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Automatic Detection of Road Surface States from Tire Noise Using Neural Network Analysis

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ABSTRACT

This report proposes a new processing method for automatically detecting the states from the tire noise of passing vehicles. To detect tire noise, we use a commercially available microphone as an acoustic sensor, which enables us to easily reduce the cost and size in realizing a practical detection system. We propose several feature indicators in the frequency and time domains to successfully classify the states into four categories: snowy, slushy, wet, and dry states. The method is based on artificial neural networks. The proposed classification is carried out in multiple neural networks using learning vector quantization. The outcomes of the networks are then integrated by the voting decision-making scheme. From experimental results obtained for more than a week in snowy areas, it has been demonstrated that an accuracy of approximately 90% can be attained for predicting road surface states.

INTRODUCTION

The detection of road surface states is an important process for efficient road management. It is a substantial challenge to remotely obtain information about the surface states with sufficient prediction accuracy. In particular, in snowy seasons, prior information such as an icy state helps road users or automobile drivers to avoid serious traffic accidents. In practice, road surface states depend greatly on weather, road users, and other relevant factors. During two years, our study on the detection of road surface states using only tire noises emitted from passing vehicles has been ongoing at two observation sites near our campus at The University of Electro-Communications and near Sapporo city. At each site, tire noise signals were collected with commercially available microphones as acoustic sensors, which enable us to easily reduce the cost and size to realize a practical system. In our previous report, we proposed a simple classification method using a few signals features that are readily extracted in the frequency domain of the noise signals [1]. The features of interest were the frequency at which the noise power spectrum reaches the maximum, the normalized magnitude at 1.5 kHz in the cumulative distribution of the power spectrum, and the frequency at which the normalized magnitude takes a value of 0.5. Our experiment results revealed that classification accuracy reaches approximately 73% at maximum when using the feature at 0.5, which is the last indicator of three features mentioned above. Interestingly, the accuracy in classification was improved by as much as 81% by combining the feature at 0.5 with the standard deviation of the cumulative distribution curves. All classifications of concern to us, however, suffered from systematic problems for automatization, in the previous study [1]. Therefore, it is necessary to continuosly develop practical classification methods with goal of remotely predicting road surface states as accurately as possible.

In this report, we extract new signals features in the time domain from recorded tire noises. The features are based on the autocorrelation function of the tire noises. The effectiveness of the features proposed is verified by noise data samples obtained at an observation site near Sapporo city and compare with visual inspections of actual road states. Furthermore, to improve classification accuracy, our approach now uses artificial neural network (ANN), which is widely used to model involved relationships between input and output data. In related works, McFall and Niitula [2] applied ANN to the classification task of the road surface states. They captured road surfaces with both a microphone for tire noise and a video camera for the visual road states, and fed these 51 signal features into their ANN system. The hybrid system that combines the surface images and tire noise revealed correct classifications at a high accuracy of more than 90%. However, the system did not work well during hours of darkness and experienced difficultly in identifying dry surface states. Our ANN system is composed of sets of multiple neural networks and the final decision-making scheme. We improve accuracy by using only tire noise data as well as a small number of input data into the ANN system.

SOUND SIGNAL ANALYSIS

In the snowy season, we acquired tire noise signals at an observation site on the side of a four-lane national road near Sapporo city. The measurement system and experimental conditions were already presented in our previous article [1]. We introduce the following six features of the noise data and apply them as input parameters of our classification systems. We classify the road surface states into three principal categories in the same framework as before [1]:

Dry: Road surfaces with no water; the surface are truly dry.
Wet: Road surfaces are covered with water and remain wet. Vehicles splash water as they pass by and the tire tracks remain for a while. This state includes slushy water from melt snow.
Snow-compacted: Snowy surfaces are compacted due to passing vehicles. The surfaces look completely white, including the wheel tracks.

Peak Frequencies

We usually observe that timbre of tire noise is dependent on the road surface state. When the road has water on its surface, the high-frequency components of noise seem to increase as a whole in comparison with the frequency components of dry surfaces and especially snowy surfaces. The most useful and predictable parameter of the features seem to be the frequency at which the power spectrum *p(f)* takes the maximum.

Cumulative Distribution Analysis

Since the sound pressure level depends greatly on the size of a vehicle and its tires, we cannot reliably detect road surface states on the basis of only the magnitude of the spectrum. Then, we introduce the following cumulative distribution function of the power spectrum $\overline{P}(f)$ that is clarified in our previous report [1]:

$$\overline{P}(f) = \frac{\int_{f_l}^{f} p(f')df'}{\int_{f_l}^{f_h} p(f')df'} \tag{1}$$

where f_l = 300 Hz is the low-cut frequency. Generally, tire noise do not significantly contain frequency components higher than 10 kHz; consequently, the upper limit of integration with repect to frequency is calculated to be f_h = 10 kHz.

