The acoustical properties of seven commonly encountered background noises for digital signal processing applications

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Abstract:
We can say that the most common noise sources through the United States are highway/cars, railroad/train, and airport/planes. These common noises and the others behave like a background noise for digital signal processing applications. The problem of reducing or removing noise in signals is very important. The problem has been addressed in many different ways over the years. Background environmental noises degrade the performance of speech-processing systems such as speech coding, speech recognition, and hearing aids. By modifying the processing according to the type of background noise, the performance can be enhanced. This requires classifying different noises. In this paper, we studied seven commonly encountered background noises: subway, highway, inside train, inside car, rain, restaurant, and airport. The acoustical properties, Auto Correlation Function (ACF), energy, and delay are calculated. Our experimental results show significant differences between some types of noises.

1.Introduction

Sound environment have changed in the last four decades. The number of sources and the number of source types have both increased. Some source types have become quieter while some have become noisier. Most people use of more noise sources now than they did before.

Actual noise monitoring systems have the shortcoming that although the intensity, duration, and time of occurrence of noises can be recorded, their source often cannot be identified. Such information would be particularly useful when multiple noise sources are possible. This has led to research directed toward providing an "intelligent" noise monitoring system able to distinguish between the acoustic signatures of different noise sources [1]. Various techniques have been proposed for that purpose, including neural networks [2-3], linear classifier [4], ad hoc methods [5], and statistical pattern recognition [6-7]. In this paper the important acoustical parameters of noise are extracted from the autocorrelation function (ACF) such as $\phi(0), \tau(1), \varphi(1)$ and τ_e are found to be very effective for analyzing acoustical properties of noise and to identify its source [10-12-13]. This noise classifier will be very useful in digital signal processing applications such as hearing aids, workers who are in noisy environments and Environmental Noise Directive (END).

Hearing instrument users often prefer different instrument-settings in different acoustic environments. Modern hearing instruments allow to the users to select between several hearing programs for different situations. These programs are to change the frequency response and compression parameters, or to activate a directional microphone, noise reduction, or feedback suppression. However, the user has the bothersome task of recognizing the acoustic environment and then switching to the program that best fits this situation, using a switch on the hearing instrument or a remote control. Automatic sensing of the current acoustic situation and automatic switching to the best fitting program would therefore greatly improve the utility of today's hearing instruments. The above assumption was confirmed by practical experiences. In a study with hearing impaired subjects, the usefulness and acceptance of an automatic program selection mode in the hearing instrument was investigated from the point of view of the user [8].

It was shown that the automatic switching mode of the test instrument was deemed useful by a majority of test subjects, even if its performance was not perfect.

Many people are exposed to hazardous noise levels at work, including firefighters, military personnel, disc jockeys; subway workers; construction workers; musicians; farm workers; industrial arts teachers; highway workers; computer operators; landscapers; factory workers, and cab, truck, and bus operators. The U.S. Environmental Protection Agency (EPA) reported that around nine million people are working in noisy environment [9].

Continued exposure to more than 85 decibels (dBA) of noise may cause gradual but permanent damage to hearing. Hearing loss is accelerated by louder noises. Noise can also hamper job performance, increase fatigue, and cause irritability [9].

Federal Occupational Safety and Health Administration (OSHA) regulations require that, when engineering controls and/or administrative controls cannot reduce noise levels in industry to an eight-hour time-weighted average (TWA) level of less than 85 dBA, a hearing protection (or conservation) program must be established. A successful hearing loss prevention program benefits both the employee and the employer. Employees are spared disabling hearing loss and may experience less fatigue and better health in general. Employers benefit from reduced medical expenses and worker compensation costs. Overall, there is improved morale and work efficiency in the workplace [9].

Noise source separation is a key issue in the Environmental Noise Directive (END), since the contribution to the overall noise level of each single source should be evaluated separately. This because each noise source should eventually be reduced independently from the other sources and the effect of the single noise source reduction should be readily compared to the corresponding of other sources [10].

These results were a strong motivation for the research described in this paper. Our database has seven major noise sources such as subway train, rain, highway, inside a car, inside a train, restaurant, and airport. All of these noise sources have different AFC parameters, which will help us to classify the noise source.

2. Method

Autocorrelation Method assumes that the samples outside the time interval $[n-M, n+M]$ are all zero and extends the prediction error interval i.e., the range over which we minimize the mean square error $\pm\ \infty$. For convenience, the short-time segment begins at time *n* and ends at time $n+N_w-1(N_w=2M+1)$.

