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Acoustic detection and classification of river boats

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ABSTRACT

We present a robust algorithm to detect the arrival of a boat of a certain type when other background noises are present. It is done via the analysis of its acoustic signature against an existing database of recorded and processed acoustic signals. We characterize the signals by the distribution of their energies among blocks of wavelet packet coefficients. To derive the acoustic signature of the boat of interest, we use the Best Discriminant Basis method. The decision is made by combining the answers from the Linear Discriminant Analysis (LDA) classifier and from the Classification and Regression Trees (CART) that is also accompanied with an additional unit, called Aisles, that reduces false alarms rate. The proposed algorithm is a generic solution for process control that is based on a learning phase (training) followed by an automatic real time detection while minimizing the false alarms rate.

1. Introduction

The goal is to detect and classify the arrival of boats of a certain type via the analysis of their acoustic signatures with minimal number of false alarms and miss-detections. This processing is done against an existing database of recorded acoustic signals. The problem is complex because many types of boats arrive at the scene. In addition, the following may constantly change: the surrounding conditions, the velocities and the directions of the boats of interest, their distances from the receiver, not to mention some affecting conditions of the recorded acoustics.

As a running example in this paper, we choose to detect the blue tourist boat (denoted **BTB**) that is seen in Fig. 1.

A successful detection depends on the constructed acoustic signatures that were built from characteristic features. These signatures enable to discriminate between the class of interest and other classes. Acoustic signals emitted by boats contain a quasi-periodic component, which stems mainly from the sounds emitted by the engines and the propellers. This component is characterized by only a few dominating bands in the frequency domain. As the boat moves, the conditions are changed and the configuration of these bands may vary, but the general disposition remains. Therefore, we assume that the acoustic signature for the class of signals emitted by a certain boat is obtained as a combination of the inherent energies in the blocks of wavelet packet coefficients of the acoustic signals, each of which is related to a certain frequency band. Thus, they can be used as candidates to become the selected features. This assumption has been corroborated in the detection and identification of ground vehicles [1,2,21,22]. The experiments in the current paper demonstrate that a choice of distinctive characteristic features, which discriminate between the *Boat* (**B**) and the *NonBoat* (**NB**) classes and between the **BTB** and *OtherBoat* (**OB**) classes, can be derived from blocks of the wavelet packet coefficients. Extraction of characteristic features (parameters) and deriving the acoustic signatures for these classes are the critical tasks in the training phase of the process.

In order to identify a boat by its acoustic signatures, in the final phase of the detection process we combine the outputs from two classifiers: 1. Linear Discriminant Analysis (LDA) [8]. 2. Classification and Regression Trees (CART) [3], which was equipped with an additional unit called Aisles that reduces false alarms.

The paper has the following structure: Section 2 briefly reviews some related work. The structure of the available data is described in Section 3. Section 4 outlines the scheme of the algorithm and Section 5 provides its full details. Section 6 presents the experimental results. Glossary provides a list of abbreviations and notations.

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Fig. 1. The Blue Tourist Boat (**BTB**)

2. Related work

Acoustical systems have been used for a long time to detect moving vehicles on land, in air and underwater. The main differences between detecting objects on land and in water stem from the medium features and from the limitations of ocean environment. The density of water makes it possible for sound to travel five times faster than on land [12]. Ocean always has a surface and a bottom and the sound waves can propagate only between these two boundaries. On the other hand, the structure of the signal from the target's vehicle is almost the same whether the vehicle is moving on the ground or cruising in the ocean. Therefore, most acoustical detection systems can be applied at some level to either on land or in-water applications.

