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On-board wet road surface identification using tyre/road noise and Support Vector Machines

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A B S T R A C T

Changes in weather have a major influence on driving safety. On wet pavement, tyre grip is reduced and drivers must adapt their driving style accordingly. The correct operation of this adaptation mechanism depends on the perception the driver has of the asphalt status. Due to certain effects, this perception does not always correspond with reality. To improve this perception, it is essential to inform the driver about the asphalt status, efficiently and as quickly as possible. This could be achieved by installing an asphalt status detection system on the vehicle itself. The system could display asphalt status information in the vehicle's console, allowing drivers to adapt their driving style accordingly.

In this paper we propose an asphalt status classification system based on real-time acoustic analysis of tyre/road noise. The proposed system uses a practical approach that allows it to be integrated into a real vehicle. We present the system architecture used to measure the noise and the signal processing algorithms used for the classification of the asphalt state. A practical implementation of the proposed system has been developed and tested. For this preliminary prototype, only wet and dry asphalt states have been covered. Obtained wet/dry classification results have been reported, showing very high success rates.

1. Introduction

1.1. Weather changes and accident risk

Changes in the state of the asphalt due to adverse weather negatively affect driving safety. Wet pavement reduces tyre grip, and accumulated water can cause *aquaplaning*, leading to a complete loss of vehicle control. It has been estimated that during rainfall, accident rates increase by 70% [1]. On icy or snowy asphalt, there is also risk of losing control of the vehicle due to slippery pavement condition. Some studies have estimated that the risk of injury accidents is 9 times greater on snowy roads and 20 times on icy roads [2,3]. Usually the snowy asphalt is easily detectable by the driver, but there are situations where ice is not readily visible, particularly when forming a thin and almost transparent layer, known as *black ice*. *Black ice* is also very slippery, making it very dangerous. A Finnish study found that only 14% of drivers were able to detect slippery pavement conditions [4]. Other studies have found that drivers are not good at adjusting the speed of their vehicle to the prevailing road conditions, even if the hazard (e.g. snow) is clearly visible [5,6].

Another phenomenon that makes difficult the driver adaptation to adverse asphalt condition is known as *anchoring* [7], which refers to the difficulty that humans have to change an initial hypothesis even with the succession of later evidences against it. This makes adaptation to slippery pavement conditions difficult, especially when these conditions change during driving (for example due to changes in ambient temperature).

It is therefore important to inform the driver about the road status. The most traditional method involves the placement of fixed signals in geographic locations of risk (such as in bridges where air currents favor the formation of *black ice*). Unfortunately fixed warning signals have shown a very low or even null influence in driving speed [8,9]. A more effective method consists in using Variable Message Signs (VMS) [10–12].

The driver does not only need to be informed, the information must be delivered as quickly as possible. It has been estimated that when a road becomes slippery, accident risk during the hour preceding maintenance actions is 12 times as high as 12 h earlier. During this high risk hour, road condition is usually known by Traffic Management Centres (TMC), but information takes some time to reach the driver, and most accidents occur during this interval [13].

Due to these factors, it appears highly advisable to have an on-board system that provides information about the state of the road in a reliable manner and in real-time. This way, drivers can always be informed about adverse pavement status conditions, and can adapt their driving style accordingly, reducing accident risk. In previous studies [12], it has been stated that *a more sophisticated system to recognize adverse weather and road conditions and low friction is needed.*

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1.2. State of the art

Automatic detection of weather condition of the asphalt has already been addressed with different perspectives and results. One approach uses a microphone installed at a fixed road location, to record the generated noise of the vehicles passing by [14–16]. Recorded noise, segmented in 5-min blocks, is pre-processed and analyzed using principal component analysis or neural networks, to estimate pavement status. Using this method, researchers have got high estimation accuracy, around 80% in most cases. This method could be used to implement fixed variable message signs, but is not suitable for integration into a vehicle.

Another approach uses 24-GHz automotive radar technology for detecting low-friction spots caused by water, ice, or snow on asphalt [17]. Laboratory and field experiments show interesting results. Radar technology used in this approach is very similar to the one used in speed control (usually operating in the 22–24 GHz range). To adapt one of these units, significant modifications must be made, including adding a dual-polarized antenna with a switch in the transmitter, the receiver or both. If the radar must be used for both speed control and road condition recognition, a switchable antenna is required such that the radar beam can be switched between the road surface and the direction of motion of the vehicle.

