Journal of Advanced Research in Signal Processing and Applications
Volume 3, Issue 2 - 2021, Pg. No. 1-5
Peer Reviewed Journal

Research Article

Robust Noise Feature Extraction for Efficient Classification

BP Mishra[1], Rupalee Dwivedi[2], Utkarsh Singh[3], Vaibhav Gupta[4]

[1]Professor, [2,3,4]Student, Department of Electronics and Communication, JSS Academy, Noida, Uttar Pradesh, India.

I N F O

Corresponding Author:
Rupalee Dwivedi, Department of Electronics and communication, JSS Academy, Noida, Uttar Pradesh, India.
E-mail Id:
rupaleedwivedi@gmail.com
Orcid Id:
https://orcid.org/0000-0003-4519-1886
How to cite this article:
Mishra BP, Dwivedi R, Singh U et al. Robust Noise Feature Extraction for Efficient Classification. *J Adv Res Sig Proc Appl* 2021; 3(2): 1-5.

Date of Submission: 2021-07-07
Date of Acceptance: 2021-08-19

A B S T R A C T

In current paper, authors try to investigate regarding robust noise parameter to be used for efficient noise classification in noise parameter analysis which will then be used for intelligent volume control. One hundred and twenty original noises from environment were recorded with the help of a microphone connected to personal computer and stored as a noise samples in the computer's memory. We have used MATLAB software for the software implementation of noise parameter analysis. Built-in programs have been used for Linear Predictive Coding (LPC) and Real Cepstral Parameter (RCEP) whereas user defined program was written for Mel Frequency Cepstral Coefficient (MFCC) to get variation in noise parameters which may be further used for analysing the noise samples and classified through any one of the soft computing techniques viz. neural networks, fuzzy logic, genetic algorithms or a combination of these. Forty samples each of three commonly encountered environmental noises (car, market and train) i.e., 120 noises in total have been considered in our study for estimation of three coefficients viz. Mel Frequency Cepstral coefficient, Linear predictive coding and real cepstral parameter. Our experimental results show that Mel Frequency Cepstral Frequencies are robust features for finding out variation in noise parameter estimates.

Keywords: MATLAB software, Mel Frequency Cepstral coefficient (MFCC), Noise Parameter Estimates, Linear Predictive Coding

Introduction

A person's life in today's world is not easy. There are many aspects of daily living that seem straightforward from outside but when we go deeper it becomes more confusing and exhausting. Any unwanted, unpleasant sound that causes us problem in hearing or interferes in our ongoing work is known as noise. Due to the increasing population, there are a lot of increasing noise sources. Environmental noise can be divided into several categories, which affect us in some or the other manner.

The following noise categories are:

- Automobile's Noise Class (ANC): Cars, buses, trucks, trains, ambulance, police cars
- Babble Noise Class (BNC): Sports, office, cafeteria etc.
- Factory Noise Class (FNC): Tools such as drilling machines, hammer
- Street noise class (SNC): shopping mall, market, busy street, bus station, gas station
- Miscellaneous noise class (MNC): Aircraft noise, thunder storm

Out of these noise classes, two noise classes have been considered viz. car noise, train noise and market noise.

Noise Parameter Analysis

The noise samples collected from the environment are analysed in MATLAB using the audio-read command. Signal representation of internet downloaded, and original car noise is as follows (Figure 1, 2, 3).