A number of papers have been published on the separation between vehicle and non-vehicle sounds on land and on their classification. Most of them describe systems for military context. Extraction of acoustic features by using the discrete wavelet transform was described in [5]. These features vectors were compared with the reference vectors in a database using statistical pattern matching in order to determine the vehicle's type. Discrete cosine transform was applied in [7] to signals and a time-varying autoregressive model was used. A system for the discrimination between different types of vehicles, which is based on the wavelet packets transforms, was presented in [1]. Classification and Regression Trees (CARTs) were used for making decisions on membership of new unknown signals. In a later paper [2], these authors used the multiscale local cosine transform that was applied to the frequency domain of an acoustic signal, in order to extract its characteristic features. The classifier was based on the *Parallel Coordinates* methodology [9]. The *eigenfaces method* [11], which was originally used for the human face recognition, was used in [20] to distinguish between different vehicles sound signatures. The data was sliced into frames – short series of time slices. Each frame was then transformed into the frequency domain. Classification was done by projecting new frames on the principal components that were calculated for a known training set. Comparison between several speech recognition techniques for the classification of vehicles types was described in [10]. These methods were applied to the short time Fourier transforms of the vehicles' acoustic signatures.

Underwater acoustics has been investigated extensively. Fractal based approaches to passive recognition of surface and underwater targets were studied in [13,16]. These approaches include wavelet analysis, fractal dimension analysis and analysis that is based on fractional Brownian motion. The project [4] in the Naval Research Laboratory tried to improve seaside surveillance systems in harbors. They developed a system that can detect, classify and identify an harbor threat. NATO Undersea Research Center [15] (NURC) conducts research on wide area of Maritime surveillance applications. Automatic identification system, which is based on anomaly detection, was investigated in [14]. NURC has underwater intruder detection projects for military and civilian areas.

There are some commercial and military related surveillance systems. One of the most famous passive hydroacoustic surveillance system is the US Navy's SOund SUrveillance System (SOSUS). It uses the bottom mounted hydrophone arrays and it is capable of detecting both surface vessels and submarines. Later, SOSUS has been used by civilian researches in various scientific projects. For example, [17] reported tracking humpback whales using the SOSUS detection system and compared it with the satellite tracking system to achieve reliable results. Northrop Grumman's Centurion [18] and DSIT's Harbour Security System (HSS) are commercial target detection and surveillance systems that are based on acoustic detection. These methods show reliable detection and tracking results.

3. The structure of the recorded data

The available audio data was recorded by a single hydrophone. These recordings were accompanied by simultaneous video footage. The audio data was recorded in different conditions. Some recordings were made when no boats were present at the scene. Some recordings contain sounds from the Blue Tourist Boat (**BTB**), which was cruising at different speeds, directions and distances from the hydrophone. From time to time, other boats of different types, such as the fire boats, the commuter boats, the fire boats, the big ferry ships, and small motor boats were present at the scene together with the **BTB**. Fig. 2 displays some vessels, which arrived at the scene.

Some of the recordings contain sounds from other boats without the presence of the **BTB**. The audio recordings were sampled at the rate of 2000 samples per second. Part of the recordings was used for training the algorithm while the remaining recordings were left for testing the algorithm.

We extracted from the training recordings fragments that did not contain boats sounds. They were stored as the *no-boat* (**NB**)-class training signals. Fragments that contain sounds emitted by various boats were stored as the *boat* (**B**)-class training signals. The signals in the latter class were highly variable. Then, this class was divided into two subclasses: 1. Fragments that contain recordings of the **BTB**. It was designated as the **BTB**-class. 2. The rest of the signals in the **B**-class signals were designated as the *other boat* (**OB**-class).

By examining the Fourier spectra of the available signals, we realized that even within the same **BTB** class, the spectra of the signals differ significantly from each other. However, there are some common properties to all these acoustic signals that were recorded in the harbor. First, these signals are quasi-periodic in the sense that there exist some dominating frequencies in each signal. These frequencies may vary as motion conditions are changed. However, for the same boat, these variations are confined in narrow frequency bands. Moreover, the relative locations of the frequency bands are stable (invariant), to some extent, for signals that emitted by the same boat. We illustrate this observation in Fig. 3, where the spectra of two fragments from the **BTB** recordings are displayed versus the spectra of two fragments from the other boats.

Therefore, we conjectured that the distribution of the energy (or some energy-like parameters) of acoustics signals that belong to some class in different areas in the frequency domain, may provide a reliable characteristic signature for this class. In other words, they can be used as the foundations for generating unique features that characterize the signal.