Identification of Exploitation Conditions of the Automobile Tire while Car Driving by Means of Hidden Markov Models

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Abstract. This article describes the implementation of the Hidden Markov Models for identification of exploitation conditions of the automobile tire by means of analyzing tire noise while car driving. This requires the development of special recognition algorithms of tire noise and cleaning of the signal from the background noise, it can be done by means of extraction of the clean signal from the noise by adaptive filters and by pattern recognition methods, typically used in speech recognition, to recognize a tire noise corresponding to a particular operating condition. In this way, we can diagnose the condition of a tire while car driving, which will reduce overloaded tire wear, due to improper use to a minimum and help prevent accidents as a result of tire failure.

Keywords: Hidden Markov models, Adaptive filters, tire noise, pattern recognition, feature extraction

1 Introduction

The problem of the road transport accidents, caused by the failure of automobile tire, is one of the most important ones for traffic safety. A key reason for the failure of automobile tire is its increased wear as the result of improper use. It may be caused by many factors: the collapse of the incorrect angles of convergence, high or low tire pressure, overheating, etc. It is impossible to control all the factors, influencing the dynamics of tires while driving, and, therefore, there is a need for a comprehensive new indicator. We think that this indicator is the sound of tires. There is a lot of research of tire dynamics in the field of automobile safety. In general, models of tire/road noise can be divided into four major types. The first type includes statistical models. A popular example of this approach is introduced in the article by Sandberg, U. and Descornet, G. [1]. The second type is composed of physical models. The examples of such a modeling approach are analysed in the book by Kropp, W. [2]. The third type of models for tire/road noise is hybrid theoretical models. The examples of hybrid theoretical models are described by De Roo, F., Gerretsen, E. and Hamet, J.F., Klein, P. [3, 4]. Finally, statistical models can be extended with pre or post processing, based on well-known physical relations, often derived from theoretical models. The examples of hybrid statistical models are introduced by Beckenbauer, T. and Kuijpers A. [5]. We think the disadvantage of these models is that they only describe the noise generation mechanisms of the tire, independently of the condition of the tire. In contrast, we attempt to model dependencies between tire sounds and tire conditions, based on the hypothesis that the operational status of the tire is reflected in its noise characteristics. We must develop dedicated recognition algorithms of tire noise and also algorithms of clearing up the signal of the background noise. It can be done by means of extraction of the clean signal from the noise by adaptive filters and pattern recognition to classify a tire noise as corresponding to a particular operating condition.

2 Data Preparation

2.1 Adaptive Filtering

First, it is necessary to clear the tire signal from the background noise. It can be done by using adaptive filters. In our research we use adaptive filter, based on the least mean square algorithm [6], which is realized in the Matlab Simulink (see Fig.1).
The acoustic signal $x(t)$, which contains the tire signal $s(t)$ and noise $l(t)$ is recorded by the first microphone, which is installed near the tire. The pattern of noise $l_0(t)$ is recorded by the second microphone, which is located near the engine of the automobile. There is a correlation between $l(t)$ and $l_0(t)$. The output of the adaptive filter will contain the measure of the noise $\hat{l}_0(t)$. The error of the filter will contain a clear tire acoustic signal $\hat{s}(t)$. The spectrogram of the clear tire signals which we received as the results of the experiments (the experiments are described in Section 4) is shown in Fig 2.

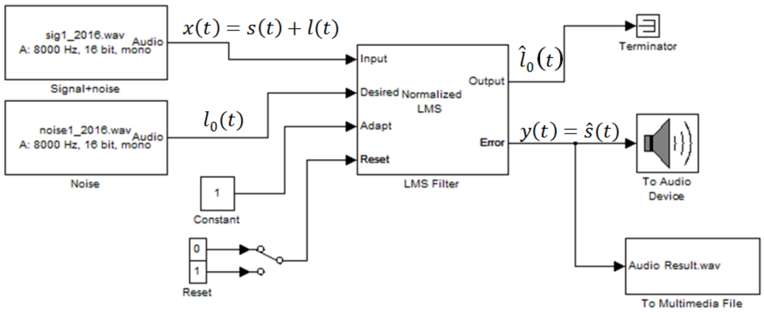

Fig. 1. The scheme of adaptive filter from Matlab Simulink

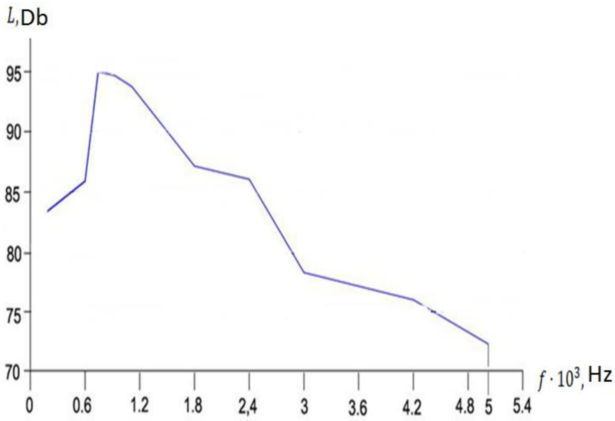

Fig. 2. The tire signals spectrogram

The frequency range of the clean acoustic signals of the tire is between 400-5000 Hz.