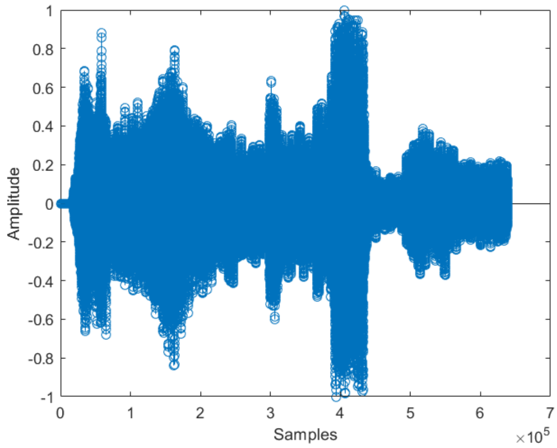

Figure 1.Original car noise representation in MATLAB

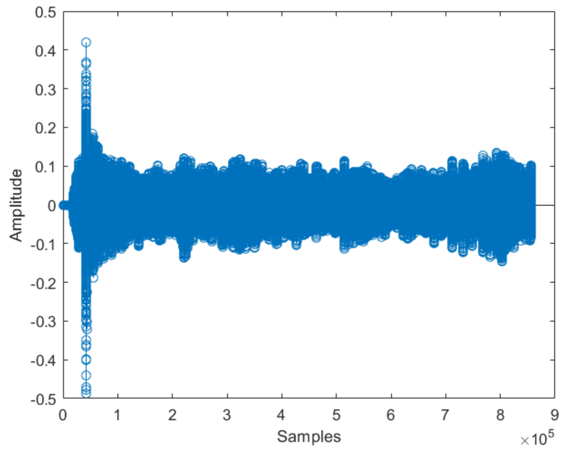

Figure 2.Recorded market noise representation in MATLAB

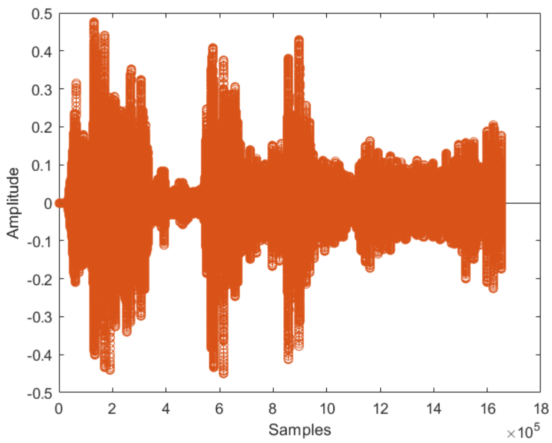

Figure 3.Recorded train noise representation in MATLAB

Models used for Feature Extraction

There are in total 27 noise parameters which can be used to predict the figure of noise, in this paper we will be studying three of them.

MFCC

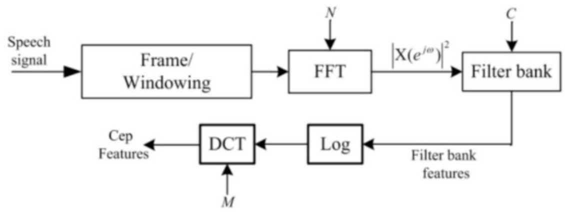

Figure 4.Block diagram of MFCC

The first step involved in extracting the mel-frequency cepstral coefficient is to input the noise data samples collected from the environment and recorded from the internet. The selected properties for the noise input signals are in WAV audio. (Figure 4, 5).

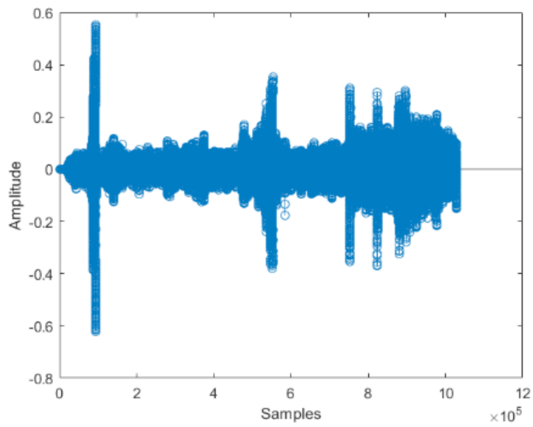

Figure 5.Recorded Market noise representation in MATLAB

The second step involved in feature extraction is framing. Human speech is a non-stationary signal, but when segmented into parts, they become quasi stationary. Due to this reason the noise sample input is to be divided into frames before feature extraction takes place. (Figure 6).

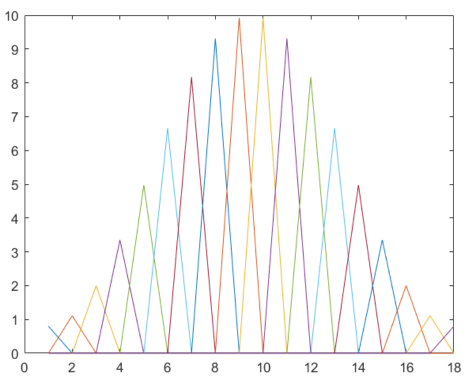

Figure 6.Frame of recorded market noise in MATLAB

The third step involved in MFCC extraction is windowing. The agenda behind using the windowing function is to smooth the edges of each frame to reduce discontinuities or abrupt changes at the endpoints. The windowing serves a second purpose and that is the reduction of the spectral distortion that arises from the windowing itself. (Figure 7).