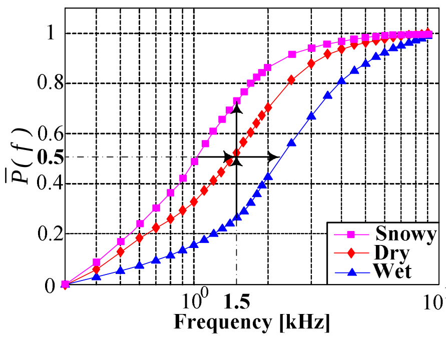

Figure 1. Typical cumulative curves of the power spectrum of tire noises for five minutes.

Typical cumulative distribution curves obtained from passing vehicles for a five-minute signal are shown in Fig. 1. The magnitudes in the wet state are lower than those in the dry and snowy states at all frequencies. This means that the wet state predominates at high frequencies in comparison with the other two states. From the cumulative curves in Fig. 1, we propose two classification features based on the appearance of distinct differences between the three curves. One feature is the normalized magnitude of $\overline{P}(f)$ at a frequency of 1.5 kHz (feature at 1.5 kHz). The other feature is the frequency at which the normalized magnitude of $\overline{P}(f)$ takes a value of 0.5 (feture at 0.5). From our examination of one-day sound data, both features are good predictors of the changing of surface states with time [1].

Figure 2(a) shows the natural transition diagram for the different surface states. As expected, the snowy state changes to the wet state as the temperature rises, and changes to the dry state due to water evaporation when the temperature is further elevated. Our method allows for the change from the dry to wet states and the wet to snowy states. However, the direct transition from the snowy to dry states is not allowed, for example: the slushy state and/or wet state always exist in above processes. Unfortunately, the features at 0.5 in the slushy state have almost the same frequencies as those in the dry state, as shown in Figure 2(b). It is then difficult to classify these into two states successfully. The main reason for high detection errors must be a defect that the road is covered with slushy water and is recognized as the dry state incorrectly.

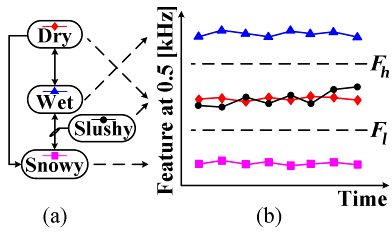

Figure 2. Transitions and threshold frequencies of the four states. (a) Natural transition diagram for the different states; (b) threshold frequencies F_l and F_h for the feature at 0.5.

The slushy state is not always covered with snow: that is, parts of the road surface can still be snowy and other parts can already be dry due to water evaporation. Additionally, all vehicles do not always pass on the slushy or dry surfaces. It can then be expected that when data is collected for a long observation time (e.g., 30 minutes), the cumulative curves of the remaining three states, particularly the curves of the dry state, are potentially scattered in a random manner. It seems feasible from this speculation to discriminate the dry and slushy states by introducing statistical measures such as standard deviation.

Autocorrelation Analysis

Tire noise signal is a type of stochastic signal and can be considered to be a stationary or quasi-stationary process if the running conditions of a vehicle do not often change. The autocorrelation function (ACF) for a stationary signal is a measure of the time-related properties in data that is delayed by a fixed time. ACF tells us more about the signal, such as whether significant correlation between the time series exists and whether the similarity tendency of the same state remains from one observation to another. We focus here on the autocorrelation function that is readily calculates from the power spectrum using FFT to extract new signal features in the recorded tire noises.

Autocorrelation curves for five minutes are shown in Fig. 3. We confine our attention to the first main lobe in each curve because important information about signal similarities generally appears here. As can be seen, the three curves decrease in magnitudes relatively absruptly with time lags. However, great differences exist in their shapes: the magnitudes for the wet state are entirely lower than those for the dry and the snowy states. This result is somewhat expected from the fact that the magnitude of the high-frequency components in the tire noise signal emitted from the road surface in the wet state is dominant in comparison with the magnitudes in the other two states. Since the high frequencies are equivalent in short time periods, the correlation in the wet state becomes small as the time lag is increased. To the contrary, when road surfaces are snowy and low-frequency components predominate, a relatively strong correlation should remain at even short time lags.

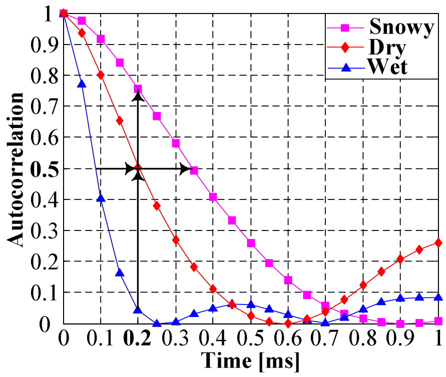

Figure 3. Autocorrelation curves for five minutes

Two features are indeed inferred from the autocorrelation data in Fig. 3. One feature is the magnitude of the autocorrelation at 0.2 ms (feature at lag 0.2 ms), where the largest differences in magnitude appear. The other feature is the time lag at which the magnitude takes a value of 0.5 (feature at ACF 0.5). In Fig. 3, the feature at lag 0.2 ms is 0.76, 0.5, and 0.04 for the snowy, dry, and wet states, respectively. The feature at ACF 0.5 is 0.34, 0.2, and 0.08 ms, respectively.

