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Traffic volume detection based on vehicle noise

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Abstract

The Short-Term Energy Analysis (STEA) is a powerful method, capable of working with endpoint detection of vehicle acoustic signals (VASs). Many variations of the standard methodology have been proposed in recent years improving the performance or addressing specific shortcomings, however, some urgent problems remain unresolved. One of such issues occurs when adjacent VASs overlapped partially, hardly detecting the number of vehicles from overlapping VASs, hampering the method ability to maintain satisfactory endpoint detection. Also, another difficulty arises when traffic acoustic signals of multiple lanes are analyzed: some specific VASs cannot be detected. To circumvent these issues, a new method which combines the Spectrum and Short-Term Energy Analysis (SP-STEA) has been proposed. The SP-STEA method is first tested on sample data for which overlapping VASs and specific VASs of dual-lane are considered. It is then applied on complete data collected from dual-lane. This paper provides an implementation of this algorithm and some experiments are shown to illustrate the improvements achieved.

Keywords

Traffic detection; overlapping vehicle acoustic signals; short-term energy analysis; spectrum analysis; endpoint detection.

1. Introduction

As of day, there are two main approaches that are applied for traffic measurements: inductive-loop detector that is buried under a pavement and visual analyzing system based on installation of cameras above roads [1-2]. Inductive-loop detection has the advantages of low cost, convenient installation, high sensitivity and little influence of climate [3]. However, Inductive-loop detectors remain quite expensive and constraining because they require civil works and maintenance and cameras are expensive due to integration requirements in the infrastructure and to the complexity of video processing [4-5]. Compare to traffic monitoring systems based on image processing, the acoustic approach is not affected by lighting condition [6]. In view of these facts, the goal of this work is to detect traffic based on acoustic signals. Traffic acoustic signals (TASs), which are consist of vehicle acoustic signals (VASs) and environmental noise signals (ENSs), carry significant traffic parameter information and provide data support for the Intelligent Transportation System (ITS). In regard to the exploitation of TASs information, most papers focus on the traffic assessment [7-10]. Then the more specific topic of vehicle classification is presented [11-14].

Paper [15] presents measurement results recorded by noise and traffic volume monitoring station Krakowska Street, Kielce, Poland. Then a new parameter is proposed for variability assessment of the equivalent sound pressure level. In [16], several machine learning algorithms are used for addressing a prompt assessment of potential road-traffic-noise related problems, as well as for gathering information in order to take more well-founded actions against urban road-traffic-noise. In order to quickly and effectively evaluate the quality of an urban acoustic environment, paper [17] uses the traffic noise propagation model to predict instantaneous sound levels. Paper [18] focuses on the problem of selecting those sound-describing features that make the vehicle classifier work properly. The proposed method helps the Extreme Learning Machine-based classifier to increase its performance from a mean probability of correct classification of 74.83% (with no feature selection) up to 93.74% (when using the optimum subset of selected features). Paper [19] addresses automatic vehicle and engine identification based on audio information, and the experiments show that the error is below 15% for binary classifiers in most cases (with the exception of car) for on-road data, and in many cases improves after feature selection (below 5%, except bus for SVM and DL, and van for SVM), for 7 classes. A Time Delay Neural Network (TDNN) was chosen to classify individual travelling vehicles based on their speed-independent acoustic signature [20], and the experiments show that a TDNN network was successfully trained with 94% accuracy for the training patterns and 82.4% accuracy for the test patterns.

However, there is less research on traffic detection when VASs overlap each other. Paper [21] proposes an approach based on Local Spectrogram Features (LSFs) which represent local spectral information that is extracted from the two-dimensional region surrounding 'key points' detected in the spectrogram, and the experiments on a set of five overlapping sound events, in the presence of non-stationary background noise, demonstrate the potential of their approach. An endpoint-detection method based on short-term energy feature is proposed for the traffic detection [22], however, the overlaps between VASs are not considered. Therefore, aiming at the problem of overlapping VASs, the Spectrum and Short-Term Energy Analysis (SP-STEA) method is proposed.

