2013 IEEE 10th International Conference on Ubiquitous Intelligence & Computing and 2013 IEEE 10th International Conference on Autonomic & Trusted Computing

Vehicle type recognition in WSN based on ITESP Algorithm

Yan Wang
Department of Electronic and Information Engineering
Sichuan University, SCU
Chengdu, China

Jiliu Zhou*
Department of Computer Science
Sichuan University, SCU
Chengdu, China

***Abstract*—Vehicle type recognition is a demanding application of wireless sensor networks (WSN). In context of applying the sound recognition technology on the vehicle type recognition, in this study, a new feature extraction method is proposed based on the improved time encoded signal processing (ITESP) algorithm. The conventional TESP algorithm, which is effective for the speech signal feature extraction, however, is not suitable for the vehicle sound signal which is more complex. To solve this problem, we design an extensional symbol table with 40 characters according to the characteristic features of the vehicle sound signal, and then construct the one-dimensional S-matrix and the two-dimensional A-matrix respectively based on the symbol stream which is encoded by the symbol table. After that, support vector machine (SVM) is used as the classifier to recognize different vehicle types. The simulation results indicate that the vehicle type recognition systems with ITESP features give better performance compared with the conventional TESP based features.**

Keywords—vehicle type recognition; improved time encoded signal processing (ITESP); symbol table; S-matrix; A-matrix

I. INTRODUCTION

Along with the development of communication technology, wireless sensor network (WSN) is playing an increasingly important role in our daily life. Recent advances in wireless communications, electronics and ubiquitous computing, in combination with intensive research on the field of WSN, have changed the way we interact with the physical environment. Vehicle type recognition, which can be used in intrusion detection, transportation and border monitoring, is a significant and demanding application of WSN [1]. In most cases, the using of fast Fourier transform (FFT), wavelet transform (WT) and Hilbert-Huang transform (HHT) to extract the frequency or time-frequency features of the signals acquired from the acoustic and seismic sensors, are common approaches for the vehicle recognition [2-4]. These methods, while providing convincing results, are quite demanding in computational power and energy. However, in WSN, the sensor nodes process signals locally to come to a decision rather than transmitting the measurements. Due to network bandwidth limitation and energy consumption of sensor nodes, we usually wish to use low-complexity and low-energy consumption algorithms to recognize the vehicle type [5]. In this paper, we investigate a novel feature extraction method based on time domain, known as the improved time encoded signal processing (ITESP) algorithm. The conventional time encoded signal processing (TESP) algorithm, which uses a symbol table with 29 characters to encode the time-domain information of the signal, has been performed well in speech recognition [6]. However, it turns out that TESP is not suitable for the vehicle sound signal which is more complex. To solve this problem, the improved time encoded signal processing feature extraction method is proposed for the vehicle sound signal recognition. Fig.1 shows the flow chart of vehicle type recognition system based on ITESP algorithm.

This work is supported by the grants from the National Science Foundation of China (No. 61272448, 61302028), STMSP project (No. 2012RZ0005) and the Foundation of Sichuan University Early Career Researcher Award (No. 2012SCU11036, 2012SCU11070).

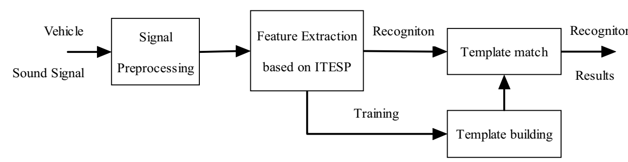


Fig.1 Flow chart of vehicle type recognition system based on ITESP algorithm

II. METHODOLOGY

A. TESP algorithm

TESP is a digital language that originated as a means of coding signals for speech recognition, and it describes signal waveforms according to its real and complex zeros based on a mathematical waveforms representation. TESP quantisation procedure has been developed to encode signals according to the period between two consecutive zero-crossings and the shape of the curve thus contained [7]. This period is named an epoch. The TESP procedure can be described using four simple steps:

Step 1: divide the signal into successive epochs.

