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Acoustic Noise Pattern Detection and Identification Method in Doppler System

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***Abstract*— This paper discusses detection and identification of the moving vehicles based on prerecorded acoustic noise patterns. Object movement and object type differences would lead to the significant vehicle pattern changes. Doppler shift estimations of the measured signal spectral components will improve the recognition and classification performance. The proposed pattern identification methods could be used for the robust single sensor system or as a part of complex multi-sensor and learning solutions. The experimental results illustrate measured signal processing stages.**

***Index Terms*— Acoustic signal processing, vehicle detection, pattern matching, classification algorithms, Doppler effect.**

I. INTRODUCTION

Object detection and identification is widely used in traffic tracking, safety and monitoring systems. The sound of a moving vehicle (included tanks, off-road vehicles) plays an important role in vehicle detection and recognition. In limited visibility conditions or in multisensory solutions acoustic pattern recognition could provide supportive information for moving object identification and tracking. In some systems detection and identification of civilian and military vehicles on the street, based on shape, speed, etc., would provide perception support and understanding of threats.

The compact and low-cost hardware real-time solution data could be easily integrated in more complex monitoring sensor application. This property could be included into CARDINAL and IMECC project systems [1], [2].

These paper discuses measured acoustic noise patterns of moving vehicles considering vehicle speed changes. The Doppler shift estimations could be used for prerecorded vehicle pattern processing and for more complex learning algorithm solutions [3]. Moreover, the moving object detection and identification methods are applied to real measured acoustic signals.

II. MEASURED SIGNAL ANALYSIS

The acoustic pattern of the moving vehicle will include engine and tire acoustic signature, vibration, etc. [4]. In general, this pattern could be represented as non-stationary random signal, where the non-stationary is determined by the moving object speed changes, signal level changes and frequency component changes due to the Doppler effect. In small time intervals this signal could be considered as stationary but non-ergodic. As far as every moving vehicle work in similar conditions, it will generate a specific spectral pattern or acoustic noise signature we could apply the FT (Fourier Transform) spectral processing methods for moving object detection. The short time measured noise patterns help military or a surveillance system to detect a vehicle and recognize its class.

Fig. 1 illustrates moving car frequency component changes in time.

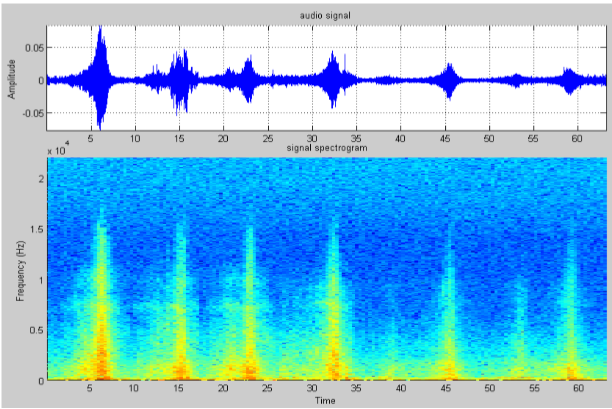

Fig. 1. Audio signal and spectrogram of the six sequentially moving vehicles.

The main energy of the car noise pattern will be in range up to 5 kHz. In practice, the other moving vehicle spectral components will be in the same range and 90% in the frequency range lower than 4 kHz [5].

The real audio measurements would have some unwanted effects that should be eliminated or minimized by the processing algorithm: background noise, vehicle speed not constant (acceleration and deceleration), unknown direction of the vehicle, reflections, hardware and sensor differences. If the application uses fixed location microphone sensor vehicle speed and direction changes would result in the Doppler effect. For instance, the 100 km/h vehicle speed would give approximately up to ± 8 % frequency component shift (here speed of sound ~340 m/s). However, the measured acoustic noise patterns of the specific vehicle classes could be processed to detect the moving object from background noise and distinguish them from one another. There are many ways to perform vehicle noise pattern recognition. One of the reliable solutions would be to use prerecorded sound signatures of the moving object classes

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and compare them to the real-time measured signal. As the measured signal is constantly changing for the more complex systems the training principles [3] should be implemented.

We used the spectrum correlation method in our test system which helps us to eliminate issues caused by the Doppler effect. The processing stages could be compared to the MFCC (*Mel-Frequency Cepstral Coefficients*) algorithm [6], [7].