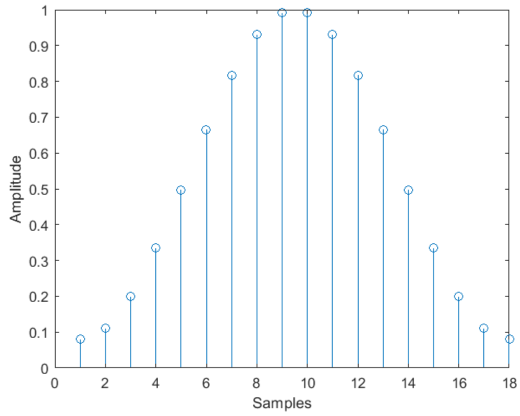

Figure 7.Windowing of recorded market noise in MATLAB

The fourth step involved in MFCC extraction is fast fourier transform. The FFT is a powerful tool, it calculates the DFT of an input in a computationally efficient manner, saving processing power and reducing computation time. (Figure 8).

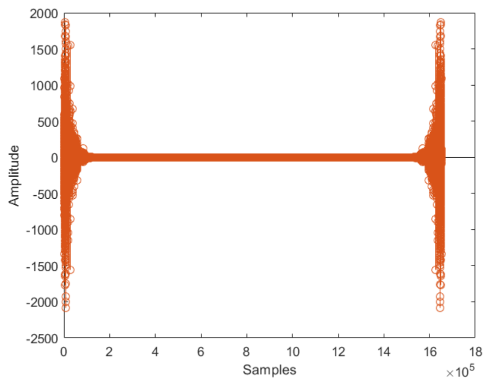

Figure 8.FFT of recorded m noise in MATLAB

Mel-cepstral coefficients are the features that will be extracted from noise during our work. The major difference between MFCC and cepstral coefficients lies in the processing involved when extracting each of these characteristics of a speech signal. The process of obtaining Mel-cepstral coefficients involves the use of a Mel-scale filter bank. The spectral coefficients of each frame are then converted to Mel scale after applying a filter bank. The Mel-scale is a logarithmic scale resembling the way that the human ear perceives sound. The filter bank is composed of triangular filters that are equally spaced on a logarithmic scale. The Mel-scale warping is approximated and represent by the following: (Figure 9, 10).

Mel (f) = 2595 log10 (1 + f / 700), where f is frequency.

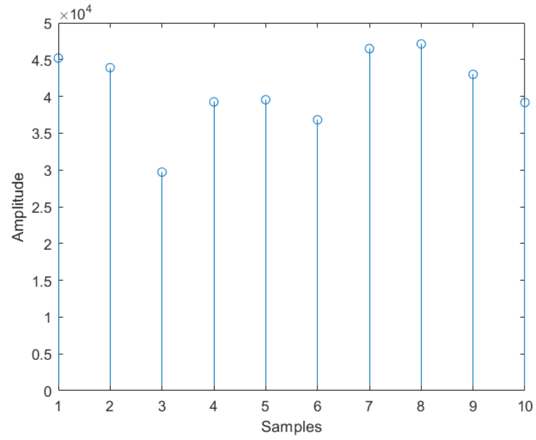

Figure 9.Mel Spectral Coefficients of Internet Car noise signal in MATLAB

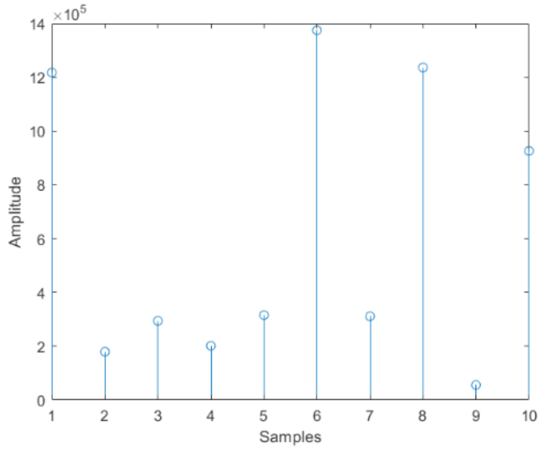

Figure 10.Mel Spectral Coefficients of Recorded Car noise signal in MATLAB

Discrete Cosine Transform- The Discrete Cosine Transform is applied to the log of the Mel-spectral coefficients to obtain the Mel-Frequency Cepstral Coefficients. (Figure 11 and Figure 12).

