Comparison of Methods of Noise Classification

Antonio Nascimento[1], Felipe de S. Farias[1], Marilia Alves [2]

[1]Programa de Pos-Graduacao em Engenharia de Defesa
Instituto Militar de Engenharia (IME)

[2]Programa de Pos-Graduacao em Engenharia Eletrica
Instituto Militar de Engenharia (IME)

3

{antonio.nascimento,felipe.farias,marilia.alves}@ime.eb.br

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.

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

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)

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

ISSO EH UMA SUGESTAO

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.

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.

References

Barchiesi, D., Giannoulis, D., Stowell, D., and Plumbley, M. D. (2015). Acoustic scene classification: Classifying environments from the sounds they produce. *IEEE Signal Processing Magazine*, 32(3):16–34.

Table 1. Accuracy per class for the methods compared.

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

Table 2. Model of confusion matrix PRA EU N TER Q FAZER ISSO DE NOVO

	Babble	Buccaneer 1	Buccaneer 2	Destroyer Engine	Destroyer Ops	F16	Factory 1	Factory 2	HF Channel	Leopard	M109	Machine Gun	Pink	Volvo	White
Babble															
Buccaneer 1															
Buccaneer 2															
Destroyer Engine															
Destroyer Ops															
F16															
Factory 1															
Factory 2															
HF Channel															
Leopard															
M109															
Machine Gun															
Pink															
Volvo															
White															

Benesty, J. (2000). Adaptive eigenvalue decomposition algorithm for passive acoustic source localization. *The Journal of the Acoustical Society of America*, 107(1):384–391.

Beritelli, F., Casale, S., and Serrano, S. (2005). Adaptive robust speech processing based on acoustic noise estimation and classification. In *Signal Processing and Information Technology, 2005. Proceedings of the Fifth IEEE International Symposium on*, pages 773–777. IEEE.

Beritelli, F., Casale, S., and Serrano, S. (2007). Adaptive v/uv speech detection based on acoustic noise estimation and classification. *Electronics Letters*, 43(4):249–251.

Cumani, S. and Laface, P. (2012). Analysis of large-scale svm training algorithms for language and speaker recognition. *IEEE Transactions on Audio, Speech, and Language Processing*, 20(5):1585–1596.

Dal Degan, N. and Prati, C. (1988). Acoustic noise analysis and speech enhancement techniques for mobile radio applications. *Signal Processing*, 15(1):43–56.

Farrell, K. R., Mammone, R. J., and Assaleh, K. T. (1994). Speaker recognition using neural networks and conventional classifiers. *IEEE Transactions on speech and audio* *processing*, 2(1):194–205.

Friesen, L. M., Shannon, R. V., Baskent, D., and Wang, X. (2001). Speech recognition in noise as a function of the number of spectral channels: comparison of acoustic hearing and cochlear implants. *The Journal of the Acoustical Society of America*, 110(2):1150–1163.

Kinnunen, T. and Li, H. (2010). An overview of text-independent speaker recognition: From features to supervectors. *Speech communication*, 52(1):12–40.

Lee, C.-H., Han, C.-C., and Chuang, C.-C. (2008). Automatic classification of bird species from their sounds using two-dimensional cepstral coefficients. *IEEE Transactions on Audio, Speech, and Language Processing*, 16(8):1541–1550.

Lei, Y., Scheffer, N., Ferrer, L., and McLaren, M. (2014). A novel scheme for speaker recognition using a phonetically-aware deep neural network. In *Acoustics, Speech and Signal Processing (ICASSP), 2014 IEEE International Conference on*, pages 1695–1699. IEEE.

Ma, L., Milner, B., and Smith, D. (2006). Acoustic environment classification. *ACM Transactions on Speech and Language Processing (TSLP)*, 3(2):1–22.

Ma, L., Smith, D., and Milner, B. P. (2003). Context awareness using environmental noise classification. In *Interspeech*.

May, T., Van De Par, S., and Kohlrausch, A. (2012). Noise-robust speaker recognition combining missing data techniques and universal background modeling. *IEEE Transactions on Audio, Speech, and Language Processing*, 20(1):108–121.

Ming, J., Hazen, T. J., Glass, J. R., and Reynolds, D. A. (2007). Robust speaker recognition in noisy conditions. *IEEE Transactions on Audio, Speech, and Language Processing*, 15(5):1711–1723.

Murty, K. S. R. and Yegnanarayana, B. (2006). Combining evidence from residual phase and mfcc features for speaker recognition. *IEEE signal processing letters*, 13(1):52–55.

Peltonen, V., Tuomi, J., Klapuri, A., Huopaniemi, J., and Sorsa, T. (2002). Computational auditory scene recognition. In *Acoustics, Speech, and Signal Processing (ICASSP), 2002 IEEE International Conference on*, volume 2, pages II–1941. IEEE.

Piczak, K. J. (2015). Environmental sound classification with convolutional neural networks. In *Machine Learning for Signal Processing (MLSP), 2015 IEEE 25th International Workshop on*, pages 1–6. IEEE.

Rabiner, L. and Juang, B.-H. (1993). *Fundamentals of Speech Recognition*. Prentice-Hall, Inc., Upper Saddle River, NJ, USA.

Reynolds, D. A. and Rose, R. C. (1995). Robust text-independent speaker identification using gaussian mixture speaker models. *IEEE transactions on Speech and Audio Processing*, 3(1):72–83.

Schuller, B., Vlasenko, B., Eyben, F., Wollmer, M., Stuhlsatz, A., Wendemuth, A., and Rigoll, G. (2010). Cross-corpus acoustic emotion recognition: Variances and strategies. *IEEE Transactions on Affective Computing*, 1(2):119–131.

Somervuo, P., Harma, A., and Fagerlund, S. (2006). Parametric representations of bird sounds for automatic species recognition. *IEEE Transactions on Audio, Speech, and Language Processing*, 14(6):2252–2263.

Varga, A. and Steeneken, H. J. (1993). Assessment for automatic speech recognition: Ii. noisex-92: A database and an experiment to study the effect of additive noise on speech recognition systems. *Speech communication*, 12(3):247–251.

Xu, C., Maddage, N. C., and Shao, X. (2005). Automatic music classification and summarization. *IEEE transactions on speech and audio processing*, 13(3):441–450.