Step 2: characterize each epoch with two descriptors, duration and shape:

- Duration (D) which is the number of samples between two successive real zeros and provides information on the fundamental frequency of the waveform.
- Shape (S) which is the number of local minima (for a positive epoch) or the number of local maxima (for a negative epoch). The shape of an epoch contains harmonic information of the signal.

Step 3: map each epoch, from its corresponding D/S descriptors, to a predefined symbol table.

Step 4: create a fixed-dimensions matrix (S-matrix) containing the appearance probability of each symbol in the entire waveform. This matrix will be used for the recognition task.

978-1-4799-2481-3/13 $31.00 © 2013 IEEE
DOI 10.1109/UIC-ATC.2013.29

Fig. 2 shows an epoch encoded into its TESP parameters where D=17 and S=2.

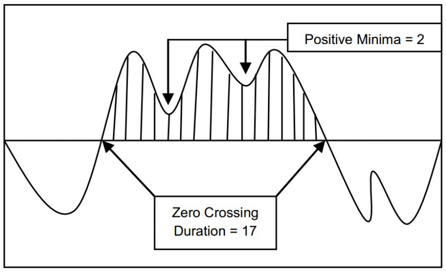


Fig.2 TESP single epoch with D=17, S=2

B. ITESP algorithm

In conventional TESP algorithm, the standard symbol table, which contains 29 characters, has been found to be sufficient for speech signals description, but may not be enough for the vehicle sound signals which is more complex. According to the characteristic features of the vehicle sound signals, an extensional symbol table with 40 characters is designed in this paper, and then the one-dimensional S-matrix is constructed based on the symbol stream which is encoded by the symbol table. Meanwhile, using the appearance probability of the two identical consecutive symbols, the two-dimensional A-matrix is constructed as well in order to obtain more accurate features of the signal. The flow chart of feature extraction procedure based on ITESP algorithm is shown in Fig. 3.

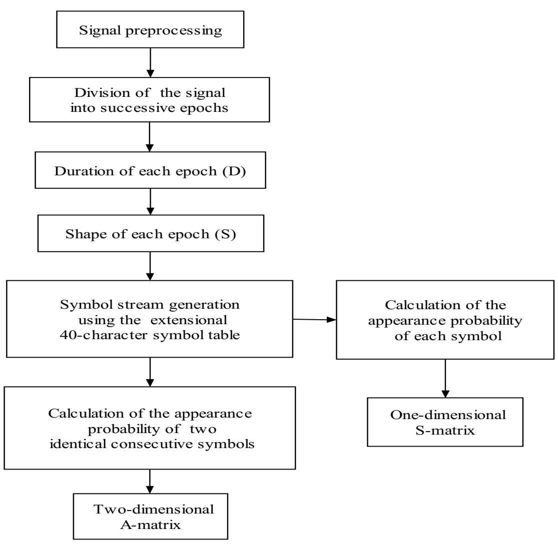


Fig.3 Flow chart of feature extraction based on ITESP algorithm

III. SIMULATION EXPERIMENT OF FEATURE EXTRACTION

A. Data acquisition

In this paper, the sound signals of two typical vehicle types (wheeled vehicles and tracked vehicles) are selected as samples to evaluate the performance of the feature extraction method. The wheeled vehicles sound signals were recorded during a real world WSN experiment at Chengdu, China, and the data set was gathered from 15 microphone and passive infra-red sensors which were deployed at three different roads. All the signals studied were sampled at 22050 Hz and quantized with 8 bits per sample. Since most of the tracked vehicles are military vehicles which are difficult for acquisition in real environment, the sound signals of tracked vehicles were downloaded from the sensor website.

