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A Comparative Analysis of Signal Denoising Schemes for Cricket DRS

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ABSTRACT

To obtain noiseless signals from the noisy signals is one of the challenging task. A lot of noise filtering techniques have been employed for noise removal from an audio signal. Wavelet denoising technique is one of the technique that using threshold algorithm for noise removal in audio signals. Double-density dual-tree discrete wavelet transform (DDDTWT) using a level dependent threshold algorithm to eradicate noise from signals and also maintain the signal quality. Audio signal contaminated with Additive White Gaussian Noise is chosen for the implementation. The results in terms of signal to noise ratio (SNR) and root mean square error (RMSE) are compared with the values of dual-tree discrete wavelet transform (DTDWT) and double-density discrete wavelet transform (DDDWT) methods and also with global thresholding method. In this paper, audio denoising techniques PCA blind signal separation, Gaussian low pass filter, Wiener noise reduction and Noise deconvolution for noise reduction are used to increase classification and accuracy of cricket DRS. The results of MATLAB simulations show that the proposed method is more effective and gives better performance for denoising audio signals in terms of both SNR and RMSE. All the denoised snick signals; were passed through PCA blind signal separation, Gaussian low pass filter, Wiener noise reduction and Noise deconvolution when tested by cricket DRS a 98 percentage of classification rate were achieved.

Key words:Gaussian low pass filter,Blind deconvolution, MISO Wiener filter, PCA BSS.

1. INTRODUCTION

Audio signals in real time are polluted with various types of realistic noises. These noises are from different sources. So, from last few years to reduce the noise level, a lot of filtering techniques are using and still it is a challenging task for researchers. But, presently there are some transform based techniques are used to remove noise from a polluted signal. One of the transform technique known as wavelet transform will be used for denoising an audio signal from realistic noise. Predominantly, the objective of this proposed research is to denoise a noisy snick that occurs on the cricket field. Moreover, the idea is to implement the audio signal denoising techniques such as decomposition, thresholding and reconstruction in the MATLAB simulation software. The proposed research work covers different noise filtering techniques. An audio data set of 250 snicks signals that's collected in open environment (playground) through various microphones place at different position. These microphones were directly connected with a personal computer. After collecting these signals then passed through four denoising techniques named Gaussian low pass filter, Blind deconvolution, MISO Wiener filter and PCA blind signal separation

A microphone array is any number of microphones spaced and placed apart from each other in a specific pattern, which work in parallel to produce a resultant output signals [1]. Each microphone working like a sensor, or spatial window, for receiving the incoming signal. The total response of the array is a superposition of the responses of each element in the array consistent with the processing algorithm used. The different microphones signals undergo 'array processing' algorithms totally based on the microphone spacing's and placing patterns, the quantity and type of microphones, and sound propagation principles. Microphone arrays are typically used to improve audio input signals in the presence of noise in hearing aids, speech recognition equipment, and telecommunication products [2]. But they may also be used to locate the direction and estimate the distance of sounds from the array.

The main purpose of a microphone array for audio communications is to provide a high-quality version of the desired speech signal while at the same time reducing the level of localized and ambient noise signals [3]. The quality aspect means that the resulting speech signal is natural sounding, without any artifacts such as pops and clicks, un-intended muting, frequency distortions, echoes, or periodic changes in signal levels associated with the signal processing methods done to achieve the speech enhancement. Therefore, the measure of signal to background noise ratio improvement (SNR) alone is NOT the only criteria to use in selection of a background noise suppression solution.

Microphone array techniques can be divided into two broad areas-namely beam forming and blind signal separation (BSS). Both of techniques share the commonality of filtering and merging the microphone signals to best extract the signal of interest. Traditional beam forming techniques require information, such as array geometry and source localization, to form a beam toward the source of interest [4]. In the second case, all of the sources are

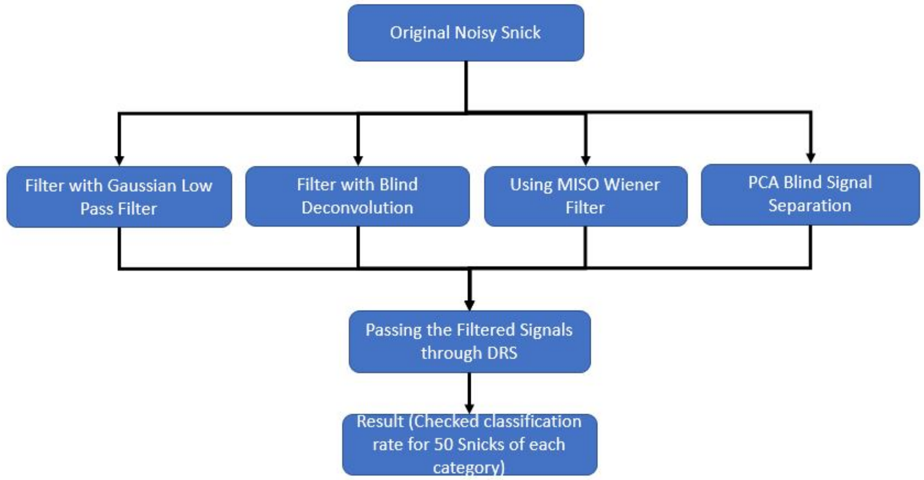


Figure 1 shows the research procedure

separated from their mixtures without prior knowledge of the sources or the arrays.