2.2 Feature Extraction

The next step is the feature extraction. The purpose of this step is to parameterize the raw tire signal waveforms into sequences of feature vectors. Here we use both FFT-based and LPC-based analysis with the purpose to identify which approach is better for the tire noise coding. The feature techniques are based on the widely known methods MFCC and LPCC [7] which are often used for speech recognition. We process the signal with the frame size 25 msec and frame period 10 msec (Fig.3).

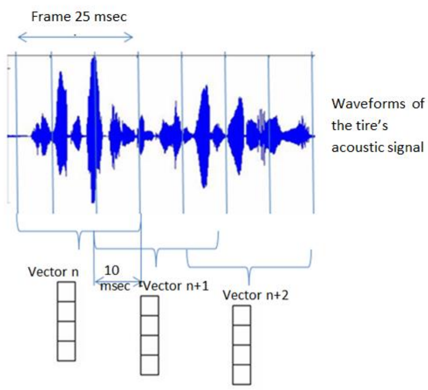

Fig. 3. Framing of the waveforms of the tire acoustic signal

The tire noise feature vectors were parameterized as follows: if the target parameters are MFCC, we use C_0 as the energy component. We use a Hamming window in FFT. The filterbank has 26 channels. In output we receive 12+1 (C_0) coefficients. The performance of the tire noise recognition system can be enhanced by adding time derivatives (delta and acceleration coefficients) to the basic static parameters [7]. If the target parameters are LPCC, we use linear prediction of the 14th order. The filterbank size is 22 channels and in output we receive 12 coefficients. Then we add delta and acceleration. After feature extraction procedure we have 39 dimensional MFCC vectors or if we use the LPCC method - 36 dimensional vector.

3 HMM Training and Recognition

3.1 Topology of the HMM

We use the left-right HMM with seven hidden states (see Fig.4) for identification of the tires exploitation condition. The first and the last states (S_1 and S_7) are not emitted as we need these nodes to create composed HMM (see Fig.5).

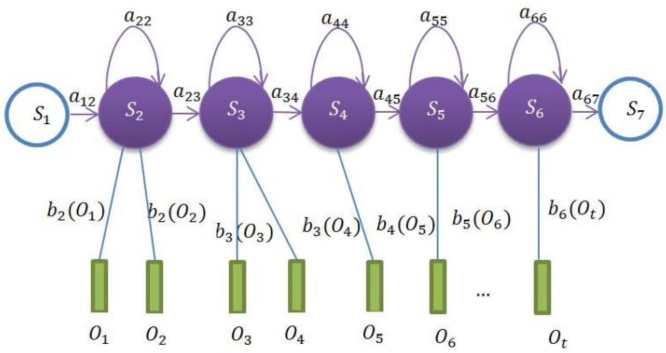

Fig. 4. The left-right HMM for identification of the tire exploitation condition

Here N – number of hidden states of the model (N=7); $A = \{a_{ij}\}$ – the matrix of the transition probabilities:

$$a_{ij} = P\left[q_{t+1} = \frac{S_j}{q_t} = S_i\right], 1 \leq \mathrm{i}, \mathrm{j} \leq \mathrm{N} \quad (1)$$

q_t- hidden state of the HMM ($S_1, \dots, S_7$) at the moment t; j – next state of HMM; i – actual state of HMM; $B = b(O_t)$ – observation probability; $O_1, \dots, O_t$ – feature vectors of the tire noise.

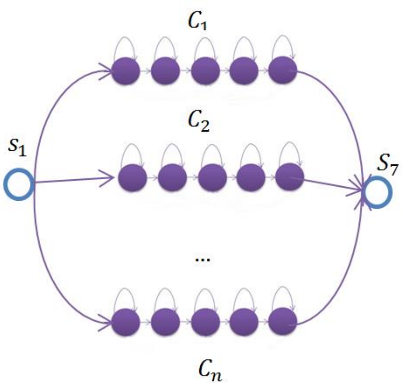

Fig. 5. Composed HMM; $C_{1,\dots,}C_n$ –exploitation conditions of the tire

3.2 HMM Training

For HMM training we use the same method as for speech recognition [7]. We record a training database of the tire noise which relate to every exploitation condition of the tire. It is necessary to make 3-5 recordings of the tire noise

