Comparison of Methods of Noise Classification

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Abstract. *Noise is one of the main problems affecting the performance of most acoustic signal processing tasks. Thus, understanding and analyzing noise is fundamental to pursue better results. One of the paths in this better understanding is the automatic classification of noise. In this work we compare four classification methods widely researched in the literature in the task of noise classification. This classification was performed in the NOISEX database and the methods chosen to be compared were the K-means, Gaussian Mixture Model, Support Vector Machines and Neural Network. Results show that the SVM performs the classification better than the other methods studied.*

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

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.

In this work, we used $K = 13$, and the $\delta_n = c_n - c_{n-1}$ and $\delta\delta = \delta_n - \delta_{n-1}$ coefficients were calculated, thus rendering 39 coefficients by frame.

2.2. Classification Methods

2.2.1. Vector Quantization LGB

This is a quantization (summarization) method based on k-means. It's commonly used in data compression [Kekre and Sarode 2008]. One of the most famous implementations of this method is the LBG algorithm [Linde et al. 1980].

It divides the training data in clusters of equal size and represents each group by it's centroid point. In the test phase, we calculate the euclidian distance between each sample and all the centroids and label the sample with the class of the closest cluster.

2.2.2. Gaussian Mixture Models (GMM)

The GMM is used based on the knowledge that a set of acoustic signal classes can be represented by it's component densities [Reynolds and Rose 1995]. The GMM is a weighted sum of K component densities, given by:

$$p(\vec{x}|\lambda) = \sum_{k=1}^{K} p_k b_k(\vec{x}) \tag{3}$$

Where $\vec{x}$ is a random vector representing our input signal, K is the number of components of the signal, $p_k, k = 1, ..., K$ are the mixture weights and $b_k(\vec{x}), k = 1, ..., K$ are the component densities.

Each class is represented by it's model λ:

$$\lambda = \{p_k, \vec{\mu}_k, \sum k\}, k = 1, ..., K \tag{4}$$

Where $\vec{\mu}_k$ is the mean and $\sum k$ is the covariance matrix of each component density $b_k(\vec{x})$.

2.2.3. Support Vector Machines (SVM)

The SVM is a machine learning technique that has successfully been used in pattern recognition tasks, such as audio classification [Dhanalakshmi et al. 2009]. The basic idea of this technique is to estimate the hyperplane that better separates a group of data [Cumani and Laface 2012]. The hyperplane can be linear or be created using a kernel function to better do the separation.

There are two distinct phases: in the training phase, the algorithm estimates the best hyperplane, searching for the one that maximizes the distance between the training

data of different classes. In the test phase, the classification using the trained hyperplane is performed using different data. This way, we can assess the generalization capacity of the model.

The experiments shown in Section 3 were performed using the quadratic kernel.

2.2.4. Neural Network

Neural Network is an interconnected group of artificial neurons designed to simulate the functionality of a brain. It is organized in layers: the input layer, the hidden layer and the output layer. Each neuron has it's own weight and a activation function [Wu et al. 2007].

In the classification task, the weights of the neurons are updated by training the network with labeled data, until the network can yield the expected result in the output layer.

In this work we used a network with 50 neurons.

3. Experiments

This section will describe our experiments. They follow these steps: First we divide the dataset in train and test data. After that we divide the audio files in samples of 20ms, overlapping 50%. Than we extract the MFCC of those samples. In the training phase, the MFCC of the training data are used to build models based on the methods described in Section 2.2. In the test phase, we classify the data using those models. This procedure is outlined in Figure 1.

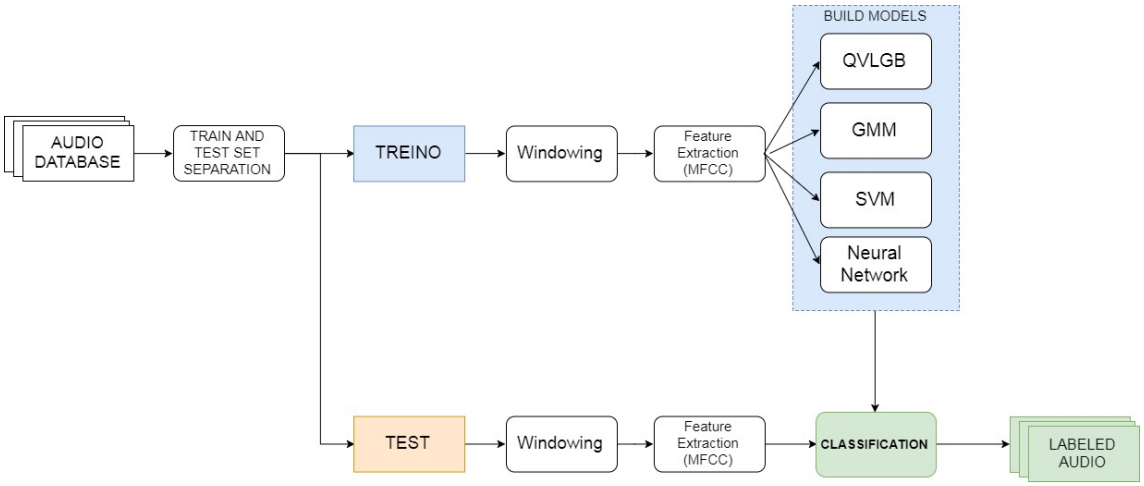

Figure 1. Outline of the experiments.