BSS techniques for signal separation has many applications in acoustics, where different sounds from different sources are recorded promptly either with individual microphones or microphone arrays [5, 6]. These signals sources may be music or speech or surrounding sounds. In all these cases noise is reduced and the desired signals are separated from hinders and other noise sources.

Denoising Schemes

We collected 250 signals in the open environment from the five classes as a snick resulting from contact of the cricket ball with either (i) ball on bat (ii) ball on gloves (iii) ball on pad or (iv) bat on ground (v) a combination of bat and pad. The collected signals were very noisy. To clean up these signals the following four techniques were applied on them.

The schemes are briefly presented as follows

Gaussian low pass filter

In electronics and signal processing, impulse response of Gaussian filter is a Gaussian function (or an approximation to it). Gaussian filters have the properties of having no overshoot to a step function input while minimalizing the rise and fall time [7]. This behavior is strictly connected to the fact that the Gaussian filter has the least possible group delay. It is considered the domain filter of ideal time, just as the sinc is the ideal frequency domain filter [8]. These properties are much more important in the field such as oscilloscopes and digital telecommunication systems. Mathematically, a Gaussian filter convert the input signal by convolution with a Gaussian function; this transformation is also known as the Weierstrass transform [9].

MISO Wiener filter

In signal processing and speech processing, the MISO Wiener filter is that type of filter which is used to produce an estimated and expected random process by linear time-invariant (LTI) filtering of a detected noisy process, presumptuous known stationary signal and noise spectra, and additive noise [10]. The MISO Wiener filter shrinkages the mean square error between the estimated random process and the desired process. The blocking equalizer output or result is self-governing of the signal of interest and is used as the input to a multiple input single output (MISO) Wiener filter that reduces the noise in the matched filter output.

Blind deconvolution

The blind deconvolution module eradicates linear distortions introduced to the signal by the transmission channel or environmental distortion. These distortions amend the signal spectrum: some frequency bands are enlarged and other bands are attenuated. This results in unnaturally sounding speech. The same algorithm as the noise whitening module used by the blind deconvolution module. The main difference is that a speech signal (the pattern) is used in the processing instead of part that contains only noise. In an ideal, the pattern should contain only acoustic signal from the same microphone as in the processed recording and it should not contain any noise [11, 12]. The aim of the processing is to match the spectrum of the parts of recording that contain speech signal to the spectrum of the pattern.

The algorithm works as follows.

1 The average and smooth spectrum of an audio signal is calculated.

2 All parts of the recorded signals that contain audio signal are first detected and then segmented.

3 The averaged and smoothed spectra of each section that is detected are calculated.

4 The inverse transfer functions calculated for each recorded section;

5 The filtered Signal finally.

PCA Blind signal separation

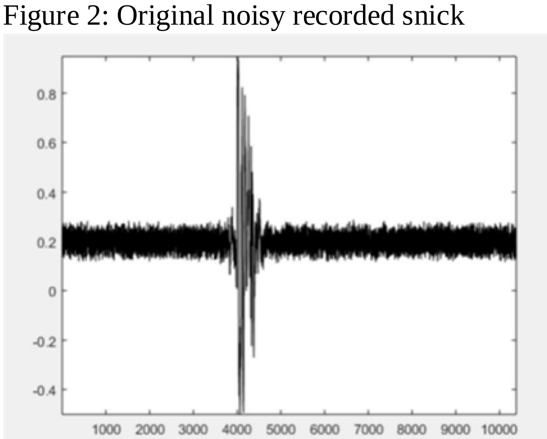
Blind Signal Separation (BSS) method is used in many applications of digital signal processing andspeech processing where signal is parted by using blind methods and is also applicable, radio communications, including acoustics, as well as image processing in the field of IT. Blind Source Separation or Blind Signal Separation (BSS) is the that separate of signals set from a mixed signals set without the help of information about the signal source or the mixing process[13]. Blind source separation method depends on the hypothesis that the source signals do not associate with each other. For example, a set of signals may be statistically autonomous or decorrelated. Because of this independence, the set can be parted into another signal set, such that the symmetry of each resulting signal is maximized, and the symmetry between the different signals is minimized [14].