B. Signal preprocessing

To reduce the complexity of data processing, the down-sampling frequency of 4096Hz is firstly employed. Moreover, the vehicle sound signals must be filtered before the encoding procedure for three main reasons [8]:

- To minimize the number of symbols needed for the symbol table by keeping only the important frequency range of the signal. In this way the dimensions of the S matrix is minimized.
- To eliminate high frequency “flicker” on the waveform which can be translated to local minima or maxima inside an epoch, thus increasing its S descriptor.
- To prevent the introduction of quantization noise.

By analyzing the main noise source of the sound signals, we find that the frequencies of the vehicle sounds are mainly below 800Hz. Therefore, an 800Hz low-pass Butterworth filter is employed accordingly. Furthermore, frequency components below 50Hz for the vehicle sound signals are not very important in recognition task [9]. Such low frequency signals can be ignored without decreasing performance, which can significantly reduce the maximum value of D descriptor.

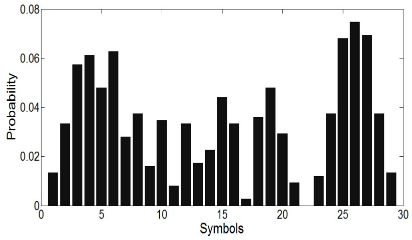
C. Feature extraction based on ITESP

1) One-dimensional S-matrix

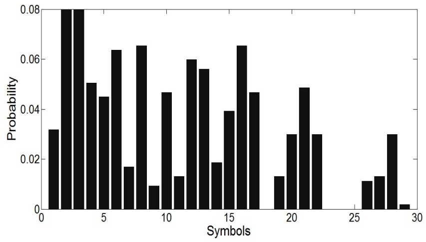
The recognition performance and the S-matrix length depend on the symbol table used. In most cases of speech recognition, a standard 29-character symbol table shown in Table 1 is employed, allowing for a maximum D of 35 and a maximum S of 5. The standard symbol table is optimized for speech signals, however, its performance in vehicle sound signals should be examined. Fig. 4 shows the S-Matrices of the two types of vehicle sound signal based on 29-character symbol table.

TABLE I. STANDARD SYMBOL TABLE USING 29 CHARACTERS

D↓/S→	**0**	**1**	**2**	**3**	**4**	**5**
1	1					
2	2	2				
3	3	3	3			
4	4	4	4	4		
5	5	5	5	5	5	
6	6	6	6	6	6	6
...	...	...	...	...	...	...
34	24	25	26	27	28	29
35	24	25	26	27	28	29



(a) wheeled vehicle



(b) tracked vehicle

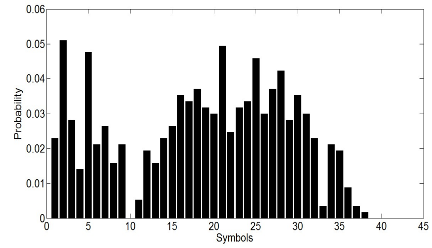
Fig.4 S-Matrices of the two types of vehicle sound signal based on 29-character symbol table

As can be seen from Fig. 4, the differences between the appearance probabilities for the two-type sound signals are small and scattered, which could not be used to obtain high recognition rate in theory. The main reason of the undesirable S-matrices is that the standard 29-character symbol table is not suitable for the vehicle sound signal which is quite different from the speech signal in frequency distribution. Compared with speech signal, the low-frequency part of vehicle sound signal is lower, which means more D is needed to describe the waveforms. Besides, the vehicle sound signal contains more harmonic component, consequently, the numeric values of S should be a little larger. According to the characteristic features of the vehicle sound signal, an extensional symbol table using 40 characters is designed to obtain more effective S-matrix. Table 2 shows the extensional 40-character symbol table.

