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Research Paper

Acoustic Signal Based Automatic Vehicle Detection System

Engineering

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Sai Sandeep.k ECE, SRM University, Chennai, Tamil Nadu 603203, India.

P. Vijay Kumar ECE,SRM University, Chennai, Tamil Nadu 603203, India

ABSTRACT

Vehicle detection system plays an important role in intelligent transportation System. a multistage hierarchical algorithm of acoustic signal analysis and pattern recognition for identification of moving vehicles in an open environment. Vehicle detection for the two wheelers, four wheelers and also heavy weight and light weight vehicles should be classified. The frequency pattern based on acoustic signal was matched with current signal and the vehicle is identified. The algorithm is tested on pre-recorded audio signals of passing passenger cars and displays promising classification accuracy.

1. Introduction

Vehicle analysis provides several effective techniques to detect target vehicle . Here we will use acoustic signal for the vehicle detection. The sound (engine, noise, etc.) of a working vehicle provides an important clue, e.g., for surveillance mission robots, to recognize the vehicle type. a vehicle emits different noise patterns. These noises can be sampled or digitized and grouped in a series of time slices (frames).

Each sound pattern is viewed as acoustic signature. Acoustic noise analysis provides the possibility to

distinguish well separable classes of motor vehicles, such as different passenger cars and trucks. A collection of typical sound samples is used as the training data set. The mean vector and the most important principal component samples together characterize its sound signature it can be a simple and reliable acoustic identification method if the training samples can be properly chosen and categorized. Acoustic signal detector, such as an ordinary household microphone, is used as the most inexpensive sensor version for stationary and transportation systems. proposed algorithms are hierarchical algorithms and FFT algorithms.

Video based methods of vehicle identification are generally more effective and robust in changing weather conditions if provided sufficient visibility and illumination acoustic signals records from different types of road vehicles in various conditions are described here. The simplified modification of acoustic microphone's signals spectral processing algorithm and noise filtering are solved. Detection of moving road vehicles results, using records for their acoustic signals, is also discussed. The restrictions of using acoustic sensors to estimate sound parameters are established the possibilities of real-time system implementation. Acoustic systems on the other hand do not rely on visibility factors, yet are sensitive to background acoustic noise variation. Thus the accuracy of acoustic system vehicle identification is directly dependent on its ability to distinguish the sound patterns of passing vehicle noise from a limitless amount of noises occurring in the environment.

2. Signal Analysis

The audio signal is analyzed in frequency domain. The frequency domain representation of the signal is achieved by applying a temporal signal decomposing operation, namely the Fourier Transform (FT).The frequency spectrum of a temporal signal frame consists of half as many points as there are in the temporal frame, which is relevant in computation complexity critical systems. These frequency spectrum these can be calculated from the Fourier transform algorithm these can finding the RMS energy by keeping the threshold value we can classify the type of the vehicle .In these we will discuss FFT algorithm and First audio file of .mp3 is converted into wav file of .wav format since MATLAB supports wav command directly.

2.1The Fast Fourier Transform

The discrete temporal signal is decomposed by the Discrete Fourier Transform (DFT). For a finite duration discrete signal x(m) of length N the DFT function is

$$X(k)=\sum_{m=0}^{n-1} x(m)e^{-\frac{j2\pi}{N}mk}, \quad k = 0 \ldots\ldots N-1 \qquad (1)$$

The transform is performed along two integer dimensions: m and k, thus having quadratic complexity. In order to reduce its computation the Fast Fourier Transforms were developed. The proposed system applies a specific implementation of the FFT developed by Frigo and Johnson, called FFTW.

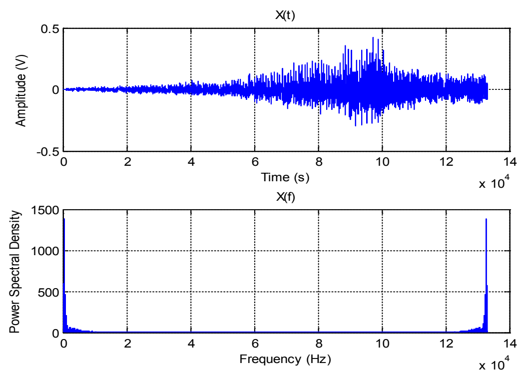

Figure1: Power spectral density of a bike.

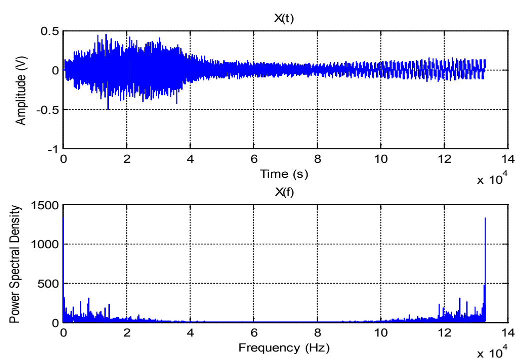

Figure2:power spectral density of a car.

The resulting frequency spectrum [X(0), X(1),...,X(N-1)] is symmetrically divided into complex conjugate "positive" and "negative" frequencies

2.2 Instantaneous Feature Extraction

The signals that are collected from the different data the signal properties several features are extracted from the amplitude frequency spectrum. The four spectral features considered in this paper are extracted from the absolute magnitude spectrum frame X (k) of length K.