10-15 seconds long for every exploitation condition with the purpose to create the robust recognition system. Then for each exploitation condition of the tire $C_{1,\dots,}C_n$ we initialize one HMM with seven hidden states.
Using maximum likelihood we estimate the matrix of transitions between the states in the hidden part of the model. After that we estimate the mean $\hat{\mu}_j$ and the matrix of covariance $\hat{\sum}_j$ by means of these formulas:

$$\hat{\mu}_j = \frac{1}{T}\sum_{t=1}^{T} O_t \tag{2}$$

$$\hat{\sum}_j = \frac{1}{T}\sum_{t=1}^{T}\left(O_t - \mu_j\right)(O_t - \mu_j)^T \tag{3}$$

where T – is a number of the feature vectors;
Then we can calculate the observation probability of the feature vectors of the tire noise:

$$\mathrm{b_j}(O_\mathrm{t}) = \frac{1}{\sqrt{(2\pi)^n|\hat{\sum}_j|}} \mathrm{e}^{-\frac{1}{2}(\mathrm{O}-\hat{\mu}_j)'\hat{\sum}_j{}^{-1}(\mathrm{O}-\hat{\mu}_j)} \tag{4}$$

Where n – is a dimensionality of the feature vectors.
It is necessary to estimate corresponding probability for each state, and to use the Viterbi algorithm [7] for reassigning the observation vectors for each state. We re-estimate model parameters in this way until we stop getting their improvements.
The next step is to create $M = 16$ Gaussian mixtures [9]. It is necessary to create a robust system of the tire exploitation condition recognition.
We use the Baum – Welch [8] algorithm to define $\psi_{jm}^r(t)$ – the probability of observation vector being in the particular state. Here R is the number of training data $1 \leq r \leq R$. After that, we re-estimate the parameters of the model. The observation probability $b_j(O_t)$ is:

$$b_j(O_t) = \sum_{\mathrm{m}=1}^{\mathrm{M}} \mathrm{c_{jm}} \mathrm{N}(\mathrm{O_t}; \mu_{\mathrm{jm}}, \textstyle\sum_{\mathrm{jm}}) \tag{5}$$

$$N(O_t; \mu_{jm}, \textstyle\sum_{jm}) = \frac{1}{\sqrt{(2\pi)^n|\sum_{jm}|}} e^{-\frac{1}{2}(O-\mu_{jm})'\sum_{jm}{}^{-1}(O-\mu_{jm})} \tag{6}$$

Re-estimation of the mean and covariance matrix is:

$$\mu_{jm} = \frac{\sum_{r=1}^{R}\sum_{t=1}^{T_r}\psi_{jm}^r(t)o_t^r}{\sum_{r=1}^{R}\sum_{t=1}^{T_r}\psi_{jm}^r(t)} \tag{7}$$

where T_r – is the number of the observation vectors.

$$\widehat{\Sigma}_{jm} = \frac{\sum_{r=1}^{R}\sum_{t=1}^{T_r}\psi_{jm}^{r}(t)(O_{st}^{r}-\hat{\mu}_{jm})(O_t^{r}-\hat{\mu}_{jm})^T}{\sum_{r=1}^{R}\sum_{t=1}^{T_r}\psi_{jm}^{r}(t)} \tag{8}$$

The weights of the Gaussian mixture components are:

$$c_{jm} = \frac{\sum_{r=1}^{R}\sum_{t=1}^{T_r}\psi_{jm}^{r}(t)}{\sum_{r=1}^{R}\sum_{t=1}^{T_r}\sum_{l=1}^{M_s}\psi_{jm}^{r}(t)} \tag{9}$$

We re-estimate the parameters of the model until $b_j(O_t)$ stop getting improvements of the model parameters.

3.3 Recognition

We use the Viterbi decoding [7] for the tire noise recognition (Fig.6). This algorithm could be used to find the maximum likelihood state sequence of HMM and identify the tire exploitation condition. Let $\delta_t(j)$ represent the maximum likelihood of the observing tire noise vectors O_i to O_t in state j at time t. This likelihood can be computed efficiently using the following recursion:

$$\delta_t(j) = \max_i\{\delta_{t-1}(i) \cdot a_{ij}\} \cdot b_j(O_t) \tag{10}$$

where

$$\delta_1(1) = 1 \tag{11}$$

$$\delta_1(j) = a_{1j} b_j(O_1) \tag{12}$$

The maximum likelihood for observing sequence of vectors O_i to O_t given the HMM model:

$$\delta_T(N) = \max_i\{\delta_T(i) \cdot a_{iN}\} \tag{13}$$

As for the re-estimation case, the direct computation of likelihoods leads to underflow, so it will be better to compute log likelihood:

$$\delta_t(j) = \max_i\{\delta_{t-1}(i) + \log(a_{ij})\} + \log(b_j(O_t) \tag{14}$$

This algorithm can be visualized as searching the best path through a matrix, where the vertical dimension represents the states of the HMM and the horizontal dimension represents the frames of the tire noise.