The short-time autocorrelation function can be given as,

$$\phi[\tau] = \sum_{m=0}^{Nw-1-\tau} s_n[m]s_n[m+\tau] \qquad (1)$$

where

$$s_n[m] = s[m+n]*w[m] \text{ for } m = 0,1,2,\ldots,N_W-1 \qquad (2)$$

The short-time sequence $s_n[m]$ convolved with itself flipped in time in Eq.1. The autocorrelation function is a measure of the "self-similarity" of the signal at different lags τ as shown in Figure1. When $\phi(\tau)$ is large, then signal samples spaced by τ are said to be highly correlated [11].
One of the main important property of autocorrelation function is $\phi(0)$ equals the energy in $s_n[m]$ i.e.,

$$\phi(0) = \sum_{-\infty}^{\infty} |s_n[m]|^2 \tag{3}$$

The normalized ACF of the discrete-time signal is defined by

$$\varphi(\tau) = \phi(\tau)/\phi(0) \tag{4}$$

Four physical factors were extracted from the ACF [13]:

1. Energy represented at the origin of delay, $\phi(0)$,
2. Effective duration of the envelope of the normalized ACF, τ_e,
3. The amplitude of the first maximum peak of the normalized ACF, ϕ_1, and its delay time, τ_1.

The value of τ_1 corresponds well to the fundamental frequency of signal and the value of ϕ_1 is regarded as the strength of the fundamental frequency. When the band noise is used as a source signal, the value of τ_1 corresponds to the center frequency of the band noise and the value of ϕ_1 decreases as the bandwidth increases. To vary the value of factor ϕ_1, the visual stimuli consisted of a sinusoidal wave with frequency of 1 Hz (ϕ_1 = 1.0) and band noises with four different bandwidths centered on 1 Hz; thus, ϕ_1 = 0.7, 0.55, 0.4, and 0.3 and the value of τ_1 = 1 ms for all stimuli [13]. This can be seen in the Figure 1.

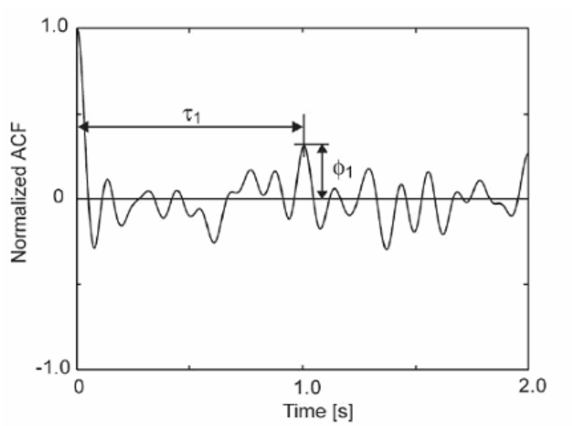

Figure 1: Normalized ACF of a signal and definition of factors ϕ_1 and τ_1.

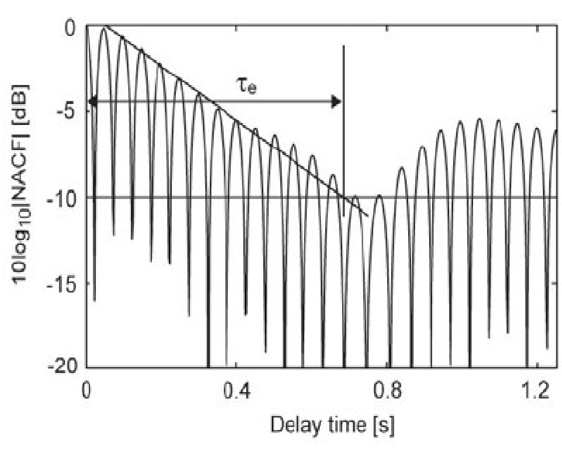

Figure 2: Definition of effective duration of ACF (τ_e)

The value of τ_e, which represents a repetitive feature contained within the source signal and it is defined by the delay time at which the envelope of the normalized ACF becomes 0.1 [12]. It is given in the Figure2.

3. Results

We studied the acoustical properties of seven commonly encountered background noises: subway, highway, inside train, inside car, rain, restaurant, and airport. Noise signals are sampled at 44100 kHz. Acoustical parameters, which are energy $\phi(0)$, delay τ_1, amplitude ϕ_1, and effective duration τ_e, are calculated using the Auto Correlation Function (ACF). ACF graphics of the seven background noises are given in Figure 3.

ACF results of the signals belong to rain and restaurant show some similarity. Their ϕ_1 and $\phi(0)$ values are smaller than the other signals' ϕ_1 and $\phi(0)$ values. Numerical results are given in Table 1.