III. THE MOVING OBJECT IDENTIFICATION METHOD

Concerning the methods proposed for vehicle identification [5], [6], [8] the moving object noise could be represented as

$$s(t) = \int_{-\infty}^{\infty} S(\omega) e^{j\omega t} \mathrm{d}t \,, \tag{1}$$

where $S(\omega)$ is a spectrum of $s(t)$ signal [9].

Obviously, we could not compare the measured moving vehicle noise with prerecorded data $s_p(t)$ from the same vehicle class due to the unknown delay and $s(t)$ signal spectrum component and amplitude changes. The spectrum analysis showed that direct comparison will not give the best result [5], and we need to eliminate the phase uncertainty and spectrum component amplitude decrease. Thus, for the calculation we should use normalized prerecorded and measured object energy spectrums

$$S_n(\omega) = \frac{1}{\sqrt{E}} |S(\omega)| \,, \tag{2}$$

where $E = \frac{1}{2\pi} \int_{\omega_l}^{\omega_u} |S(\omega)|^2 \mathrm{d}\omega$ is measured signal energy, ω_u is object upper spectrum angular frequency and ω_l is lower spectrum angular frequency [9]. The prerecorded signal spectrum will be:

$$S_{np}(\omega) = \frac{1}{\sqrt{E_p}} |S_p(\omega)| \,, \tag{3}$$

$$E_p = \frac{1}{2\pi} \int_{\omega_l}^{\omega_u} |S_p(\omega)|^2 \mathrm{d}\omega \,. \tag{4}$$

In this case we could compare the signals by the correlation coefficient

$$C_{sp} = \int_0^{\infty} S_n(\omega) S_{np}(\omega) \mathrm{d}\omega \,, \tag{5}$$

with values from 0 up to 1.

The object movement, acceleration or deceleration will result in the Doppler effect and would be seen in measured spectrum component shift and object noise spectrum widening. Moreover, this will lead to the decrease of the correlation coefficients. As the Doppler shift is defined by

$$f_d = f \cdot \frac{v}{c} \cos\varphi \,, \tag{5}$$

where f is prerecorded object signature frequency component, v – moving object velocity, c – sound velocity in air, φ – angle between moving object direction in correspondence to the measurement point [10]. Therefore every spectrum component of the measured signal spectrum would be converted into the frequency

$$F_D = fK + f = f(1+K), \tag{6}$$

where $K = \frac{v}{c}\cos\varphi$.

In this case the correlation coefficient could be calculated as cross-correlation of the measured and prerecorded signal spectrums in the possible Doppler shift area

$$C_{f_d \max} = \max\left\{ \int_0^{\infty} S_n(\omega) S_{np}(\omega + 2\pi f_d) \mathrm{d}\omega \right\}, \tag{7}$$

where f_d – the Doppler frequency shift in a range from $-f_{d\max}$ up to $+f_{d\max}$. The value of the frequency shift f_d at the stage of object identification by correlation coefficient $C_{f_d \max}$ will estimate relative object velocity.

The proposed correlation method could be successfully used for narrow band object noise patterns. The difference between upper f_u and lower f_l frequencies in specific object noise spectrum is

$$F_\Delta = f_u - f_l \,. \tag{8}$$

In this case, Doppler shift will have minimal and neglectable effect.

The wideband object noise spectrum, according to (6) and (8) would give the upper and lower frequency difference

$$F_{\Delta w} = Kf_u - Kf_l = K \cdot F_\Delta \tag{9}$$

and as a result the significant spectrum widening. This could be avoided by the use of logarithmic frequency scale in measured and prerecorded signal processing

$$\gamma = f_0 \log\left(\frac{f}{f_0}\right), \tag{10}$$

where f – linear frequency $f > 0$, f_0 – unique frequency step (1Hz). In the case of the object spectrum width will be

$$\gamma_\Delta = \gamma_u - \gamma_l =$$
$$= f_0 \left(\log\left(\frac{f_u(1+K)}{f_0}\right) - \log\left(\frac{f_l(1+K)}{f_0}\right) \right) = f_0 \log\left(\frac{f_u}{f_l}\right) \tag{11}$$

and all spectrum components will have the same shift

$$\gamma = f_0\left(\log\left(\frac{f(1+K)}{f_0}\right)\right) = f_0\log\left(\frac{f}{f_0}\right) + f_0\log(1+K). \quad (12)$$

The main object identification estimation will be according to the (5) and (7)

$$C_{\gamma_d \max} = \max\left\{\int_0^{\infty} S_n(\gamma)S_{np}(\gamma+\gamma_d)\mathrm{d}\gamma\right\}. \quad (13)$$

IV. Measured Signal Processing Stages

The hardware implementation will be based on the created processing models. The basic model includes three processing stages: the real vehicle detection, vehicle class identification, based on the prerecorded audio signature database, and collecting necessary information for the learning and other sensor data fusion stage.