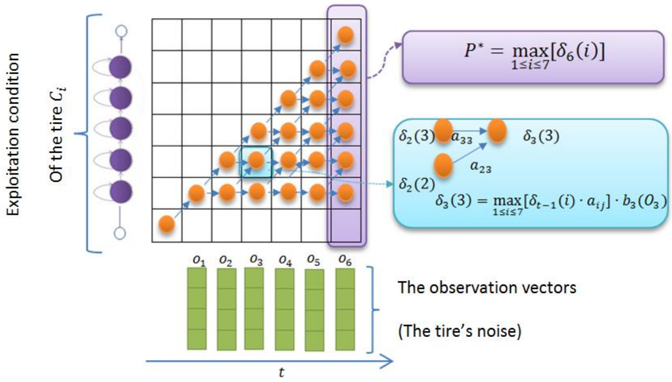

Fig. 6. – Scheme of the Viterbi decoding

Each large dot in the picture represents the log probability of observing that frame at that time and each arc between dots corresponds to the log transition probability. The log probability of any path is computed simply by summing the log transition probabilities and the log output probabilities along that path. The paths grow from left-to-right, column-by-column. At time t, each partial path $\delta_{t-1}(i)$ is known for all states i, hence, equation 14 can be used to compute $\delta_t(j)$,thereby, extending the partial paths by one time frame.

4 Experiments and Results

4.1 Experiments

We carried out field tests with the purpose to record the tire noise while car driving with different exploitation conditions of the tire. Our experiment is based on the standards ISO 10844 [10] and ISO 13325:2003 [11], which determine the conditions for the tire noise measurement, but we included the following changes:

- The noise of the tire was measured with the engine working
- Microphones were installed near the front right wheel (Fig.7) with the purpose to provide adaptive filtering of the background noise

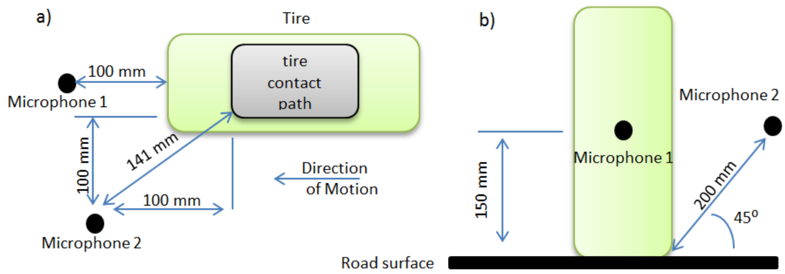

Fig. 7. – Scheme of the microphones' positions, during field tests: a) Upside view b). Front view

We recorded the tire noise with three different speeds of the automobile 20, 40 и 60 km per hour and three different pressure levels: 1.9, 2.1 and 2.3 atmospheres. The automobile used for field tests was Mitsubishi L200 (year of construction: 2011), with new tires 265/75R16.

4.2 Evaluation

We made three different experiments. For each experiment we used 405 records of the tire noise, the total duration of 1 hour 41 minute 15 seconds for HMM training.

Table 1. The experiment results

Features	HMM (1 Gaussian)	HMM (8 Gaussian mixtures)	HMM (16 Gaussian mixtures)
The results of the tire pressure identification			
LPC/LPCEPSTRA	78%	87.5%	88.2%
MFCC	68%	77.4%	78.2%
The results of the automobile's speed identification			
LPC/LPCEPSTRA	81.2%	94.3%	95.7%
MFCC	78.6%	89.4%	91.8%
The results of the identification of the tire speed and pressure			
LPC/LPCEPSTRA	61.4%	74.7%	75%
MFCC	58.6%	59.4%	61.9%

To evaluate the efficiency of the system we used 50 records, a total duration of 12 minutes 30 seconds. As we can see in table 1 the accuracy of our method for the tire pressure is 88,2%; for the automobile speed - 95,7%; and for both the speed and tire pressure - 75%.

5 Conclusions

We have found the correlation between the tire noise and the tire exploitations characteristics. The cleaning mechanism, based on adaptive filters, and the recognition mechanism, based on the HMM have shown prospective results. We found out that the performance of the recognition system depends on exploitation parameters. They show better results for the automobile speed than for the tire pressure identification. Moreover, we have also discovered, that the performance of the recognition system runs low when more than one parameter are identified.

6 References

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