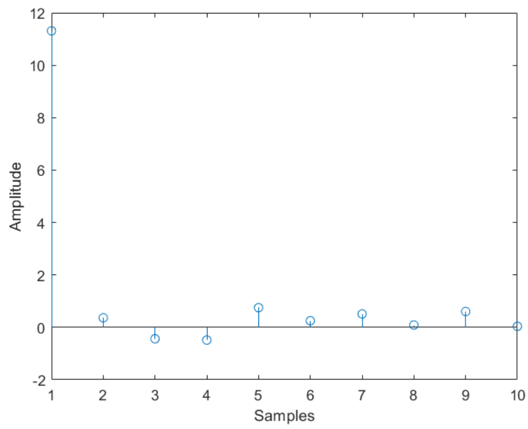

Figure 11.Mel Frequency Cepstral Coefficients of Internet Market noise in MATLAB

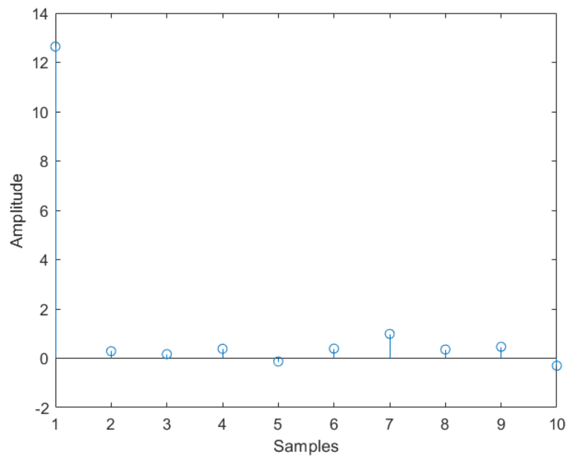

Figure 12.Mel Spectral Coefficients of Recorded Market noise in MATLAB

LPC

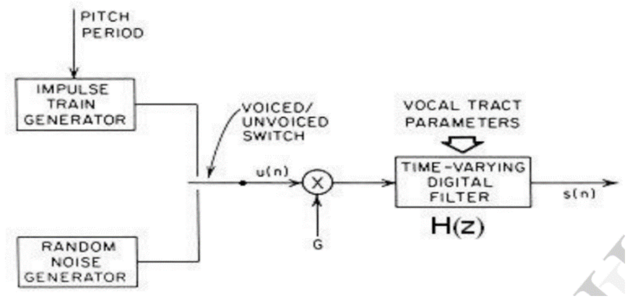

Figure 13.Block diagram of LPC

The objective of linear prediction is to form a model of a Linear Time Invariant (LTI) digital system through observation of input and output sequences. The basic idea behind linear prediction is that a noise sample can be approximated as a linear combination of past noise samples. By minimizing the sum of the squared differences (over a finite interval) between the actual noise samples and the linearly predicted ones. (Figure 13).

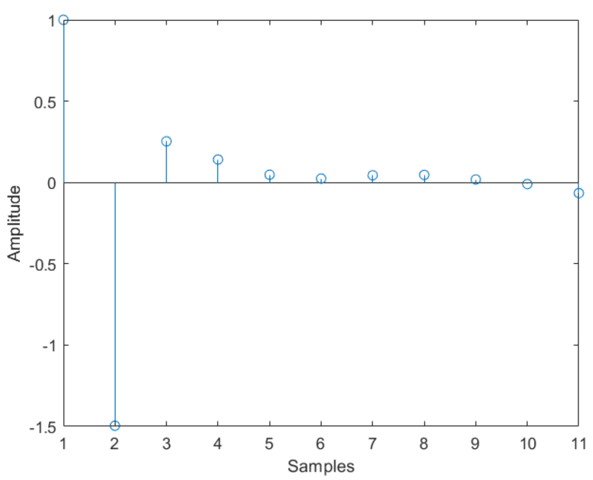

Figure 14.LPC of Internet Market noise in MATLAB

If u(n) is a normalized excitation source and scaled by G, the gain of the excitation source, then LPC model is the most common form of spectral analysis models on blocks of noise and is constrained to be of the following form, where H (z) is a pth order polynomial with z-transform and the coefficients a1, a2, ..., ap are assumed to be constant over the noise analysis frame H (z) = 1 + a1z-1 + a2 z -2 + a3 z -3 + ... + ap z-p Here the order p is called the LPC order. (Figure 14).