The first stage of the model provides moving vehicle detection in a noisy environment. For the experimental part we used prerecorded moving vehicle signature classes. The different kinds of vehicles were moving at a specific registered speed. Real time application compares the microphone sensor measured data with prerecorded signature database, extracts the moving vehicle estimations form the background noise (minimizing false detection rate) and assigning the detection parameters for every detected moving vehicle.

The second stage would do vehicle identification, according to the introduced vehicle classes. As the prerecorded database contained only civil vehicle information, the discussed identification results allow us to identify between 3 vehicle classes (2 different cars and large truck). For the future research the prerecorded database should be updated with specific vehicle signatures.

The identified vehicle information is stored with a timestamp and could be used for the other supported sensor data fusion. Moreover, the acoustic data measurement system consists of different measurement separate nodes with learning ability. Every node collects and processes the real time data, providing the identified vehicle type estimations. Based on the all audio sensor information the system could estimate the speed and direction of movement.

The proposed methods and processing steps were tested on real measured single microphone sound data, which includes background noise components. The following pictures illustrate the model performance and recorded sound spectral analysis. The experimental pictures show the moving vehicle detection and identification process of the measured acoustic signal. Prerecorded and normalized sound signature frequency spectrums, which we have chosen from the identification database, consist of different spectral components (Fig. 2).

For this illustration we used two different civil car sound signatures and one large truck signature, moving at the speed ~20 km/h.

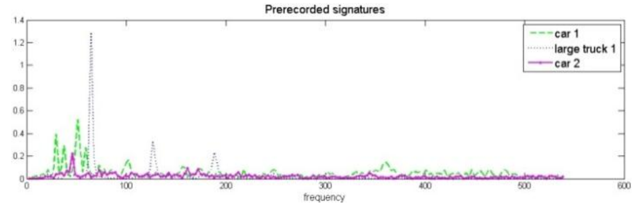


Fig. 2. Prerecorded sound signature spectrum (44.1 kHz, time interval 0.37 s, vehicle speed 20 km/h).

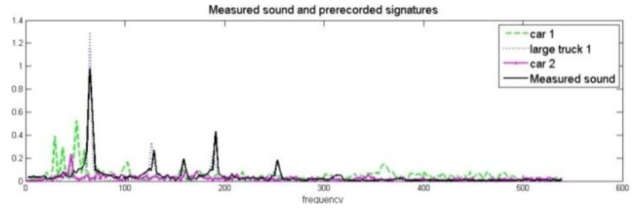


Fig. 3. Measured audio signal spectrum compared to prerecorded signatures (time interval 0.37 s, vehicle speed 20 km/h).

The following Fig. 4 illustrates the real vehicle spectrum differences, measured at different moving speed compared to prerecorded ones. In practice, the real vehicle differences, acceleration, deceleration, speed and background noise change the number of signature frequency components significantly. Therefore, the vehicle detection and identification should be done with correlation methods.

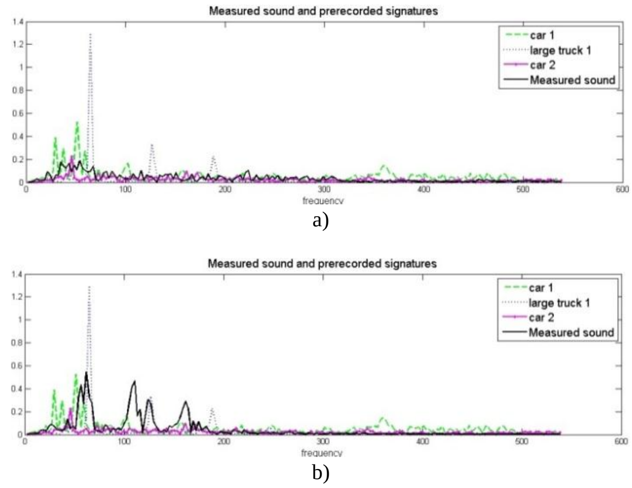


Fig. 4. Prerecorded and measured spectrums (44.1 kHz, time interval 0.37 s, vehicle speed 20 – 40 km/h).