3.1. Experimental Setup

The experiments were performed using MATLAB, using the Neural Network toolbox and the SVM toolbox. They were performed in two separated computers. The K-means and GMM experiments were performed with an Intel-i7 1,8GHz processor, with ram memory of 8GB and Windows10 OS. The Neural Network and SVM experiments were performed with an an Intel-i3 processor, with ram memory of 4GB and Linux OS.

3.2. Database Description

For this work we used the NOISEX database [Varga and Steeneken 1993]. This database is composed by 15 audio files, one for each of the 15 different classes of noises, which are shown in Table 1. All the audio files are in .wav format, 3 minute and 55 seconds long and they have a bit rate of 319 kbits per second.

Table 1. Classes existing in the NOISEX database.

Babble	Buccaneer 1	Buccaneer 2	Destroyer Engine	Destroyer Operations Room
F16	Factory Floor 1	Factory Floor 2	HF Channel	Leopard
M109	Machine Gun	Pink Noise	Volvo	White Noise

3.3. Cross-Validation

The 4-fold cross-validation was performed. The accuracy reported in Table 2 are the mean of the results in each test. This way, the generalization of each model is better asserted.

3.4. Results

In this section we present and analyze the results obtained in the experiments. The accuracy of the classifiers is presented in Table 2, overall and divided by class.

The first thing to be noted is that the best result is obtained by the SVM classifier, followed closely by the overall accuracy of the Neural Network and the GMM classifiers. The k-means classifier is almost 10% less accurate than the other three.

The most accurate classes are 'white' and 'hf channel' and the result for 'machine gun' in the k-means classifier is inexplicably low.

Table 2. Accuracy per class for the methods compared.

Class	K-means	GMM	Neural Network	SVM
Babble	88,2%	98,9%	97,5%	
Bucanneer 1	96,6%	99,1%	99,1%	
Bucanneer 2	98,8%	99,7%	99,8%	
Destroyer Engine	99,8%	99,7%	99,7%	
Destroyer Ops	90,8%	96,9%	98,3%	
F16	95,2%	99,1%	97,6%	
Factory 1	59,3%	87,6%	92,3%	
Factory 2	93,9%	95,0%	94,7%	
HF Channel	100,0%	100,0%	99,9%	
Leopard	99,1%	99,6%	99,4%	
M109	94,1%	99,3%	99,3%	
Machine Gun	7,1%	99,5%	99,5%	
Pink Noise	99,7%	98,0%	96,9%	
Volvo	90,8%	99,4%	99,7%	
White Noise	99,9%	99,9%	100,0%	
OVERALL	89,2%	98,0%	98,4%	

The confusion matrices for each method are shown in Tables 3, 4, 5 and 6, in the Appendix A.

4. Conclusions

In this work, we aimed to compare four classification methods widely known in the literature. For this, we did the classification in NOISEX, a known noise database. Three of the four methods performed above 95%, ensuring noise classification is feasible as part of enhancement techniques for acoustic signal processing tasks. The inconsistencies of the performance as well as the poorer result renders the k-means method the less suitable of the ones studied in this work. Another shortcoming of the methods is the need of training, which is time consuming and demands a large training data set.

4.1. Future Works

Some possible future paths for this work are listed below:

- Explore Deep Learning techniques. The experiments performed in this work depend on pre-processing the audio data before doing the classification. Deep learning techniques can use the raw data to classify, thus eliminating this step.
- Expand the dataset. This work focused on a well known database, but it would be more representative to use them in more extensive data, or noise mixed with clean audio, which is the usual in Audio Signal Processing tasks;
- Explore the state-of-the-art classification methods. This work focused in methods widely used and known in audio classification. There are evolutions of these methods that yield better results than the ones pictured here in other applications of audio classification, and may yield better results in this specific task.

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A. Extra Results

Table 3. Confusion Matrix for the K-means classifier

	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 4. Confusion Matrix for the GMM classifier

	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 5. Confusion Matrix for the SVM classifier

	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 6. Confusion Matrix for the Neural Network classifier

	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%