Other approaches that can be integrated in a vehicle, use image processing to distinguish the condition of the asphalt. Yamada et al. [18] tried to detect the wet/dry road condition using a standard video camera installed at the rear of the vehicle, trying to get the polarization of the image. Another more complex study in this line was carried out in the IcOR project, which has developed a prototype system that can detect the road condition (dry/wet/ice/snow), using two cameras mounted on top of the vehicle [19]. These cameras detect changes in polarization of light reflected on the asphalt surface, achieving a very high success rate for the condition of asphalt ice (up to 90%) but with much poorer results for the other cases. Other drawbacks of this method are that it is very expensive and requires a complex installation.

1.3. Objectives

The goal is to be able to detect road weather condition using a cheap and easy to install on-board system, achieving also a high success rate. The system should be able to detect dry, wet, icy and snowy conditions, but in a first approach, only dry and wet states are considered. The proposed system is based on the analysis of the tyre/road noise, in a similar approach to the one taken by Kongrattanaprasert et al. [15]. However, the system is designed to be mounted on-board, and the audio analysis approach is completely different.

2. Methodology

The system is based on the principle that the acoustic footprint of the tyre/road noise generated by the tyre/road interaction, differs depending on the road surface status. The noise generated when driving on a dry surface will be different to the one generated when driving on the same surface, if it is wet, icy or snowy. Tyre/road noise is well known when driving on dry roads. It has a very characteristic profile with a prominent peak around 1 kHz [20]. There is a lot less information about tyre/road noise on wet, dry and icy roads, but there is some work confirming the variation on the acoustic footprint [15,21]. As the acoustic footprints are different for each road status, it should be possible to know the road status by analyzing the tyre/road noise.

Fig. 1 shows the blocks comprising the proposed system. During driving, generated noise due to the tyre/road interaction is captured with a microphone. The signal generated by the microphone is adapted and amplified by the *Signal Conditioning* block. The *A/D conversion* block converts it from analogic to digital. The *Feature extraction* block pre-processes the audio signal and extracts its features, providing the feature vector to the Support Vector Machine (SVM) Classifier. The *SVM classifier* uses the pre-calculated *Support Vectors* and the feature vector to run a classification algorithm and outputs the estimated class. The final result is output by the *Spurious events filter* block. It filters the results from the SVM blocks, to avoid wrong classifications produced by glitches on the input signal. The SVM is a supervised learning based classifier. To obtain the *Support Vectors* and to select the relevant features, the system must be trained first.

2.1. Training, feature extraction and feature selection

Support Vector Machines are learning machines. Before the SVM is used as a classifier, it has to be trained. In Fig. 1, blocks in dashed lines need to be implemented only during the training stage, and do not need to be deployed in the final system. The training stage serves two purposes:

1. Selecting the relevant features of the signal.
2. Computing the support vectors.

One of the most important tasks when implementing a pattern recognizer is to correctly extract and select the features fed to the classifier. It is advisable to keep the dimensionality of the feature vector as low as possible. Keeping the dimensionality of the feature vector low, usually enhances generalization performance. It also reduces memory footprint and CPU power required by the classifier. In this system, features contain the frequency components of the acoustic input signal. The *Feature extraction* block, groups the audio samples into chunks of the same duration. Each of these chunks is processed by a 1/3 octave filter bank. Calculated frequency bands are normalized and overall sound pressure level is discarded by the feature extraction block. Keeping the overall sound pressure level as a separate feature is not needed, because the acoustic footprint generated by the tyre/road interaction is contained in the relative variations of the frequency components of the signal. Signal normalization has the additional benefit of making the system immune to microphone sensitivity deviations due to temperature, humidity, ageing, etc.

While training the system, the feature vector comprises all the 1/3 octave bands in the frequency range from 20 Hz to 20 kHz. The feature vector is output to the *Feature selection* block, along with the class corresponding to the feature vector. This block runs in parallel two algorithms on the feature vector: Recursive Feature Elimination (RFE) [22] and zero-norm minimization (L0) [23]. RFE algorithm tries to choose the features leading to the largest margin class separation by using a SVM classifier. The algorithm runs several iterations. At each iteration, the input dimension that decreases the margin the least is removed. L0 algorithm selects a feature subset that minimizes the zero-norm of the weight vector of the classifier. This poses a NP-hard problem, so the approximation method proposed by Weston et al. [23] has been used.

Once the relevant features have been selected, the process is repeated, but the feature vector is trimmed down to the selected features, and it's handed over to the *SVM training* block, along with the class corresponding to the feature vector. This block trains the SVM, computing the support vectors. Resulting support vectors data is stored in the *Support Vectors* block.

Once the training stage has finished, the system can start working in the normal (classifier) mode. In normal mode, only 1/3 octave bands selected during the training stage are computed and