Fig. 5 shows measured object noise wideband spectral components compared to the prerecorded spectrum in linear frequency scale. Obviously, the second maximum component frequency shift will be greater than the first one $\Delta_2 > \Delta_1$.

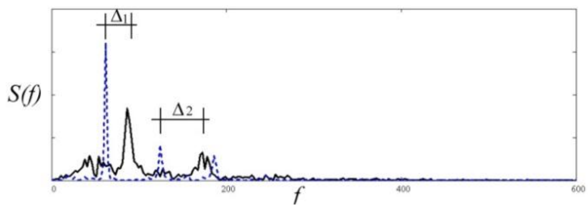


Fig. 5. Prerecorded and measured object spectrum components.

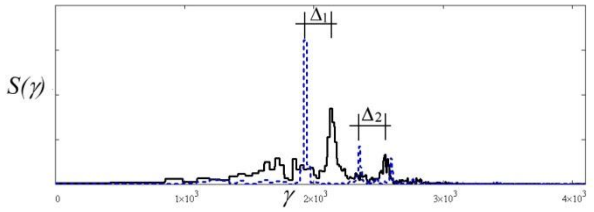
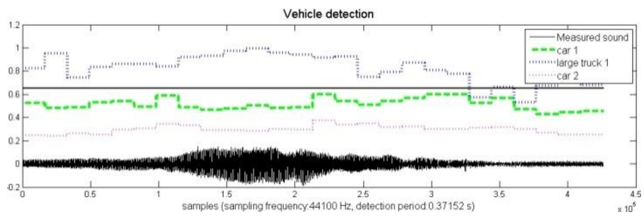


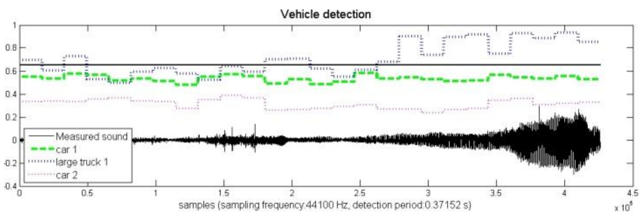
Fig. 6. Prerecorded and measured object spectrum components in logarithmic scale.

The logarithmic scale implementation would result in similar frequency shifts for all spectral components $\Delta_2 \approx \Delta_1$ (Fig. 6).

Vehicle identification results based on sound signal processing are shown in Fig. 7. For the identification we used three vehicle classes, which are named car1, car2 and large track. The identification is done by the constant leveling (black line), and the real time identified vehicle type is shown as a dotted line. The identification results are shown with measured audio signal time representation.



a)



b)

Fig. 7. Vehicle detection and identification results (large truck identification at ~ 20 and 40 km/h).

From Fig. 7 we can see, that a large truck is successfully detected in case of two different speeds based on the 20 km/h prerecorded signature.

The modeling results showed that it is possible to implement real time moving vehicle detection and identification based on the prerecorded signatures. Obviously, it is not possible to do exact vehicle type identification based on prerecorded information. Furthermore, the processing will be supported with hierarchical algorithm stages [11]. Nevertheless, the audio sensor data should be supported with other sensors and this will also decrease the audio system false detection rate.

V. Conclusions

Measured signal analysis showed that the real vehicle differences, acceleration, deceleration, speed and background noise change the number of object acoustic pattern frequency components significantly. Therefore, the vehicle detection and identification should be done with correlation methods. Generally, sound signal processing methods will not provide a standalone audio system for exact object (vehicle) identification. Moreover, the complex learning multi-sensor solution, where the real-time vehicle detection data is combined with other sensor data (vibration signature, magnetic data, visual data, etc.) will give more reliable results. The data from separate audio measuring nodes, with exact location, could be used for vehicle position and direction estimations. However, simple solution could be used for moving vehicles robust detection and give supportive information or other system sensor triggering.

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