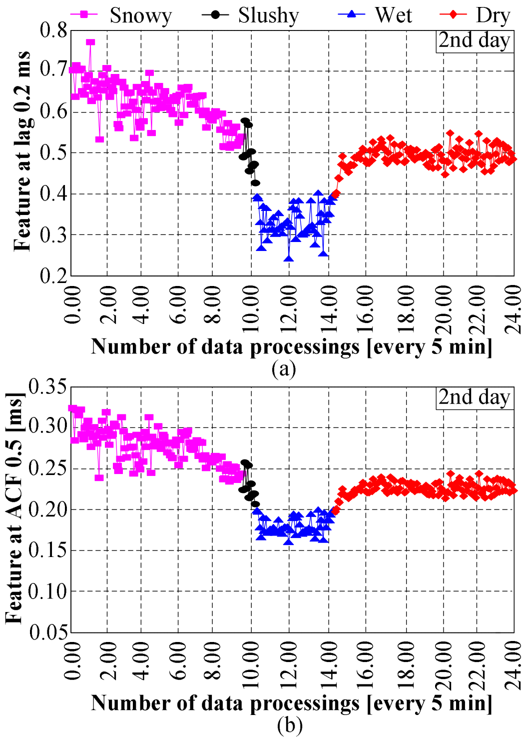

Figure 4. One-day observation near Sapporo city. (a) The feature at lag 0.2 ms, and (b) at ACF 0.5

To determine whether both the proposed features of the ACFs, we first examine typical one-day sound data that were collected on the second day of the three-day observation in our previous report [1]. The reason why we use such data is that the data include all four different states. Figure 4 shows the time histories of two new features. The observation started at 0 a.m. and ended the next day at 0 a.m. At the same time, we visually monitored the surface states with a video camera. Interestingly, even if observation with a camera is unavailable, we can generally assume that the road surface changed from the snowy to slushy state before changing to the wet state in the morning, remained wet until 2 p.m., and after that changed to the dry state. Therefore, more accurate classification into snowy, wet, and dry states seems to be feasible by employing either feature on the basis of certain threshold values. The classification ability by using only two ACFs shows high precision and they achieve a classification accuracy rate of 93%, as shown in Table 1.

Table 1. One-day experiment results of detecting the road surface states using 5-minute sound signals

Methods	Threshold values				Accuracy [%]
	Upper	Lower	Standard deviation [Hz]		
	Wet	Snowy	Dry	Slushy	
Feature at lag 0.2 ms	< 0.41	> 0.56	< 151	> 151	93
Feature at ACF 0.5 [ms]	< 0.20	> 0.25	< 151	> 151	93

APPLICATION OF ANN TO CLASSIFICATION

ANN is a sophisticated network system that is made of many neurons connected with each other in a way similar to the human brain. The neural network is composed of a number of highly interconnected processing neurons working in parallel to solve a specific problem. Our proposed classification method is carried out in sets of multiple neural networks using a learning vector quantization (LVQ) network. The LVQ network is a hybrid network which uses both unsupervised and supervised learning to form classifications [3, 4]. The construction of the cumulative curves and ACF plots for a neural classifier is based on the conceptual block diagram shown in Fig. 5. The schematic block diagram consists of preprocessing, processing, and post-processing.