Root Mean Square (RMS) Energy of the power spectrum conveys the general spectral energy level:

$$X_{RMS} = \sqrt{\frac{1}{K}\sum_{k=1}^{K}|X(k)|^2} \quad (2)$$

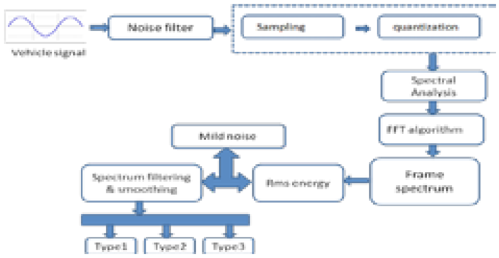

Figure 3: Block Diagram of algorithm for vehicle detection and classification.

2.3 Lower Energy Threshold

The first stage of the hierarchical procedure is the estimation of sufficient signal energy. The energy level of a signal frame is calculated and compared to the lower energy threshold, if the threshold is not exceeded, the procedure terminates and the frame is marked as mild noise. The estimation of the lower energy threshold occurs during algorithm parameter estimation by means of test signal analysis. The initial threshold is chosen as the minimal value of RMS energy of all the frames that correspond to vehicle passing instances.

3.COMPLEXITY MINIMIZATION OF ALGORITHM

Using a power of two as the signal frame length also reduces computation complexity due to the fact that in this case many multiplications and divisions are replaced by simpler and faster bitwise arithmetic shifts.

A. First Test Signal

The first test audio signal was measured using a microphone and digitized using audio signal processor at 44.1 kHz sampling rate in mono channel mode and saved in a Waveform Audio File (WAV) format. For the acquisition of the test signal a microphone was placed at an empty parking lot and two cars (swift vdi and hyundai verna) were in turn passing the microphone stand at a speed of 35- 45km/h at the passing point, starting to accelerate from a distance of approximately 40 meters. Each car has overall passed the microphone three times: the swift first three passes and the hyundai second three passes. And bajaj pulser (180cc) and karizma(225 cc)passes. The sounds were acquired during summer time in mild weather conditions.

B.Second Test Signal

The second test signal was acquired using a miniature condenser microphone (256MB RAM, 4GB microSD). The signal was also sampled at 44.1 kHz mono channel mode and saved to a WAV For the acquisition of the test signal a microphone was placed at an empty parking lot and two bikes were in turn passing the microphone. Each bike bajaj pulser (180cc) and karizma(225 cc)1 for passenger cars and 2 for trucks and busses. Feature vectors comprise of eight features, which are the same as for the first signal, except the bands for the band energy features are less spread: 44440-42010, 44320-44100, 4215-4100, 6438-14780 Hz.

The results are as follows: out of 46 instances of class 1 vehicles, 37 were successfully detected and classified, 5 were undetected and 4 were confused with class 2; for instances of class 2 vehicles, 9 were correctly classified,

1 was not detected and 1 confused with class 1. Thus the classification accuracy for class1 vehicles is 80.43% and for class 2 – 81.82%. The vague differences between passenger and heavy cars of some vehicles lower the classification quality. A heavy truck can emit a noise loud enough for it to mask the sound of a nearer lighter car thus making it undetectable.

Table1: sample collection of trained data.

Type of vehicle	Vehicle Model	Vehicle is on motion with noise (hZ)	Vehicle is stop condition with out noise (hz)	Duration In sec
Two wheeler	Bajaj pulser(180cc)	44410	4400	0.7
Two wheeler	Karizma(225 cc)	44320	4100	0.6
Four wheeler	Hyundai fludic verna(1600cc)	4805	4100	0.29
Four wheeler	Maruti swift(1250cc)	4215	3989	0.31
Four wheeler	Bmw	3908	3200	0.21

For testing, the frame length of 44410hz,44320hz samples is chosen, which corresponds to 0.7,0.3 seconds at a sampling rate of 44.1 kHz.. The reference spectral vectors used in correlation analysis are estimated by averaging several spectra of sounds produced by vehicles of the same class, in total one reference vector per class is applied. After the conversion of spectrum and the wav signals are converted to text signals and those text signals are converted .they are in time domain signals are converted into frequency domain signals are finding the RMS energy value we can classify the type of the vehicle. Implemented on DSP kit and algorithm and trained to identify the general vehicle feature space, succeeds in doing so for the majority of signal frames thus allowing the correlation.

c.Testing Results

The algorithm operates well in both the cases of motor vehicles passing with a certain time interval between the passes and heavy traffic. The influence of background noise, such as wind, is reduced due to the algorithm's multistage decision making logic. Thus the algorithm is applicable under different weather conditions. In these paper we discussed about RMS energy and by finding

the power spectral density of a bike and car and truck to get more accurate . By using more parameters can find more accurate .This provides the opportunity to apply the algorithm for classification of various types of moving objects not limited to motorized vehicles.

4.CONCLUSION

The algorithm is developed specifically for real-time application and is therefore computationally inexpensive and simple in computation. results indicate the algorithms potency in the task of detecting and classifying motor vehicles. For future developments algorithm we find more accurate to classify the vehicle. The final class label therefore may be decided based on degrees of membership.

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