.

The fast Fourier transform

Due to its importance in this study, the Fast Fourier Transform (FFT) signal will be discussed in detail as shown in Fig. 6 as an example of the way the ASPS approach uses FFT. As shown in Fig. 7, the higher frequency portion of the FFT wave is partitioned into smaller sections, while the low-frequency segment is omitted due to its minimal frequency content. In this case, six sections are considered, generating six distinct sub-signals for optimal feature extraction. For the FFT alone, there will be a total of 6 sub-signals multiplied by 16 functions for signal processing, resulting in 96 Sensitivity Characterized Features (SCFs) for each sound

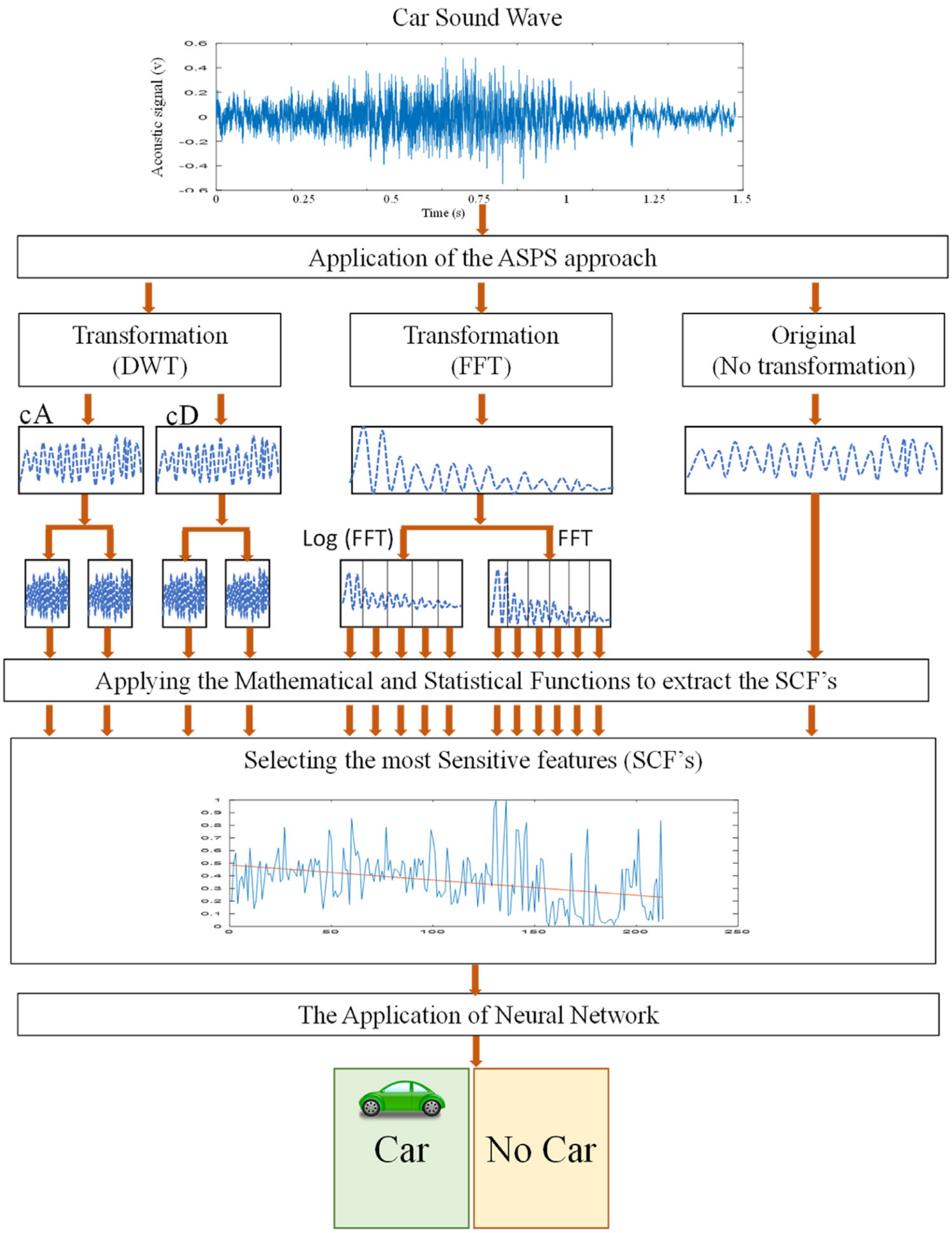

Fig. 5. The ASPS method used to detect cars with internal combustion engine.