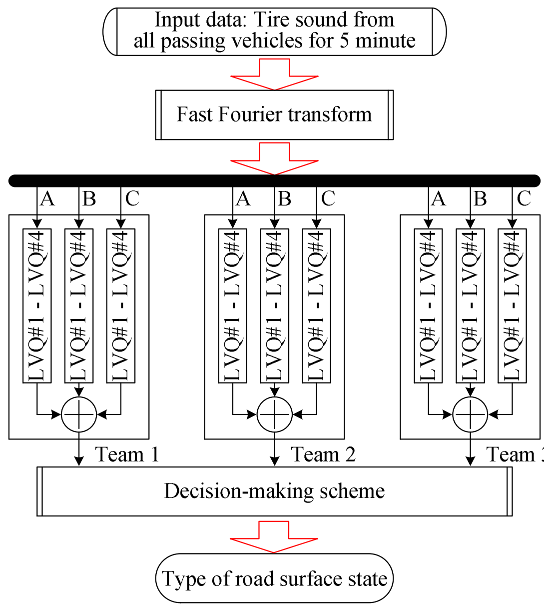

Figure 5. Schematic block diagram of automatic detection of road surface states

Input data for the neural network are the pre-processed tire noise signals with the following six features extracted from the noise signals: peak frequeny, the feature at 1.5 kHz, and at 0.5, standard deviation, the feture at lag 0.2 ms, and at ACF 0.5, as described above. The processing phase uses multiple neural networks with these six features. We employ three teams in the ANNs, in which each team consists of 12 LVQ networks. For example, Team 1 contains three groups, A, B, and C, and individual group with four LVQs from #1 to #4 are classifiers for each surface state. In this report, the work of LVQ#1 is assigned for specifying the snowy state. At the same time, the input data of LVQ#2 to #4 are provided for classifying the slushy, wet, and dry states, respectively. Therefore, the output data of the processing phase are the four types of the surface states. When multiple neural networks are utilized, the post-processing phase is required to combine the outcomes of the multiple neural networks for making a decision on road surface states and to provide a level of confidence for the decision. The output of each team is then combined to produce the final decision-making schemes.

All LVQs must be trained using known road surface states before they are used as part of a classifier. Each of the LVQs is trained separately and their weight vectors are initialized independently. After the training process, the individually different weight vectors are determined definitely. In the testing phase, the states are examined along with all the other prespecified ones. The schematic diagram for the testing phase is the same as the one shown in Fig. 5. The use of multiple sets of neural networks arises from the need to achieve a higher accuracy rate and provides a way of calculating a degree of confidence for each identified state. The voting scheme is the simplest method of combining the output of multiple neural networks. A decision is made based on which type of road surface states receives the most votes [5].

To evaluate the performance of the present automatic detection method, we examined the noise data of two weeks at the same observation site as before (near Sapporo city). The data of the first week is the training set and the remaining data of second week is the testing set. Table 2 shows the numbers of tire noise records required for each surface state. The total number of the feature data for each day is 288 by 24×60 min/5min. For one-week testing observation, the total number of data is 2016. The total number of noises recorded for training the classifier is 400 per team.

The ANN method in this study is performed using a MATLAB program. To test the neural networks, 288 recorded tire noise signals for each day are used. Table 3 summaries the verification results. The results show the performance of the automatic classification of the four types of the surface states. For example, the total number of tire noise signals for the snowy state is 721. Of these data, 706 signals are correctly recognized as snowy; therefore, the accuracy rate is 98%. It can be noted that the error rate changed daily, although the changes are slight. In our analysis, the highest accuracy of 96.5% is attained on the 3rd day, while the accuracy on the 5th day gives the lowest, 73%. The accuracies in the remaining days are greather than 89% and average value for the entire one-week is approximately 90%. It is also noted that the classification of the snowy state gives the highest accuracy rate. The classification of the slushy state gives the lowest accuracy rate. Unfortunately, these factors cannot be completely avoided in only the present classification method. However, by including more appropriate sound features as input data that specify road surface states and additional meteorological information such as road surface temperature, the classification accuracy must be increased.

CONCLUSIONS

We advanced the research of multiple neural network analysis using both the two signal features and the four features proposed in our preceding report [1]. By comparing tire noise data samples obtained near Sapporo city with visual inspection data of the actual road surfaces, we evaluated the automatic classification capability at all hours of the day and night using only the noise signals. Typical one-week sound data and sufficient training data demonstrated that the four types of road surface conditions can be classified with a high classification accuracy of 90% on average, which is almost the same accuracy rate stated in the previous related report [2]. The present study leads us to believe that six signal features together with the neural network structure offer great potential for the automatic detection of road surface states.

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Table 2. Feature data set of detecting the road surface states over one-week using 5-minute sound signals

Road surface state	Training data	Daily test data							Total number of test data
		1st day	2nd day	3rd day	4th day	5th day	6th day	7th day	
Snowy	100	8	144	131	34	30	259	115	721
Slushy	100	86	72	39	25	133	29	17	401
Wet	100	35	72	118	164	124	-	156	669
Dry	100	159	-	-	65	1	-	-	225
Total	400	288	288	288	288	288	288	288	2016

Table 3. Results of automatic detection of road surface states over one-week using 5-minute sound signals

Road surface state	Correct results of each daily road surface state							Total number	Accuracy rate [%]
	1st day	2nd day	3rd day	4th day	5th day	6th day	7th day		
Snowy	7	140	129	30	27	258	115	706	98
Slushy	73	52	33	7	82	18	9	274	68.3
Wet	34	70	116	161	100	-	149	630	94.2
Dry	143	-	-	61	1	-	-	205	91.1
Accuracy rate [%]	89.2	91	96.5	90	73	95.8	94.8	1815	90