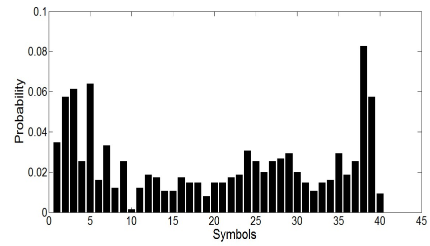
TABLE II. EXTENSIONAL SYMBOL TABLE USING 40 CHARACTERS

D↓/S→	0	1	2	3	4	5
1	1					
2	1	1				
3	2	2	2			
4	3	3	3	4		
5	4	4	5	5	5	
6	5	5	6	6	6	6
...	...	...	...	...	...	...
36	34	35	36	37	38	39
37	35	36	37	38	39	40

Compare with Table I, the characters of the extensional symbol table in Table II change more frequently with the increase of D and S, resulting in higher separability of different D/S descriptors. For the vehicle sound signal that contains more harmonic information, using the extensional symbol table can obtain more time-domain features of the signal. The S-Matrices of the two types of vehicle sound signal based on 40-character symbol table are shown in Fig. 5.



(a) wheeled vehicle



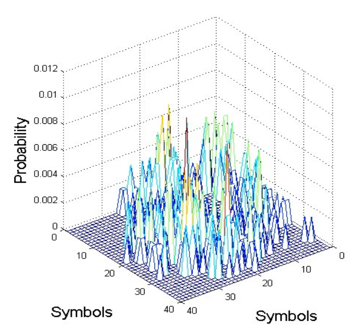
(b) tracked vehicle

Fig.5 S-Matrices of the two types of vehicle sound signal based on 40-character symbol table

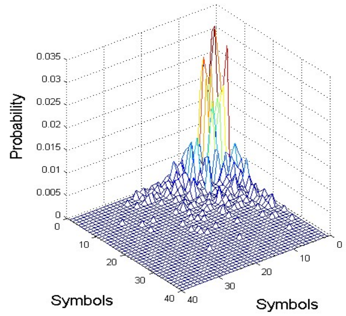
Fig. 5 indicates that, after encoding the signal using the 40-character symbol table, the symbol possesses enough difference for the different signals. Thus we can assume that S-matrices abstracted from wheeled vehicles and tracked vehicles are different enough to enable recognition.

2）Two-dimensional A-matrix

Using the extensional 40-character symbol table, the sound signal is encoded and a one-dimensional symbol stream is generated accordingly. In the previous section (3.2.1), the S-matrix is obtained by calculating the appearance probability of each symbol. In order to obtain more accurate time-domain features of the signal, we use the appearance probability of the two identical consecutive symbols to construct the two-dimensional A-matrix. Fig. 6 shows the A-Matrices features distribution of the two types of vehicle sound signal, where the x-axis and y-axis represent the symbols while the z-axis represents the appearance probability.



(a) wheeled vehicle



(b) tracked vehicle

Fig. 6 A-Matrices features distribution of the two types of vehicle sound signal

As can be seen from Fig. 6, the two-dimensional A-matrices of the wheeled and tracked vehicles sound signals present obvious feature distribution differences from each other. Compared with the one-dimensional S-matrix, A-matrix not only shows the probability features of each symbol, but also presents the spatial probability features of the symbols. Thus, more accurate time-domain features of the signal are obtained, which can further improve the recognition rate in theory.

IV. Recognition experimental results

After the extraction of the time-domain features from S-matrix and A-matrix based on ITESP respectively, the classifier is employed to evaluate the performance of the proposed algorithms. In this paper, the support vector machine (SVM) is designed as the classifier for the recognition system. SVM, originally introduced by Vapnik, has been shown to be effective in learning linear and non-linear decision boundaries. SVM performs classification by constructing an N-dimensional hyperplane that optimally separates the data into two categories. In fact, a SVM model using a sigmoid kernel function is equivalent to a two-layer, perceptron neural network. SVM has been used very successfully in recent years as a substitute to neural networks [10].

In the recognition experiments, the data set is randomly divided into two subsets, 30 for training and 50 for validation to study the recognition performance. The recognition rate is defined as the percentage ratio of the number of vehicle sounds correctly recognized to the total number of sounds considered for recognition. To evaluate the performance of the proposed ITESP algorithm, we take the conventional TESP algorithm based on 29-character symbol table for comparison. Table 3 shows the comparison of the recognition results using different feature extraction methods based on SVM classifier.

