Comparison of Methods of Noise Classification

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Abstract. *Ok here we make the abstract. Needless to say it comes last. Should have max 10 lines.*

1. Introduction

Many Acoustic Signal Processing (ASP) tasks are performed in noisy conditions. The presence of noise, additive or otherwise, decreases the performance of those tasks, be it speaker recognition [Ming et al. 2007], emotion recognition [Schuller et al. 2010], source localization [Benesty 2000] or speech recognition [Friesen et al. 2001]. Thus, it is imperative to study noise so we can better assess how it affects ASP tasks and how we can deal with it. Automatic classification of types of noise is an important part of this study, since the knowledge of the kind of noise present in a given situation is useful knowledge to better treat it [May et al. 2012].

There is extensive previous work in the field of audio classification. There is great variety in the methods used to perform this task, such as statistical methods [Dal Degan and Prati 1988, Peltonen et al. 2002], methods using stochastical knowledge such as *Hidden Markov Models* (HMM) [Ma et al. 2003], using neural networks [Beritelli et al. 2005] and support vector machines [Cumani and Laface 2012]. There is variety also in the applications sought, such as speaker recognition [Kinnunen and Li 2010, Murty and Yegnanarayana 2006, Farrell et al. 1994], acoustic scene recognition [Piczak 2015, Barchiesi et al. 2015] or animal species recognition [Somervuo et al. 2006, Lee et al. 2008]. The noise classification is different only in application, but can be performed using any method used for audio classification [Beritelli et al. 2007, Ma et al. 2006].

This work proposes to evaluate the performance of four common methods used in audio classification in the specific task of classify noise. To this end, we implement those methods in the same set of audio files containing different types of noise. These files are taken from the NOISEX database [Varga and Steeneken 1993], a database comprised of audios of 15 types of noise. The evaluation follows these steps: The extraction of attributes of each audio file, construction of the models according to each method, classification and evaluation of the results. The methods compared are the Neural Network, Gaussian Mixture Model, Support Vector Machines and K-means.

The remainder of this paper is organized as follows. Section 2 introduces the task of noise classification, as long as the methods used in this paper. Section 3 describes the experiments performed and the results obtained and, finally, in Section 4 we present our conclusions about the results found, as long as the future works.

2. Noise Classification

In this section we should describe the audio classification task and how it applies to our specific problem, the noise classification.

Additionally, we have to describe each method we use, in subsections.

2.1. Extraction of Audio Attributes

The first step towards classification is the extraction of attributes from the data that are useful for the classification algorithms. In this Section we present two of the most widely used in the literature, the Linear Predictive Coefficient [Rabiner and Juang 1993] and the Mel-Frequency Cepstral Coefficient (MFCC) [Xu et al. 2005]. In this work, we will use the MFCC to represent our audios.

2.1.1. Linear Predictive Coefficient (LPC)

In the Linear Predictive analysis of audio, the audio is divided into frames of the same size, usually 20ms, and each frame is predicted as the linear weighted sum of the *n* previous frames, there *n* represents the order of the prediction [Rabiner and Juang 1993].

$$\hat{s} = \sum_{k=0}^{n} \alpha_k s(n-k) \tag{1}$$

The difference between the prediction and the actual values of the frame is computed as error. The coefficients α_k are obtained minimizing the prediction error through the least squares minimization.

2.1.2. Mel-Frequency Cepstral Coefficient (MFCC)

The Mel-Frequency cepstrum is efficient in modeling pitch and frequency content of audio signals. It yields better results when coding audio for in classification tasks than the LPC [Li et al. 2001].

In the mel-cepstral analysis, the audio signal is filtered by *K* bandpass filters, which have constant mel-frequency interval and cover the $0 - 4000$Hz frequency range. The MFCCs are calculated by the following equation:

$$c_n = \sqrt{\frac{2}{K}} \sum_{k=1}^{K} (\log S_k) \cos[n(k-0.5)\pi/K] \tag{2}$$

In which c_n is the coefficient for the n^{th} frame and $S_k, k = (1, 2, ..., K)$ are the output of each bandpass filter.

2.2. Classification Methods

2.2.1. Neural Network

One or two paragraphs should do. Don't forget the proper references (like this one [Lei et al. 2014]).

2.2.2. K-means

This is a method used in summarization. Didn't find references.

2.2.3. Gaussian Mixture Models

This section describes the use of Gaussian mixture models (GMM) in the task of noise representation and classification. Here is a good journal article for further reference [Reynolds and Rose 1995].

2.2.4. Support Vector Machines

Here we have a paper in audio classification using SVM [Cumani and Laface 2012].

3. Experiments

Here we will describe the experiments. It should contain an introductory paragraph containing the purpose of the experiments.

3.1. Experimental Setup

This paragraph should have all the requirements to perform the experiment, including hardware, software and general conditions. Sometimes people put the database here, but i think it will provide greater value if we put it in it's own subsection.

3.2. Database Description

Here we describe the NOISEX database. Since it's an important part of this work, we should take our time to properly describe it.

3.3. Evaluation Metrics

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Here we can describe how we evaluate the performance of each experiment.

3.4. Results

You may be wondering why have only the 'results' and not the 'experiments' subsection. This is because we already told the reader everything he has to know in the previous sections. Section 2 describes the different methods and Sections 3.1 and 3.2 describe the details of the experiments.

Table 1. Confusion Matrix for Neural Network

	Babble	Bucc 1	Bucc 2	Dest Eng	Dest Ops	F16	Fac 1	Fac 2	HFChn	Leop	M109	MachGun	Pink	Volvo	White
Babble	6,5%						0,1%	0,1%							
Buccaneer 1		6,6%													
Buccaneer 2			6,7%												
Destroyer Engine				6,6%											
Destroyer Ops					6,5%										
F16						6,6%									
Factory 1							6,0%	0,2%					0,1%		
Factory 2							0,3%	6,4%							
HF Channel									6,7%						
Leopard										6,6%					
M109											6,6%				
Machine Gun												6,6%			
Pink							0,2%						6,6%		
Volvo														6,6%	
White															6,7%

Table 2. Accuracy per class for the methods compared.

Class	K-means	GMM	Neural Network	SVM
Babble	86,01%	98,90%	97,5%	
Bucanneer 1	97,11%	99,31%	99,1%	
Bucanneer 2	98,86%	99,69%	99,8%	
Destroyer Engine	99,64%	99,67%	99,7%	
Destroyer Ops	91,79%	97,66%	98,3%	
F16	96,67%	99,10%	99,2%	
Factory 1	59,06%	91,11%	92,3%	
Factory 2	94,10%	95,26%	94,7%	
HF Channel	100,00%	99,99%	99,9%	
Leopard	98,69%	98,93%	99,4%	
M109	93,89%	99,01%	99,3%	
Machine Gun	7,45%	99,77%	99,5%	
Pink	99,76%	98,38%	96,9%	
Volvo	90,78%	99,67%	99,7%	
White	99,95%	99,96%	100,0%	
OVERALL	87,78%	98,43%	98,4%	

4. Conclusions

Here we conclude the paper. I suck at this, so pls someone do it for me. The one thing I know is that we have to summarize our findings and link it to our problem stated in the introduction, telling the reader whether we were successful or not in the task we proposed in the beginning.

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