2. METHODOLOGY

2.1. Sample data of TASs

The TASs data was recorded in a place located approximately at 1 m from the dual-lane. The measuring tools are respectively smartphone and sound recorder. The smartphone is used to video vehicle passing, and the sound recorder is used to record TASs data. Sample TASs are shown as Figure 1 in which the vehicle acoustic signal (VAS), the overlapping vehicle acoustic signals (VASs) and the environmental noise signal (ENS) are marked.

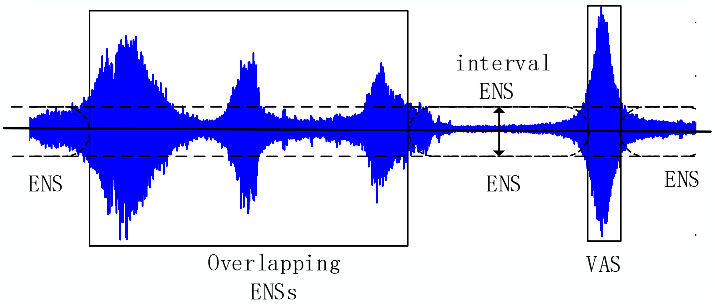

Figure 1 Traffic acoustic signal waveform.

2.2. Problems of STEA Method

Generally, the STEA method is used to detect traffic. The calculation of the Short-Term Energy (STE) is shown as formula(1),

$$E_i = \sum_{n=1}^{N} y_i^2(n) \tag{1}$$

where $y_i(n)$ represents the amplitude of the nth sample point of the i th signal frame, N represents the number of sample points of each signal frame.

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In terms of the STE feature, it can be seen from Figure 2 that the VAS is different from the ENS. The values of the STE feature of VAS are generally more than that of ENS, that is, the VAS can be easily recognized according to such rule. Meanwhile, in order to smooth the STE feature curve, the median filtering algorithm is applied.