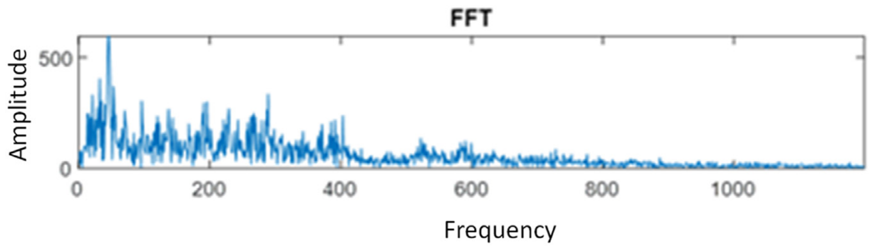

Fig. 6. The FFT signal from applying the FFT on the sound wave.

Table 1
Statistical/mathematical equation used in signal processing.

Definition	Equation
Max	$E_1 = \max(x_i)$
Min	$E_2 = \mathrm{m}in(x_i)$
Mean	$E_3 = \frac{1}{n}\sum_{i-1}^{n} x_i$
STD	$E_4 = \sqrt{\frac{\sum_{i=1}^{n}(x,-E_3)^2}{n-1}}$
Absolute mean	$E_5 = (\frac{1}{n}\sum_{i=1}^{n}\sqrt{\lfloor x_i \rfloor})^2$
RMS	$E_6 = \sqrt{\frac{\sum_{i=1}^{n}(x_i)^2}{n}}$
Absolute max	$E_7 = max\lfloor x_i \rfloor$
Variance	$E_8 = \frac{\sum_{i=1}^{n} s(n)-(\frac{1}{n}\sum_{i=1}^{n} s(n))}{n-1}$
Skewness	$E_9 = \frac{\sum_{i=1}^{n}(x_i-E_3)^3}{(n-1)E_4^3}$
Kurtosis	$E_{10} = \frac{\sum_{i=1}^{n}(x_i-\lvert x\rvert)^4}{(n-1)E_2^4}$
RSS (Root sum of squares level)	$E_{11} = \sum_{i-1}^{n}(y_i - f(x_i))^2$
Covariance	$E_{12} = \sum_{i=1}^{n}\frac{(x_i-\lvert x\rvert)(y_i-\lvert y\rvert)}{n}$
IQR (interquartile range of time)	$E_{13} = Q_3 - Q_1$
Range (Range of radio wave propagation)	$E_{14} = E_1 - E_2$
Crest factor	$E_{16} = \frac{E_7}{E_6}$
Clearance factor	$E_{16} = \frac{E_7}{E_5}$

wave during FFT analysis. In fact, the overall count of features increases when the same methodology is applied to Discrete Wavelet Transform (DWT) and Logarithm of FFT (Log(FFT)) signals. Following this, the most sensitive SCFs are chosen to construct the required monitoring system. The assessment of SCF features' sensitivity or dependency relies on the slope of the best-fit line between 'no car' status and 'the existence of car' status, with a higher slope indicating greater feature sensitivity. The identified, most sensitive SCFs are then employed as inputs to neural networks to identify the presence of cars in the system.

Extracting the most sensitive features

Fig. 8 shows the result of only one feature (SCF-30) as an example. This feature shows that the waves are typically of a higher value when there is a car compared to when there is no car present. It should be noted that SCF-30 is a range function applied on the approximation wave of the DWT. The slope of the line, as shown in Fig. 7, is used to rank and to choose the best features for the monitoring system.

