A Hybrid Approach for Acoustic Signal Segmentation by Computing Similarity Matrix, Novelty Score and Peak Detection for Vehicular Classification in Wireless Sensor Networks

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Abstract— **Vehicle acoustic signals have long been considered as significant source in sensor networks for classification. In this research acoustic signals generated by each vehicle will be used to detect its presence and classify the type. Vehicle acoustic signal segmentation is important for continuous signal recognition because it reduces the search space effectively in vehicle's signal recognition. However, for Vehicle classification, it is difficult to segment the signal input reliably into useful sub-units because i) vehicle sound units can often be located roughly via intensity changes ii) energy changes in signal spectrum or amplitude help to estimate unit boundaries, but these cues are often unreliable. In this paper the series of steps proposed are signal segmentation is presented. includes decomposition of signals into successive frames of 50 ms without overlap. The computations of the spectrum representation (FFT) of the frames are carried out. The similarity matrix that shows the similarity between the spectrums of different frames is computed. Estimation of the novelty score related to the similarity matrix is done. The detection of the peaks in the novelty score is made and finally segmenting the vehicle acoustic signals using the peaks as position is done. These segmented signals are further used for feature extraction and classification.**

Keywords— **vehicle acoustic signals; signal segmentation; peak detection; vehicle classification; wireless sensor networks.**

I. INTRODUCTION

Vehicle Identification in Wireless Sensor network (WSN) is an important application in Battlefield surveillance. The development of wireless sensor networks was originally motivated by military applications like battlefield surveillance. However, Wireless Sensor Networks are also used in many areas such as industrial, civilian, Health, Habitat Monitoring, Environmental, Military, Home and Office application areas [1]. The Wireless Sensor Networks comprise of relatively inexpensive sensor nodes capable of collecting, processing, storing and transferring information from one node to another. These nodes are able to autonomously form a network through which sensor readings can be propagated. Since the sensor nodes have some intelligence, data can be processed as it flows through the network. Sensing devices will be able to monitor a wide variety of ambient conditions: temperature, pressure, humidity, soil makeup, vehicular movement, noise levels, lighting conditions, the presence or absence of certain kinds of objects, mechanical stress levels on attached objects and so on [2]. These devices will also be equipped with significant processing, memory and wireless communication capabilities. Emerging low-level and low-power wireless communication protocols will enable us to network these sensors. This capability will add a new dimension to the capabilities of sensors: Sensors will be able to coordinate among themselves on a higher-level sensing task. Visual image processing is widely applied in vehicle identification. This approach, however, may not be suitable for sensor networks because a large volume of data needs to be processed and occupies more memory space as the sensor has only limited built in memory. Finally, vehicle identification using sound is the most promising approach. So the vehicle acoustic signals as a wav file can be used for vehicle identification. These vehicle acoustic signals are preprocessed and segmented. Segment the preprocessed signals using the peaks as position for segmentation. The segmented signals are further used in feature extraction. The extracted features are used in the classification system. The remainder of the paper is organized as follows. Section II describes about the vehicle acoustic signals. Section III gives methodology used in signal segmentation. Section IV discusses about the experiments and results. Section V concludes the paper.

II. VEHICLE ACOUSTIC SIGNALS

In this study, the acoustic signals are used as a source for vehicle identification. These acoustic signals are captured by the acoustic sensors mounted in the field as well as on the vehicle. The acoustic sensor in the Smart Dust sensor node is a condenser type microphone. The schematic for a typical condenser acoustic sensor [3] [4] is shown in figure 1. It includes a stretched metal diaphragm that forms one plate of a capacitor. A metal disk placed close to the diaphragm acts as a backplate. A stable DC voltage is applied to the plates through a high resistance to keep electrical charges on the plates. When a sound field excites the diaphragm, the capacitance between the two plates varies according to the variation in the sound pressure. The change in the capacitance generates an AC output proportional to the sound pressure, which is an ultra low-frequency pressure variation. A high-frequency voltage (carrier) is applied across the plates and the acoustic sensor output signal is the modulated carrier. The Figure 2 shows a typical vehicle acoustic signal waveforms.