RCP

As per theory, the Cepstrum is defined as the inverse Fourier transform of the real logarithm of the magnitude of Fourier transform. Hence, the following function calculates the real Cepstrum of the signal x.

$$y = \frac{1}{2\pi}\int_{-\pi}^{\pi} \log|X(e^{i\omega t})|\, e^{i\omega t}\, d\omega,$$

Thus, real Cepstrum block gives the real Cepstrum output of the input noise frame and is also a popular way to define the prediction filter. (Figure 15).

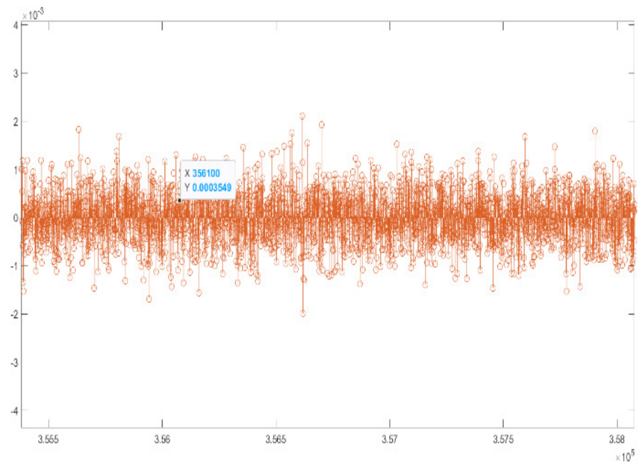

Figure 15.RCP of Internet Train noise in MATLAB

Results Obtained in MATLAB

In below tables result is tabulated: (Table 1, 2, 3).

Table 1.MFCC

Noise type	S1	S2	S3	S4	S5
Car	.3999	.2425	-.4987	.1505	-.2136
Market	.8216	.6046	.1096	-.0302	-.3035
Train	-0.0178	-0.0523	.2260	-.1510	.7826

Table 2.LPC

Noise type	S1	S2	S3	S4	S5
Car	1.0208	0.7362	0.8455	1.0796	1.0761
Market	0.9212	0.9013	0.7723	0.8617	0.7706
Train	-1.4957	-1.7966	-1.6223	-1.39408	-2.3684

Table 3.RCEP

Noise type	S1	S2	S3	S4	S5
Car	-2.6302	-1.9089	-1.4278	-1.5134	-1.3946
Market	1.3984	.8324	.8429	.8807	1.4749
Train	1.6640	-.7288	-1.3622	1.4243	2.1224

Conclusion

On experimentation, our MATLAB results show that out of three noise parameters under consideration, Mel Frequency Cepstral Frequencies are robust features in noise parameter analysis for efficient classification. By trial & error method, it was found that the best result of MFCC was obtained at maximum difference of 0.1574. As the frequency bands are positioned logarithmically in MFCC, it approximates the human auditory system response more clearly than any other system. MFCC estimates some of the speaker dependent properties of the noise sample signal along with the speech contents. Therefore, MFCC is a robust feature in noise parameter analysis for efficient classification.

References

1. Picheny M, Nahamoo D, Goel V et al. Trends and advances in speech recognition. IBM Journal of Research and Development. 2011; 55(5): 1-2.
2. Mitra V, Nam H, Espy-Wilson CY et al. Articulatory Information for Noise Robust Speech Recognition. Audio, Speech, and Language Processing. *IEEE Transactions* 2011; 19(7): 1913-1924.
3. Nadeem D, Mishra BP. Variation in Noise Parameter Estimates for Background Noise Classification. 2014; 3(2).
4. Itakura F, Saito S. Speech information compression based on the maximum likelihood spectrum estimation. *Journal of the Acoustical Society of Japan* 1971; 27: 463-470.
5. Beritelli F, Casale S, Ruggeri G. New Results in Fuzzy Pattern Classification of Background Noise. Proceedings of ICSP 2000.
6. Treurniet WC, Gong Y. Noise independent speech recognition for a variety of noise types. *Proc IEEE ICASSP 94 Adelaide* 1994; 437-440.
7. Beritelli F, Casale S. Background Noise Classification in Advanced VBR Speech Coding for Wireless Communications. Proc. 6th IEEE International Workshop on Intelligent Signal Processing And Comunication systems (ISPACS98), Melbourne. 1998; 451-455.
8. Khaled El-Maleh, Samouelian A, Kabal P. Frame-Level Noise Classification in Mobile Environments. ICASSP 99, Phoenix, Arizona. 1999; (3).