The application of the ANN for cars counting and the validation process

Once the ASPS approach is applied and the most sensitive features have been extracted, the data is utilized in creating the required ANN to count the cars, or evaluate their proximity based on the car wave sound. Fig. 9 shows the result of the ANN. A feed-forward backpropagation network neural network is used with sigmoid functions in the middle layers and a linear function in the output layer. A total of 20 Sensory Characteristic Features (SCFs) are used for the input using the top ranked features, where the output predicts the existence of a car, where 1 represents 'car ' and 0 represents 'no car'. The results show a high accuracy in counting the number of cars based on the sound wave, resulting in an error of only 9 % in training set and 10 % in the testing set, as shown in Fig. 10.

This result means that the AAN is successful in counting cars to an acceptable level to be able represent the actual number of cars and is consequently reliable enough to be used in the analysis to construct the estimation system for air pollution levels.

Integrating the number of observed cars using ANN with the GPS data

Fig. 11 presents how the suggested novel method can be used to monitor the number of cars during a cycling or E-scooter journey. This technique will allow a correlation analysis of the number of cars passing by and the measured/estimated/approximated pollution levels. The future work will relate the number of cars with the pollution levels encountered by the e-scooter or bike users.

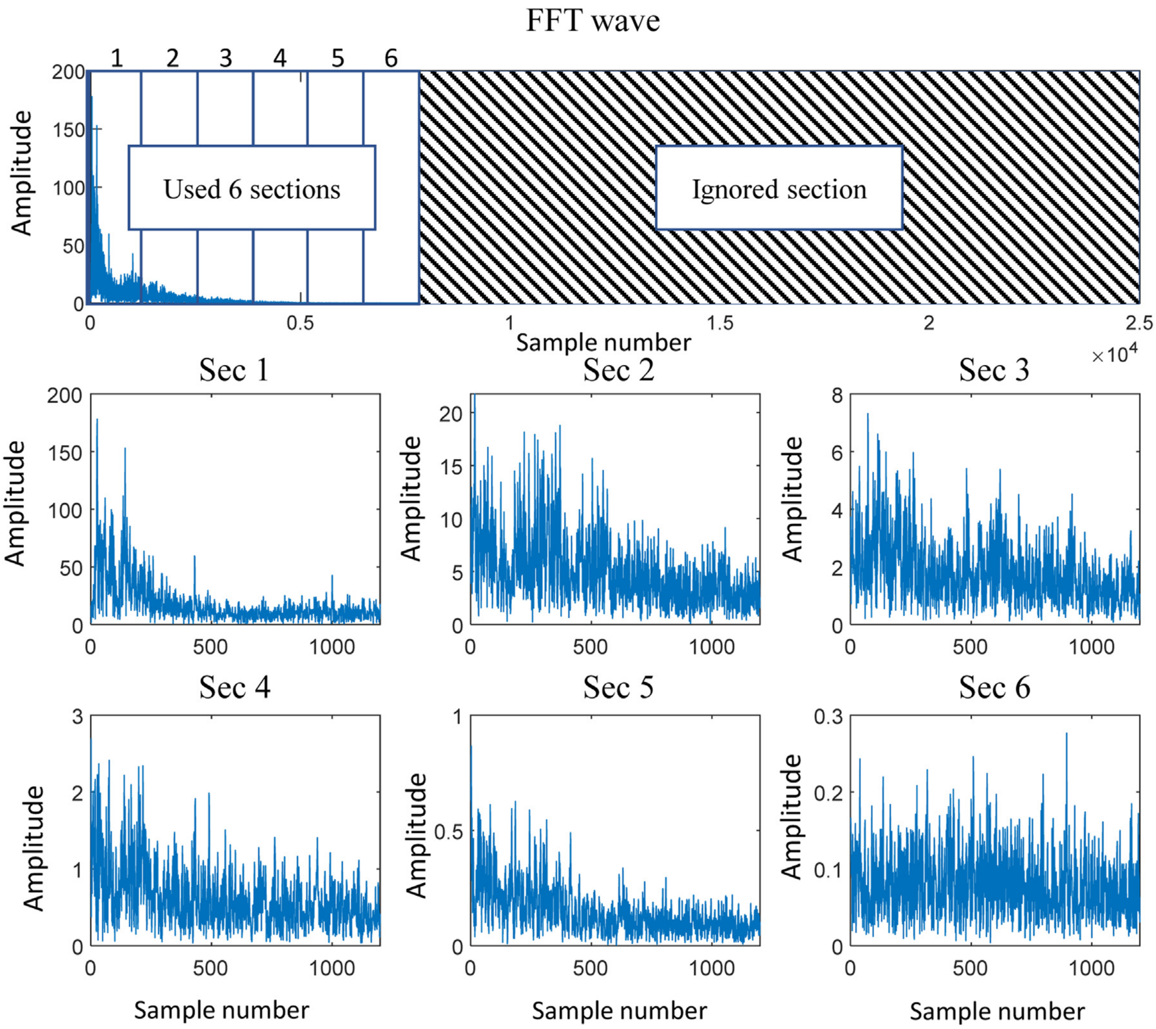

Fig. 7. Six sub-signals extracted from the main FFT signal.

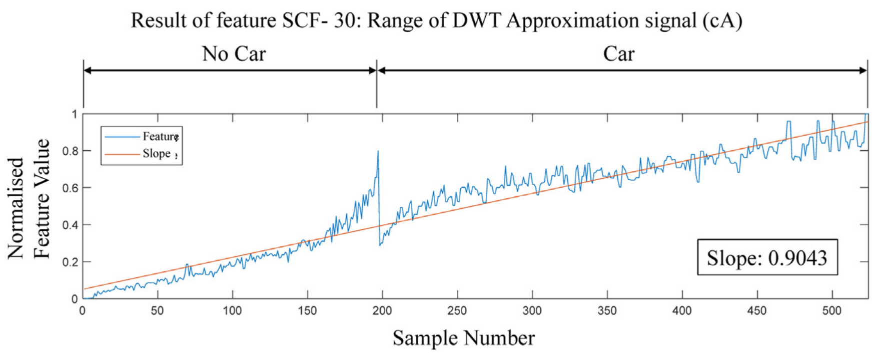

Fig. 8. The figure shows how the values of the waves are often higher than others when cars are present.

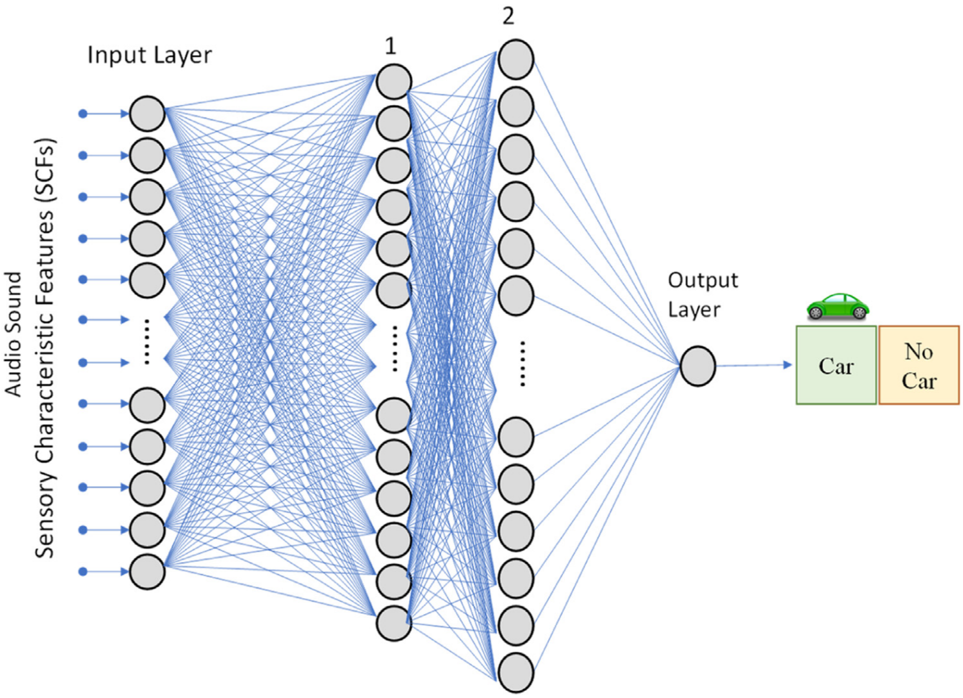

Fig. 9. The application of the neural networks to detect the proximity and number of cars.

