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Environmental noise monitoring using source classification in sensors

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ABSTRACT

Environmental noise monitoring systems continuously measure sound levels without assigning these measurements to different noise sources in the acoustic scenes, therefore incapable of identifying the main noise source. In this paper a feasibility study is presented on a new monitoring concept in which an acoustic pattern classification algorithm running in a wireless sensor is used to automatically assign the measured sound level to different noise sources. A supervised noise source classifier is learned from a small amount of manually annotated recordings and the learned classifier is used to automatically detect the activity of target noise source in the presence of interfering noise sources. The sensor is based on an inexpensive credit-card-sized single-board computer with a microphone and associated electronics and wireless connectivity. The measurement results and the noise source information are transferred from the sensors scattered around the measurement site to a cloud service and a noise portal is used to visualise the measurements to users. The proposed noise monitoring concept was piloted on a rock crushing site. The system ran reliably over 50 days on site, during which it was able to recognise more than 90% of the noise sources correctly. The pilot study shows that the proposed noise monitoring system can reduce the amount of required human validation of the sound level measurements when the target noise source is clearly defined.

1. Introduction

Environmental noise, defined as unwanted or harmful outdoor sound created by human activities [1, Art. 3], can be generated by traffic, industry, construction, and recreation activities [2, p. 12]. Airports, (wind) power plants, rock-crushing, shooting ranges, and motorsport tracks are examples of noise sources for which sound propagation over several kilometers is relevant.

One challenge in environmental noise monitoring is how to make sufficiently comprehensive measurements both in time domain and spatially. The changes in weather conditions have a significant effect on monitored noise levels [3] and in order to obtain most of the variations the noise has to be monitored for extended periods of time [4–6]. Also, a single point noise measurement is rarely representative for a whole neighbourhood and several sensor locations are needed. Because of high costs of the equipment and the amount of human resources needed, the reliability, validity, and representativeness of environmental data is usually unsatisfactory. Only a few reported scientific experiments with uninterrupted noise data captured from each relevant location over long periods of time exist [7–10].

The typical need for measurements is to monitor the noise caused by a noise source (e.g. an airport or an industrial plant) in a residential area. However, also other noise sources exist and the captured noise level is usually a result of a combination of the target and interfering sound sources: wind-generated, cars, and birds being examples. Sound level meters used for noise monitoring either capture sound levels or time domain noise data and store the data locally – or nowadays more often – on a remote server [11]. The most common method to ensure the noise was caused by the original source is listening through all the samples afterwards. This requires a huge amount of resources because of a large amount of data due to often necessary long-term measurements. Also, if only noise levels are recorded, validation by listening is not possible.

A considerable amount of manual work can be saved by automatically validating sound sources. Furthermore, privacy issues can be avoided and required network load can be largely reduced, if the automatic validation algorithm is performed on the sensor and only the measurement result is transferred. Previous validation algorithms on sensors have been limited to hand-crafted rule-based systems [12]. However, a simple hand-crafted classifi-

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cation rule can hardly provide good accuracy in a complex environment, e.g. monitored target producing several types of sounds. As another drawback, the design of a hand-crafted classifier requires an expert for every noise monitoring scenario. The increased computational capacity has made a sensor possible to classify noise sources using a pattern classification algorithm, which is capable of learning a sophisticated noise source classifier for an arbitrary scenario, simply using relevant annotated recordings as training material.

An pattern classification algorithm typically consists of a feature extractor and a classifier. Mel-frequency cepstral coefficients (MFCCs) [13] are used as common features for a wide range of acoustic pattern classification such as speech recognition [14] and music information retrieval [15]. Gaussian mixture model (GMM) [16] has been traditionally cooperated with MFCCs to model different types of sounds. Specifically, the combination of MFCCs and GMM has been used for various noise monitoring scenarios [17,18]. The use of artificial neural network (ANN) for acoustic pattern classification has been increasing with the development of computing power and new training algorithms that allow utilising large amounts of training data. Some recent studies have shown that ANN outperforms traditional GMM in sound event detection [19–21].

Together with the smaller and cheaper computing capacity, the breakthrough of wireless technology in the very beginning of 2000s have made possible to translate the physical world into information [22] and given reason to define concepts like Internet of Things and ubiquitous sensing [23]. The word "smart" was first used as an attribute to a sensor with an Internet access. Today, it is more closely related to a sensor with own intelligence, some computational capacity for data analysis and decision making [24].