TABLE III. COMPARISON OF THE RECOGNITION RESULTS USING THREE FEATURE EXTRACTION METHODS BASED ON SVM CLASSIFIER

	Feature extraction methods		
	TESP	***ITESP algorithm***	
	29-character based S-matrix	40-character based S-matrix	40-character based A-matrix
Wheeled vehicles	52%	82%	90%
Tracked vehicles	50%	86%	84%
Average recognition rate	51%	84%	87%
Average computational time	0.82s	0.79s	2.37s

From Table III, we can see that the ITESP algorithm (including 40-character based S-matrix and 40-character based A-matrix) obtains much better recognition rate than TESP algorithm. Comparing with the recognition rate based on the conventional TESP algorithm (51%), the recognition rates using the proposed S-matrix and A-matrix are up to 84% and 87%, respectively. However, the computational time based on A-matrix (2.37 s) is longer than that of S-matrix (0.79 s). Therefore, the selection between the S-matrix and the A-matrix as the feature extraction method should depend on the actual demand of the recognition rate or the computational time.

V. Conclusion

In this paper, we presented a promising method for vehicle type recognition, using improved time encoded signal processing for signal encoding and support vector machine for classification. Experimental results indicated that the ITESP methods provided high recognition rates between two types of vehicles using their sound signature. Comparing with the feature extraction methods based on frequency domain and time-frequency domain analysis, such as FFT, WT and HHT, the ITESP algorithm needs less computational power and energy while providing high recognition rates. Our future work will focus on the recognition performance using more vehicle types, hardware implementation of the classifiers on the prototype sensor nodes and field testing of the system.

References

[1] D. Li, K. Wong, Y. Hu, and A. Sayeed, “Detection, classification, and tracking of targets,” Signal Processing Magazine, IEEE, 2002, pp.17-29.

[2] P. Chakraborty, S. Kumar, R. Ghosh, and K. Sardana, “Computational techniques for classification of military vehicles using seismic signatures,” Computing Communication & Networking Technologies (ICCCNT), 2012 Third International Conference on. IEEE, 2012.

[3] R. Lee and K. Hung, “Real-Time Vehicle License Plate Recognition Based on 1-D Discrete Periodic Wavelet Transform,” Computer, Consumer and Control (IS3C), 2012 International Symposium on. IEEE, 2012, pp.914-917.

[4] P. Gil-Jimenez, H. Gomez-Moreno, P. Siegmann and S. Lafuente-Arroyo, “Traffic sign shape classification based on Support Vector Machines and the FFT of the signature of blobs,” Intelligent Vehicles Symposium, IEEE, 2007, pp.375-380.

[5] M. Duarte and H. Hen, “Vehicle classification in distributed sensor networks,” Journal of Parallel and Distributed Computing, 2004, pp. 826-838.

[6] E. Lupu, Z. Feher, and P. Pop, “Speaker Verification Rate Study Using the TESPAR Coding Method,” In Proc. of COST 276 Workshop on Information and Knowledge Management for Integrated Media Communication, 2002.

[7] S. Abdusslam, M. Ahmed, P. Raharjo, F. Gu and A. Ball, “Time Encoded Signal Processing and Recognition of Incipient Bearing Faults,” Proceedings of the 17th International Conference on Automation & Computing, 10 September 2011.

[8] G. Mazarakis and J. Avaritsiotis, “Vehicle classification in sensor networks using time-domain signal processing and neural networks,” Microprocessors and Microsystems, 2007, 31(6)pp.381-392.

[9] H. Wu, M. Siegel, P. Khosla, “Vehicle sound signature recognition by frequency vector principal component analysis,” Instrumentation and Measurement Technology Conference, IEEE, 1998,pp.429-434.

[10] Y. Wang, “Identification of normal and abnormal heart sound using wavelet-time entropy features based on OMS-WPD,” unpublished.