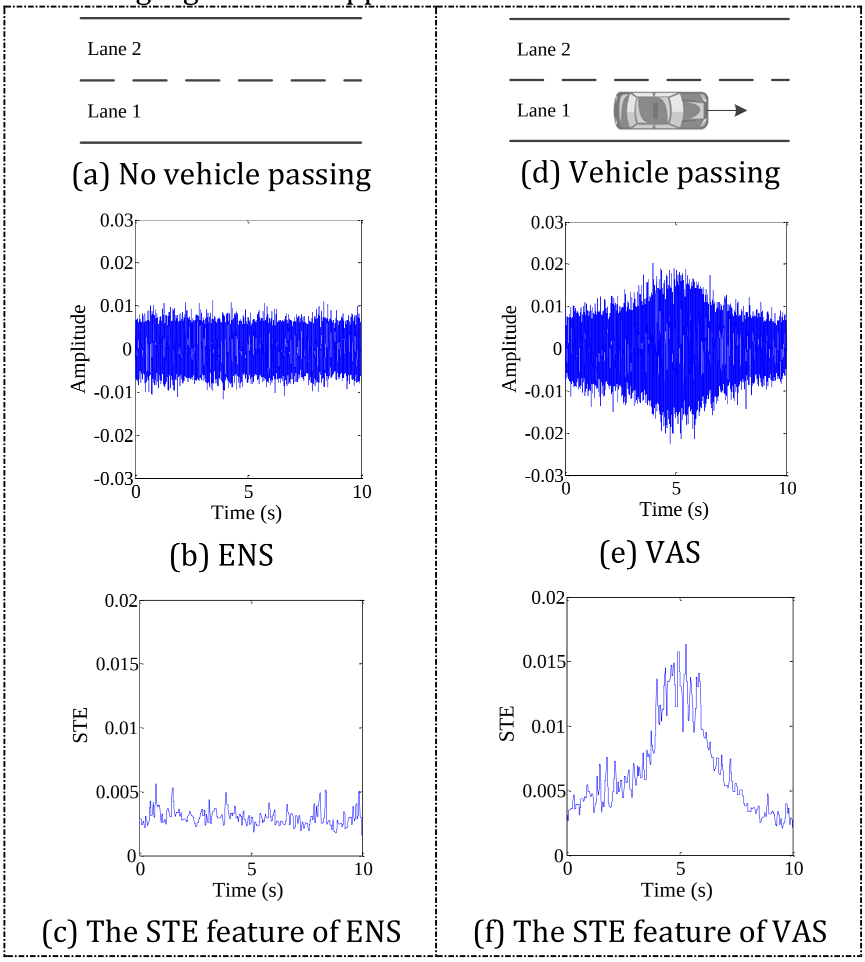


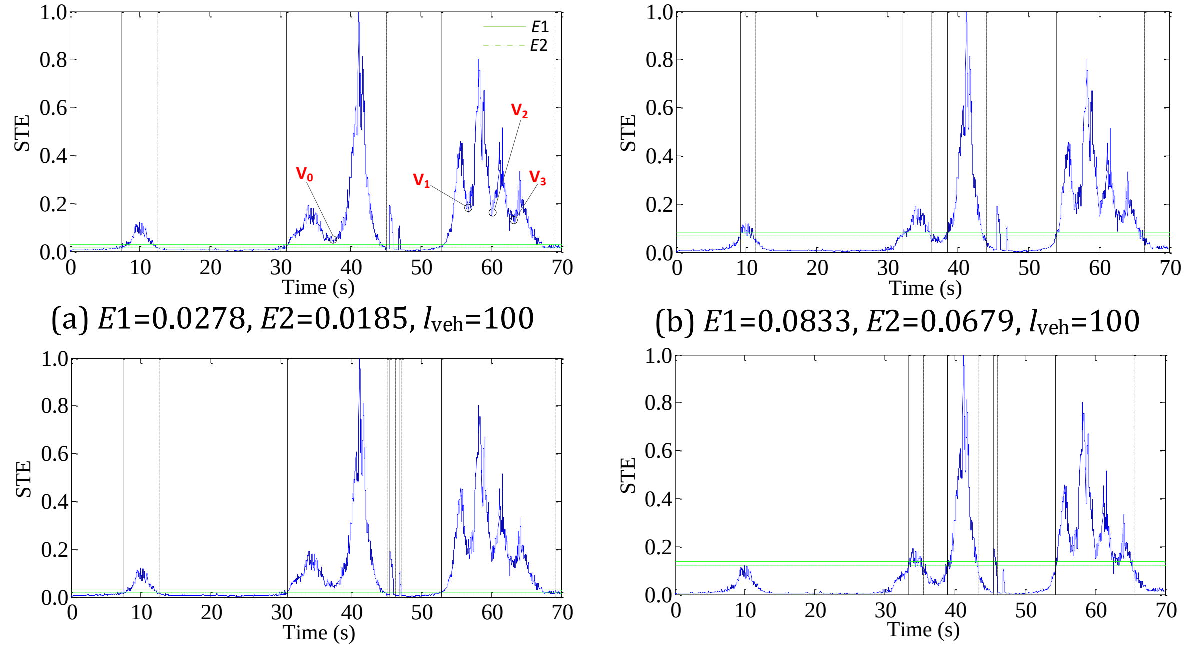
Figure 2 Difference of the STE feature between VAS and ENS.

Supposed that Q_0 represents the real number of vehicles in TASs, Q represents the number of vehicles which are detected, ε_r is the relative error limit of Q. E represents the STE feature of TASs, E_i is the feature value of the ith signal frame, $E1$ is the higher threshold while $E2$ is the lower one. The length of the VAS has a lower limit value l_{veh}. Similarly, the length of the ENS also has a lower limit value l_{noveh}. $E1$, $E2$, l_{veh} and l_{noveh} parameters can be adjusted. The STEA method works as follows:

1) Initialize $E1$, $E2$, l_{veh} , l_{noveh}, Q_0 , ε_r .

2) Firstly calculate E_i according to formula (1). Then based on the dual-threshold decision principle, adjust $E1$, $E2$, l_{veh} and l_{noveh} until $|Q-Q_0|\le\varepsilon_r$. Finally calculate every endpoint of the VAS.