The main objective of this study was to show if it would be possible to automatically capture only the noise from the original source, by adding intelligence and human hearing-like decision algorithms to the sensor. This would free the huge amount of human resources needed to validate the noise data and improve and representativeness of the results in environmental noise measurements. An implementation of a noise classification algorithms in a sensor will be introduced. The general concept of the noise monitoring system is explained in Section 2 and the pattern classification algorithms are given in Section 3. Additionally, an evaluation of the performance of the algorithms in a case study is shown (Section 4) and some discussion the requirements and the future work in Section 5.

2. Noise monitoring

The proposed noise monitoring system comprises of *smart sensors* which are connected through wireless uplink to the *cloud service*. The overview of the system is illustrated in Fig. 1. The smart sensor consist of a measurement microphone and a single-board computer with a wireless transmission unit. To alleviate the privacy issues concerning the continuous audio capturing and storage, the most of the analysis and processing is done already in the sensor and only analysed data is transferred and stored in the default setting. This approach will also lower the amount of transferred data from a sensor to the cloud service, and enables placing sensors to areas with lower quality wireless uplinks. In the sensor, A-weighted 10-min equivalent sound pressure level ($L_{p,\mathrm{A},600\mathrm{s}}$) values are calculated continuously, and predominant noise sources are detected within the measurement time segment. This information is used to decide whether the actual acoustic signal is needed for further inspection in the cloud service. For example, segments exceeding the legal maximum allowed sound level can be saved for manual inspection. All the extracted measurements are transmitted from the smart sensor to the cloud service for further analysis. The cloud service stores the data in the measurement database, and audio segments marked for later inspection are stored in the disk server. End-users access the measurement data and analysis of the measurements through a web-based portal.

2.1. Smart sensor

For the prototype, the credit-card-sized RPi (Raspberry Pi) developed by the Raspberry Pi Foundation was selected mainly due to its excellent support network and general usability. RPi1, the first generation model was used in the prototype because it was the only available model in 2012 when the implementation was made. Additional functionality was added by an audio codec (a 24-bit multi-bit sigma delta AD converter), a smart power

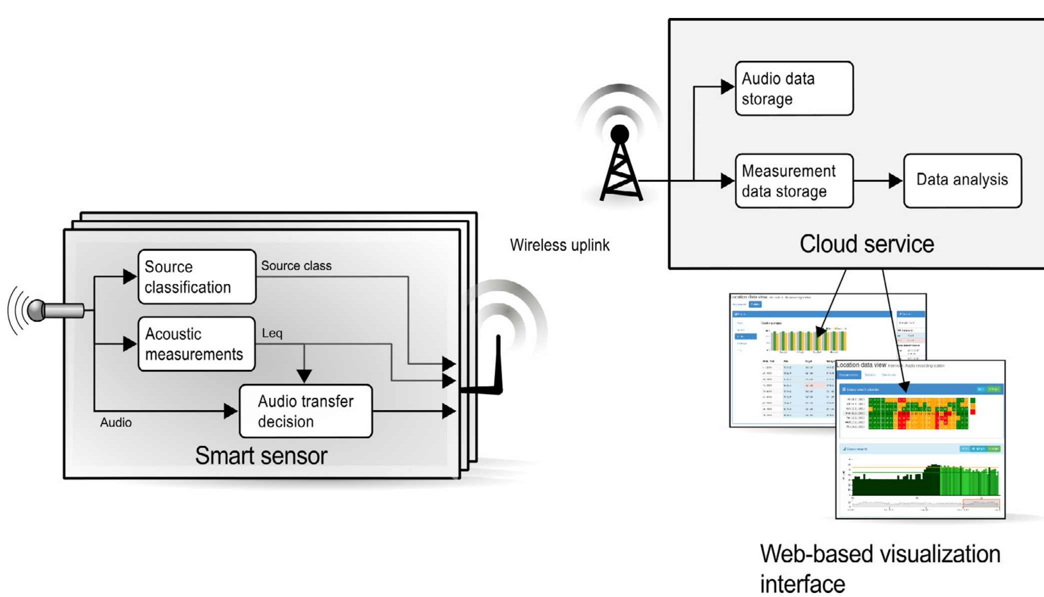

Fig. 1. Block diagram of the noise monitoring system.