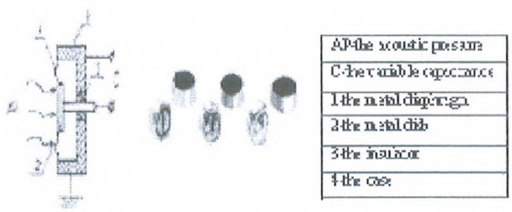

Figure 1: Condenser Microphone

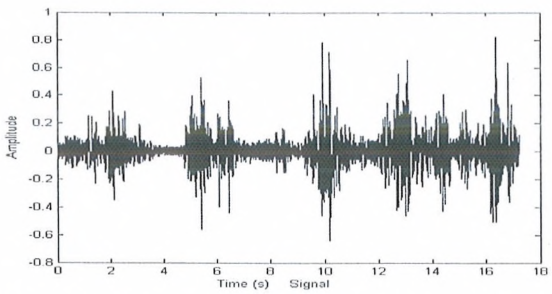

Figure 2: Waveforms of Acoustic Signals Emitted from a Truck

However, the overall acoustic signal of a running vehicle is often much more complicated; the vehicle's sound may come from multiple sources, not exclusively by the engine, but also from tires, brakes, etc. The acoustic signature is made up of a number of individual elements [6]. These include:

- Machinery noise: noise generated by a vehicle engines, propeller shafts, fuel pumps, air conditioning systems, etc.
- Cavitation noise: noise generated by the creation of gas bubbles by the turning of a ship's propellers.
- Hydrodynamic noise: noise generated by the movement of water displaced by the hull of a moving vessel.

These emissions depend on a hull's dimensions, the installed machinery and ship's displacement. Therefore different vehicle classes will have different combinations of acoustic signals that together form a unique signature.

III. Acoustic Signal Segmentation Methodology

Signal segmentation is an important phase in signal processing. It simplifies the complicated signals into simple signal segments [7] [8]. These segments are easy to process and give the valuable information. The methodology used in signal segmentation is depicted in the figure 3. The first step in signal segmentation includes the decomposition the vehicle acoustic signals into successive frames of 50 ms without overlap. These frames are used to compute the spectrum representation (FFT). Once the spectrum representation is done for each signal frames the Computation of the similarity matrix is done that shows the similarity between the spectrums of different frames. The estimate of the novelty score related to the similarity matrix is accomplished. It consists in a convolution of the diagonal of the matrix with a checker-board Gaussian kernel. Peaks are detected in the novelty score. Segment the preprocessed signals using the peaks as position for segmentation. The segmented signals are further used in feature extraction. For each of the frame sequence the following steps are done. Once the signals are segmented these segments are included into the feature extraction phase. The steps included in the segmentation is,

- Decomposition of frames
- Computation of FFT
- Compute Similarity Matrix
- Novelty Score Estimation
- Detect peaks in Novelty Score
- Segment Signal using Peaks

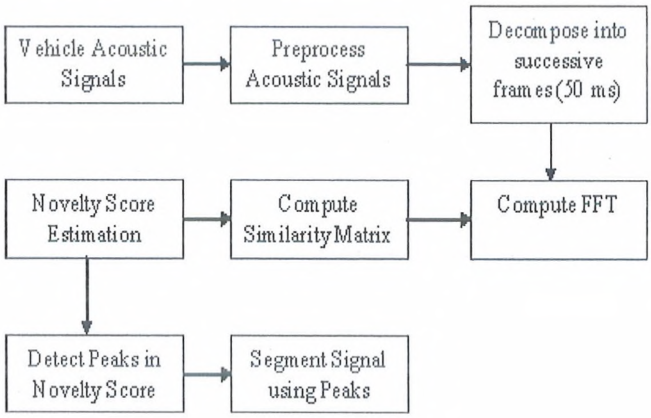

Figure 3: Methodology for Signal Segmentation

A. *Decomposition of frames*

Consider breaking an input signal 'x' into frames using a finite, zero-phase, length 'M' window 'w'. Then the 'm'th windowed data frame as,

$$\hat{x}_m(n) = \qquad - \qquad \in -\infty +\infty \tag{1}$$

or

$$\hat{x}_m = \qquad {}_m R(w) \tag{2}$$

Where, $\hat{R} = \qquad ep(hopsize)$

$\hat{m} = \qquad dex$

The hop size is the number of samples between the begin-times of adjacent frames. Specifically, it is the number of samples by which advances each successive window.

Figure shows an input signal (top) and three successive windowed data frames using a length M=128 causal Hamming window and 50% overlap (R=M/2=64).