3) Save $E1$, $E2$, l_{veh}, l_{noveh}, ε_r, Q and the endpoints of VASs. Here Q is the result of traffic detection that is detected by traffic noise.



(a) $E1$=0.0278, $E2$=0.0185, l_{veh}=100 (b) $E1$=0.0833, $E2$=0.0679, l_{veh}=100

(c) $E1$=0.0278, $E2$=0.0185, l_{veh}=30 (d) $E1$=0.1388, $E2$=0.1234, l_{veh}=30

Figure 3 Results of STEA method under different parameters.

The right result of traffic should be 9 vehicles, but the traffic detected by STEA method is not so, there is even bigger difference. In Figure 3 (a), the value of V_0 is more than or equal to $E1$, so the second VAS and the third VAS are detected as one VAS. In Figure 3 (b), the value of V_0 is more than $E2$, so the second VAS and the third VAS are detected correctly. In Figure 3 (c), l_{veh} parameter decreases from 100 to 30, so the fourth VAS and the fifth VAS are detected correctly. In Figure 3 (d), the peak values of the first VAS and the fifth VAS are less than or equal to $E2$, so they are not detected. Also, the last four VASs are not detected all the time, because the values of V_1, V_2 and V_3 are all more than the peak value of the first VAS. Therefore, the problem of STEA method is that the adjustment of parameters is useless for traffic detection in this situation.

2.3. The Propsed Method

The Fast Fourier Transform (FFT) of TASs, can provide more details for the analysis, FFT is shown as formula (2),

$$\begin{cases} Y_i(k)=\sum_{n=1}^{N} y_i(n)e^{-j2\pi(k-1)(n-1)/N} \\ k=1,2,\cdots, \quad N \end{cases} \tag{2}$$

where $Y_i(k)$ is the ith signal frame in frequency domain, $|Y_i(k)|$ is equal to $|Y_i(N-k+2)|$ when k is from 2 to N according to formula (2). Therefore, only $[N/2]_{\text{int}}+1$ sample points need to be processed. The frequency interval called Δf is equal to f_s/N, and f_s is the sampling frequency. The Spectrum View (SV) feature can be expressed as a matrix $\boldsymbol{A}_{sv}$ which is shown as formula (3),

$$\boldsymbol{A}_{sv}=[a_{ni}]_{N\times L}=\begin{pmatrix} |Y_1(1)| & |Y_2(1)| & \cdots & |Y_L(1)| \\ |Y_1(2)| & |Y_2(2)| & \cdots & |Y_L(2)| \\ \vdots & \vdots & \ddots & \vdots \\ |Y_1([N/2]_{\text{int}}+1)| & |Y_2([N/2]_{\text{int}}+1)| & \cdots & |Y_L([N/2]_{\text{int}}+1)| \end{pmatrix} \tag{3}$$

The time vector of $\boldsymbol{A}_{sv}$ is expressed by $\boldsymbol{t}$, and it is shown as formula (4). The frequency vector of $\boldsymbol{A}_{sv}$ is expressed by $\boldsymbol{f}$, and it is shown as formula (5). $\boldsymbol{t}^T$ represents the abscissa of $\boldsymbol{A}_{sv}$, and $\boldsymbol{f}$

represents the ordinate of $\boldsymbol{A}_{SV}$. $\boldsymbol{A}_{SV}$ uses two dimensional plane to express three dimensional information, so the amplitudes of points in $\boldsymbol{A}_{SV}$ are expressed by different colors. Deeper the color is, larger the amplitudes of the point of $\boldsymbol{A}_{SV}$ are.

$$\boldsymbol{t} = \frac{1}{f_s}\left((0,1,\cdots,\ L-1)^{\mathrm{T}} d_{\mathrm{inc}} + (1,1,\cdots,1)^{\mathrm{T}} [N/2]_{\mathrm{int}}\right) \tag{4}$$

$$\boldsymbol{f} = (0,1,\cdots,\ L-1)^{\mathrm{T}} \Delta f \tag{5}$$

According to formulas (2)~(5), SV feature of TASs is extracted and analyzed as Figure 5. It can be seen that the color of VAS is deeper than that of ENS. Meanwhile, the color of ENS is deeper only in lower frequency region, while the color of VAS is deeper continuously from lower frequency to higher frequency. According to the observation and analysis of Figure 4, the non-overlapping VASs can be identified directly. It can be seen that the "S" region has less information and its color depth is almost the same as that of ENS. Therefore, the overlapping VAS can be effectively separated by analyzing the "S" region's law.