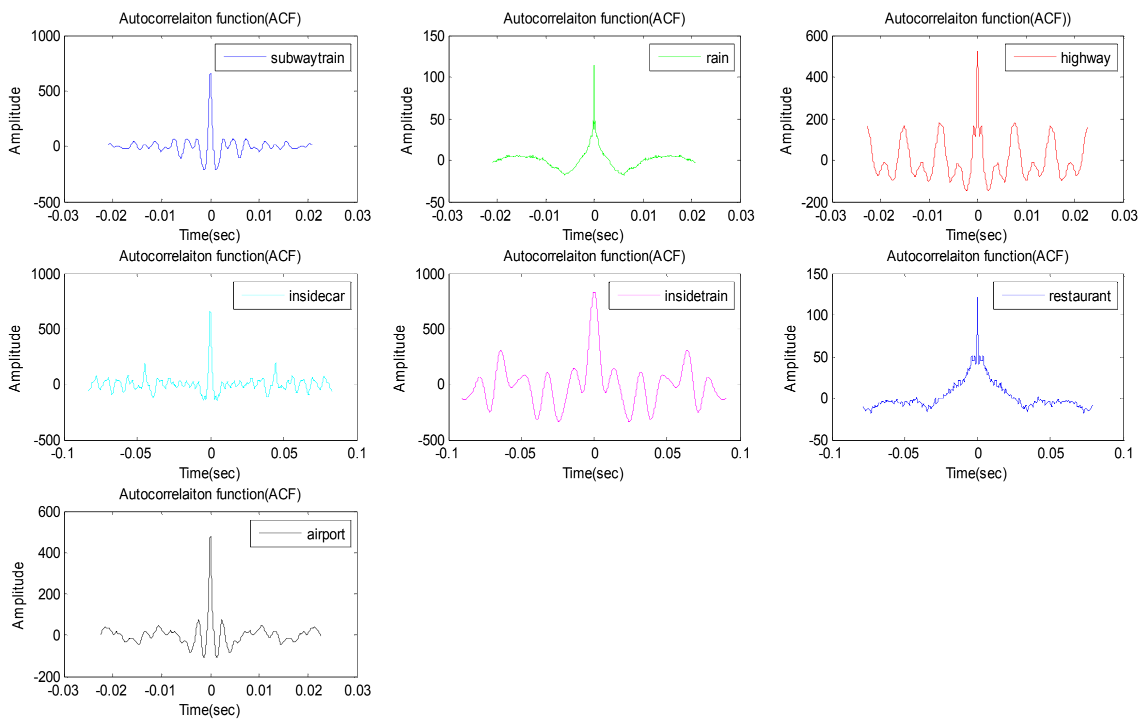

Figure 3: Autocorrelation function (ACF) for different noises sources.

Table 1. ACF parameters of seven commonly encountered background noises.

Noise Source	Energy(J) $\phi(0)$	Delay τ_1 (msec)	Amplitude ϕ_1	Effective duration τ_e (msec)
Subway Train	655.7	2.72	0.099	2.81
Highway	522	7.84	0.340	16.92
Airport	480	2.4	0.150	7.5
Rain	115	15.58	0.050	τ_e<<1
Restaurant	120	127.3	0.053	τ_e<<1
Inside Car	655	44.6	0.291	10.21
Inside Train	837	64.04	0.364	165.5

Inside car and inside train noise signals are recorded inside the vehicles. The ACF parameters of these two signals are found to be quite higher than that of the other signals. This can be related to the vehicle acoustics. With regard to the temporal aspects of vehicle acoustics, reflected signal with various delays and amplitudes superimpose the direct signal inside the vehicle. The effective duration (τ_e) of the ACF can reveal the characteristic temporal aspects of vehicle acoustics.

4. Conclusion

In this paper, we studied the acoustical properties of different noise sources using autocorrelation function (ACF) parameters. In our results, we saw that these noise sources can be grouped in to two based on the ACF parameters i.e., effective duration τ_e, amplitude of first peak ϕ_1 and energy $\phi(0)$.

The first group is the noise sources, which has some kind of machine involvement in their operation (like subway train, highway, inside car, inside train and airport noises) and the second group, which does not have any machine involvement in their operation (like rain and restaurant noises). We observed that the first group have greater values of amplitude of first peak ϕ_1, energy $\phi(0)$, and effective duration τ_e when compare to the second group.

Our future work is to develop such a system that can identify the noise source based on the ACF parameters.

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