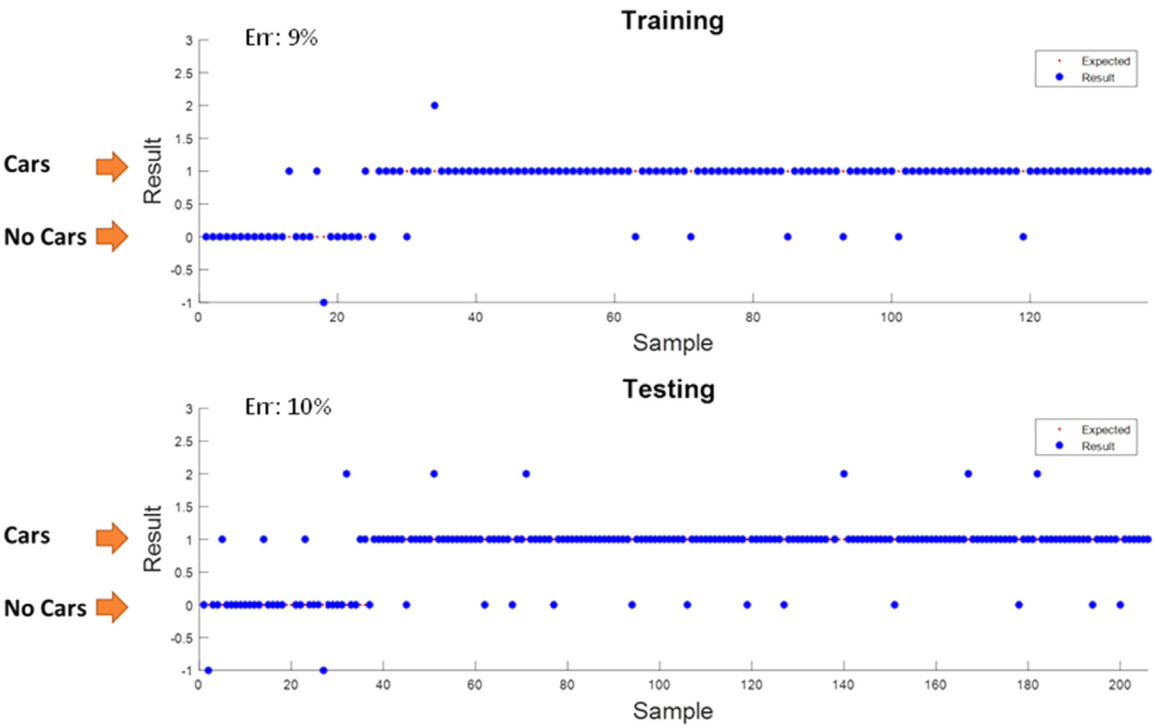

Fig. 10. ANN result for the detection of cars passing by.