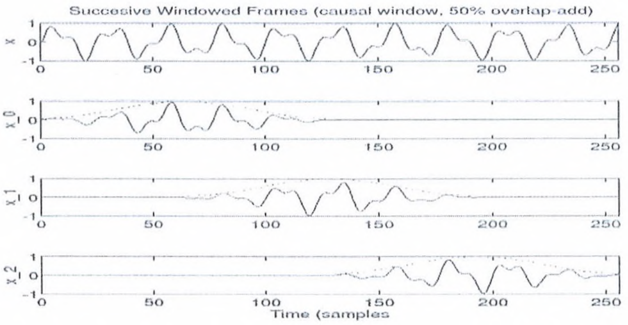

Figure 4: Input signal(top) and three successive windowed data frames

B. Computation of FFT

An FFT computes the DFT and produces exactly the same result as evaluating the DFT definition directly; the only difference is that an FFT is much faster. In the presence of round-off error, many FFT algorithms are also much more accurate than evaluating the DFT definition directly. Let x0,.....xN-1 be complex numbers. The FFt is defined by the formula,

$$X(k) = \sum_{j=} \qquad K=0,\ldots,N-1 \qquad (3)$$

Where, $\omega \; =$ is an Nth root of unity.

C. Compute Similarity Matrix

Similarity matrix is a matrix of scores which express e similarity between two data points. Similarity matrices are strongly related to their counterparts, distance matrices and substitution matrices. The elements of a similarity matrix measure pairwise similarities of objects - the greater similarity of two objects, the greater the value of the measure. These data can be viewed in graphic form as heat map.

By partitioning a signal 'x' into 'L' non-overlapping intervals of equal length, the use of element sij of similarity matrix,

$$(SM)S = \qquad \leq \quad \leq \qquad (4)$$

to represent the similarity degree between interval 'i' and interval 'j'.

D. Novelty Score Estimation

Novelty score is estimated from the similarity matrix. The novelty score is computed by two steps [4]. First, a similarity matrix is constructed by measuring the similarity of the low-level feature vectors. In this matrix, the two segments beside the boundary produce two adjacent square regions of high within-segment similarity along the main diagonal and two rectangular regions of low between-segment similarity off the main diagonal. As a result, each boundary produces a checkerboard pattern in the matrix and the interval that boundary occurs is the crux of this checkerboard. To identify these patterns, the correlation of a Gaussian-tapered checkerboard kernel along the main diagonal of the similarity matrix is considered. To compute the so-called novelty scores, this measures both the dissimilarity between two different adjacent segments beside each potential boundary as well as the similarity within these segments. The term segment is defined here to represent a set of consecutive intervals and the term section as a segment which is semantically meaningful.

E. Detect peaks in Novelty Score

In this step the peaks are detected from the estimated novelty score. The local maxima and minima are found in the signals here the maximum absolute values are known as peaks. These maximum absolute values are detected in the novelty score.

F. Segment Signal using Peaks

The signals are segmented based on the peaks estimated through the novelty score.

IV. Experiments and Results

Acoustic Signal Segmentation is an important source in signal classification. There are sequences of steps included in signal segmentation. The discussed steps are implemented for all the signals. Figure 4 shows the decomposition of the vehicle acoustic signal into successive frames of 50 ms without overlap. Figure 5 shows the spectrum representation (FFT) of the frames. Then the similarity matrix is computed that shows the similarity between the spectrums of different frames which is shown in Figure 6. The estimation of the novelty score related to the similarity matrix is shown in Figure 7. It consists in a convolution of the diagonal of the matrix with a checker-board Gaussian kernel. Figure 8 shows the peaks in the novelty score. The signal is segmented using the peaks as position which is shown in Figure 9.