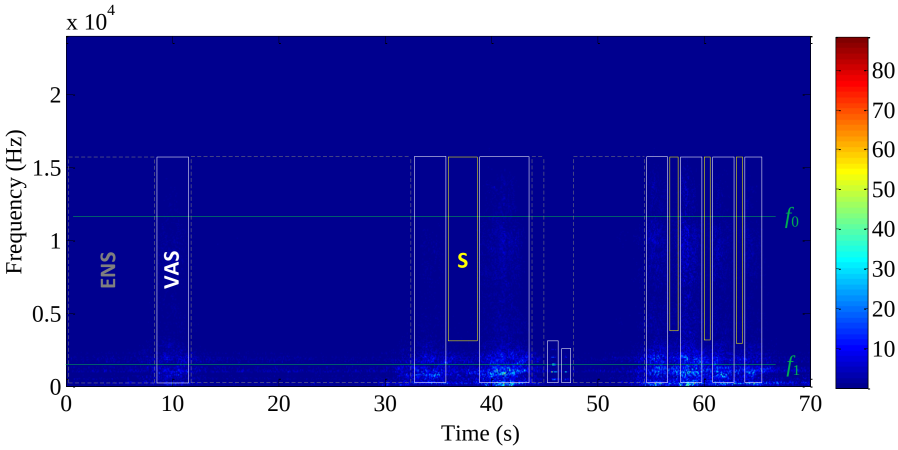


Figure 4 Analysis of SV feature.

3. Results

Take a dual-lane as an example, the complete TASs are collected by a sound detector. The sampling time is 600 s and the sampling frequency is 48 kHz. The experimental results show that it is more appropriate to analyze the TASs when the frame length is 25 ms (namely 1200 sample points) and the frame shift is 12.5 ms. TASs before and after being denoised by the spectral subtraction method are shown as Figure 5. We can count up the number of vehicles from video, finally we know the real number of vehicles is 35. That is, the hourly traffic is 420 veh/h.

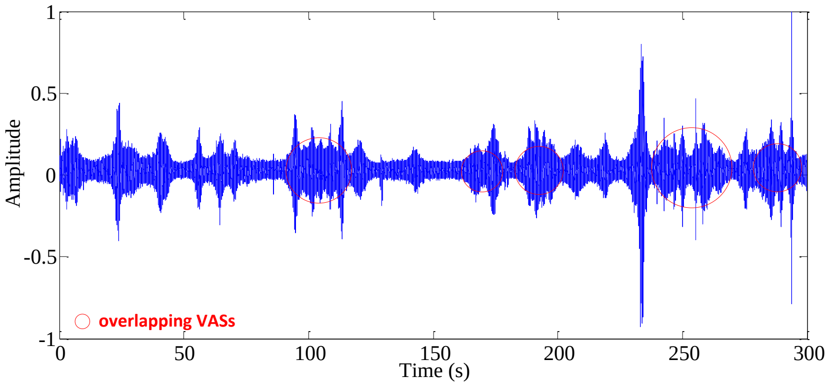


Figure 5 The complete TASs after being denoised.

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The traffic detected by STEA method is shown as Figure 6, and The traffic detected by SP-STEA method is shown as Figure 7. It can be seen that: The vehicles' number detected by STEA method is 14; the vehicles' number detected by SP- STEA is 26. The STEA method can hardly detect the overlapping VASs, however, the SP- STEA method can detect some overlapping VASs.