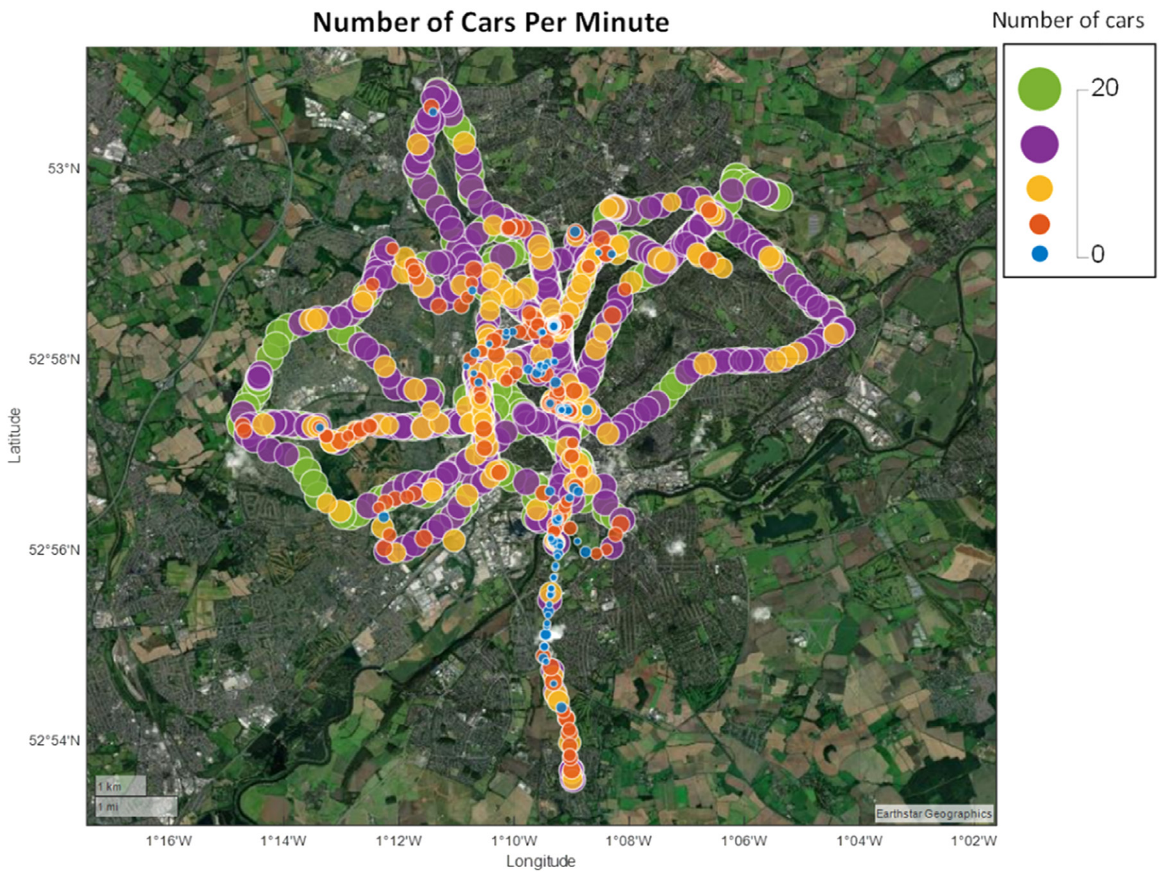

Fig. 11. The number of the cars passing nearby the cyclists along the path of the whole trips.

Conclusion

This paper has highlighted a novel method to monitor the proximity of internal combustion engine vehicles to cyclists or E-scooters users whilst commuting for health and safety and air quality monitoring. An audio signal is used to detect the sound of the vehicles passing by and then the ASPS approach [13–15] is utilised to enable the processing of data to find the most suitable Sensory Characteristic Features (SCFs) for the intended application. A back propagation neural network is used to test the suggested approach with a 90 % success rate when compared with video images. The system has been tested successfully with a GPS sensor to monitor the number of cars passing by per minute during a journey in Nottingham. A geographical data map has been produced to demonstrate the density of cars that cyclists encounter when on or near the road. The results show that the suggested technique will be useful in studying the effect of passing vehicles on pollution levels at different locations within cities. This will permit outdoor air pollution to be investigated of and the influence of vehicles around cyclists and e-scooter users during commuting periods. The proposed system is low-cost and reliable. This method will enable air quality monitoring research to detect the existence of ICE cars for future correlation with measured pollution levels. Future work will compare between electric and internal combustion engine cars in terms of sound signature and air quality issues.

Ethics statements

The authors confirm that the relevant ethical approval process has been followed for this research work and consents were obtained from any volunteer participated in this work.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

CRediT authorship contribution statement

Amin Al-Habaibeh: Conceptualization, Methodology, Software, Writing – original draft, Writing – review & editing, Visualization, Supervision, Resources, Project administration, Funding acquisition. **Bubaker Shakmak:** Software, Data curation, Validation, Formal analysis, Investigation, Writing – original draft, Visualization. **Matthew Watkins:** Conceptualization, Investigation, Resources, Writing – review & editing, Funding acquisition. **Hyunjae Daniel Shin:** Conceptualization, Resources, Funding acquisition, Writing – review & editing.

Data availability

Data will be made available on request.

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