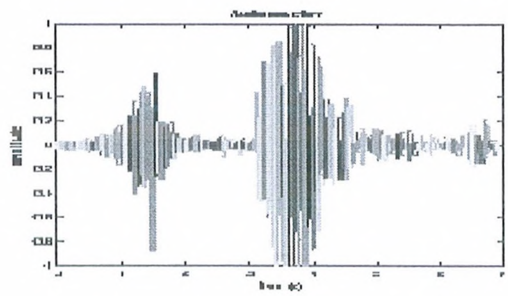

Figure 4: Acoustic Signal Frames of 50 ms

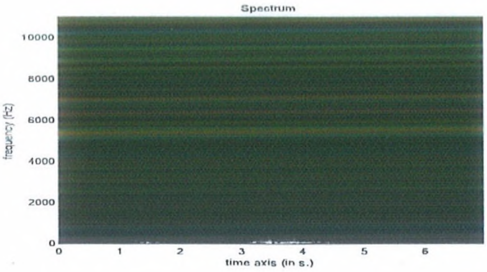

Figure 5: Spectrum Representation (FFT) of Frames

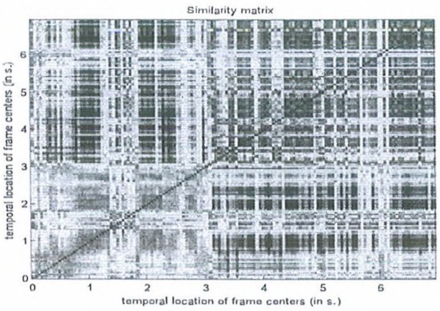

Figure 6: Similarity Matrix of each frame

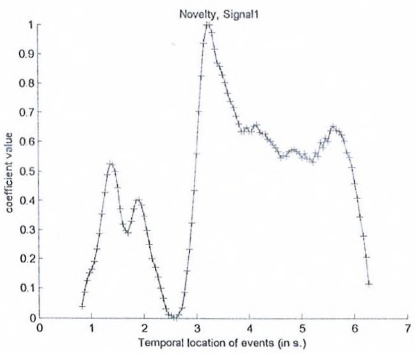

Figure 7: Novelty Score

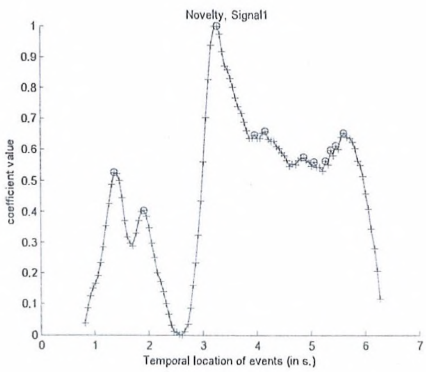

Figure 8: Peaks in Novelty Score

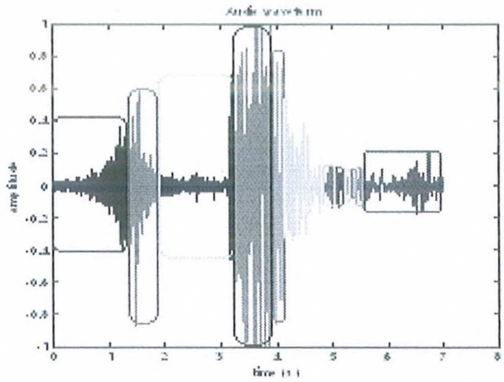

Figure 9: Acoustic Signal Segments

When the vehicle acoustic signal is segmented and the segments are included into the feature extraction phase. The feature considered here are,

- Short-Time Energy
- Entropy
- Spectral Centroid
- Spectral Flux
- Spectral Rolloff

The extracted features are further used in neural network based classifier for vehicular classification.

V. Conclusion

Vehicle acoustic signals have long been considered as significant source in sensor networks for classification. Vehicle acoustic signal segmentation is important for continuous signal recognition because it reduces the search space effectively in vehicle's signal recognition.

In this paper, a hybrid segmentation method that utilizes the Similarity Matrix, Novelty Score and Peak Detection. Furthermore, hamming short-time sliding-windows is applied on audio signals to get more obvious novelty score. These segmented signals are further used for feature extraction and classification.

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References

[1] Lan F. Akyildiz and et al., "A Survey on Sensor Networks," IEEE Communication Magazine, August 2002.

[2] F. L. Lewis, "Wireless Sensor Networks," Smart Environments: technologies, protocols, and Applications, John Wiley, New York, 2004.

[3] G. E. Sleefe, S. Peglow, and R. Hamrick, "The application of unattended ground sensors to stationary targets," in Peace and Wartime Applications and Technical Issues for Unattended Ground Sensors. SPIE, July 1997, vol. 3081, pp. 21–29.

[4] Jiagen Ding, Sing-Yiu Cheung, Chin-Woo Tan and Pravin Varaiya, "Signal Processing of Sensor Node Data for Vehicle Detection," IEEE Proceedings on International Intelligent Transportation Systems Conference, October 2004.

[5] Marco F. Duarte and Yu Hen Hu, "Vehicle Classification in Distributed Sensor Networks," Journal of Parallel and Distributed Computing, vol. 64 , issue 7, July 2004.

[6] Tatiana Bokareva, and et al. "Wireless Sensor Networks for Battlefield Surveillance," Proceedings of Land Warfare Conference 2006, Brisbane October 2006.

[7] A. Ukil, Student Member, IEEE and R. Živanović Member, IEEE "Automatic Signal Segmentation based on Abrupt Change Detection for Power Systems Applications", Power India Conference, 2006 IEEE

[8] Xufang Zhao, Douglas O'Shaughnessy, "A New Hybrid Approach For Automatic Speech Signal Segmentation Using Silence Signal Detection, Energy Convex Hull, And Spectral Variation", IEEE, 2008

[9] Glass, J.R.; Zue, V.W. "Multi-level acoustic segmentation of continuous speech", International Conference on Acoustics, Speech, and Signal Processing, 1988. ICASSP-88., 2002

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