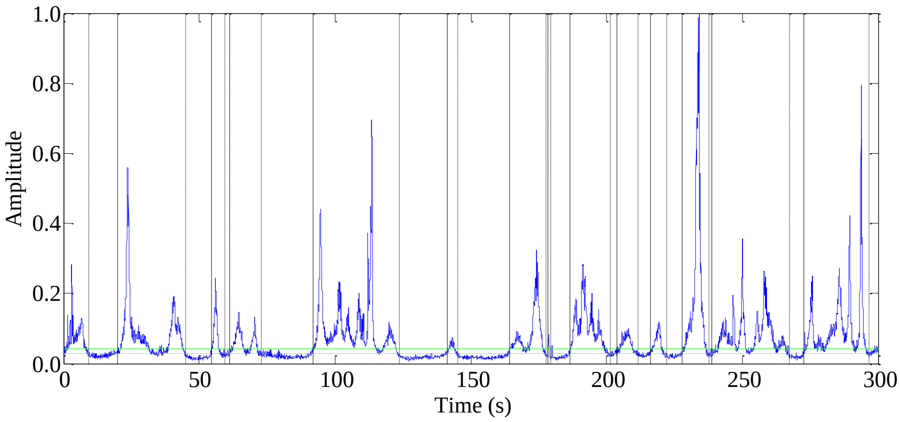

Figure 6 The result of traffic detection calculated by STEA method.

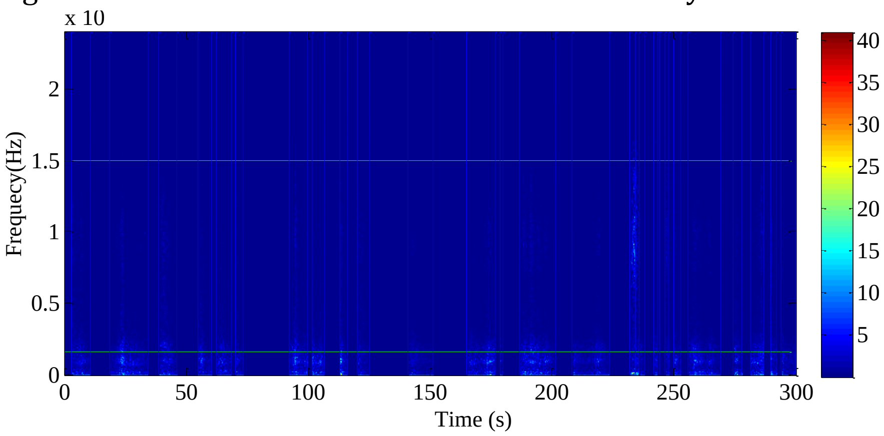

Figure 7 The result of traffic detection calculated by SP-STEA method.

The traffic detected by STEA method is shown as Figure 6, and The traffic detected by SP-STEA method is shown as Figure 7. It can be seen that: The vehicles' number detected by STEA method is 14; the vehicles' number detected by SP- STEA is 26. The STEA method can hardly detect the overlapping VASs, however, the SP- STEA method can detect some overlapping VASs.

Table 1: Traffic detection results under various methods

Method	Detected Traffic (veh/h)	Real Traffic (veh/h)	*e* (veh/h)	e_r (%)	accuracy rate (%)
STEA	168	420	252	60	40
SP-STEA	312	420	108	25.72	74.28

The results of STEA method and SP-STEA method are respectively represented in table 1. It can be seen that the accuracy of STEA method is 40%, SP-STEA method is 74.28%. The accuracy of SP-STEA method is increased by 34.28% compared to STEA method.

4. Conclusion

In this paper, the STEA method and the SP-STEA method are compared. Conclusions can be drew as follows:

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(1) When there is no overlap between the adjacent VASs, the traffic detected by STEA method are the same as SP-STEA method.

(2) SP-STEA method is more precise than STEA method for traffic detection when the overlapping VASs exist in TASs. However, the SP-STEA method cannot detect all the overlapping VASs, its accuracy depends on the "S" regions, if the "S" regions are more standard, the result is more accurate.

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