A statistical procedure, Principal component analysis (PCA) convert a set of correlated variables into a set of values of linearly uncorrelated variables that uses an orthogonal transformation called principal components. The first principal component has the largest possible variance, and each subsequent component has thehighest value of variance possible under the constraint that it is orthogonal to the prior components in this transformation. The resulting vectors are an uncorrelated orthogonal basis set [15]. PCA is sensitiveto the original variables scaling relatively. PCA and ICA are implemented as functions in this research project.

In PCA, multi-dimensional data is projected onto the singular vectors corresponding to a few of its largest singular values. Such an operation successfully decomposes the input single into orthogonal components in the directions of largest variance in the data. As a result, PCA is often used in dimensionality reduction applications, where execution of PCA yields a low-dimensional representation of data that can be reversed to closely rebuild the original data.

3. EXPERIMENTAL RESULT AND SETUP

Figure 2: Original noisy recorded snick



Sensors or microphoneswere placed at various different position in the playground and cricket bat. The audio data (snicks sound) were collected from all sensors that were located at various position. The collected data were noisy, the noise was from various sources.

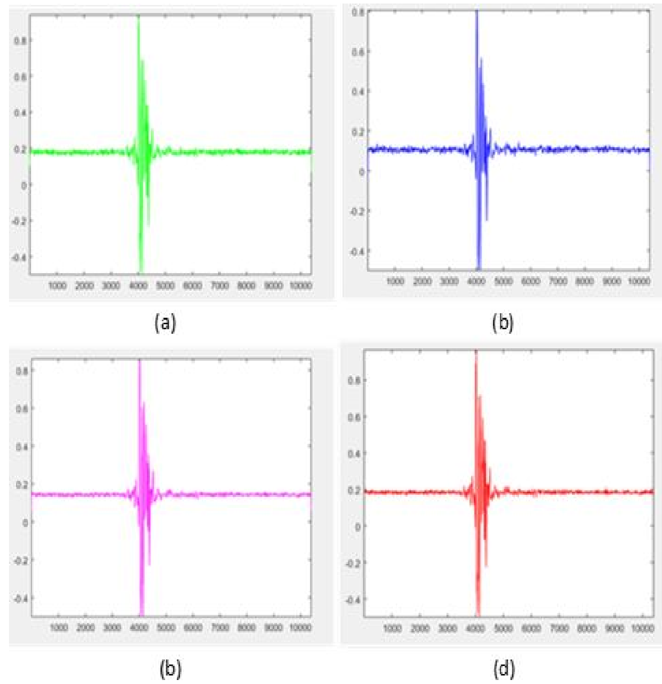
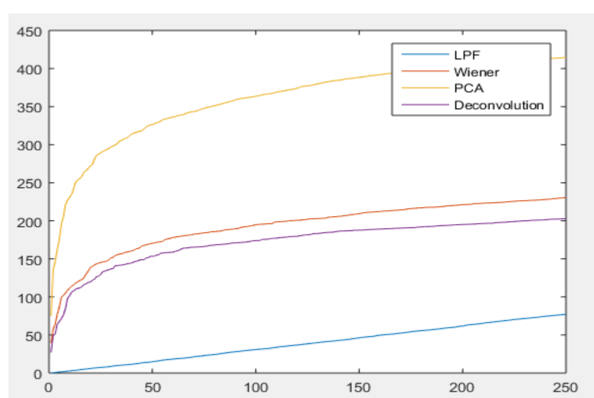


Figure 3: (a) Denoised snick with low pass filter (b) Denoised snick with low Blind Deconvolution (c) Denoised snick with MISO Wiener Filter (d) Denoised snick with PCA Blind Signal Separation.

250 snicks; these snicks were collected in open environment were passed through Gaussian low pass filter, Blind deconvolution, MISO Wiener filter and PCA blind signal separation for denoising. Through these techniques we reduce the noise but a little bit noise was still present in the original snicks as shown in fig 3(a)(b). According to visual perception if we see the above figures¸ easily we can decide that the MISO Wiener filter and PCA blind signal separation are best techniques as compared to other two filtering techniques. For verification lets we passes these filtered snicks of all techniques through cricket DRS to check the classification and accuracy rate on the data.

Figure 4: Comparative result of four techniques for our real data according to DRS accuracy rate



The filtered 250 snicks in which 50 snicks of each category were passed through DRS system for the five classes of snick resulting from contact of the cricket ball with either (i) ball on bat (ii)ball on gloves (iii)ball on pad (iv) bat on ground (v) a combination of bat and pad. The accuracy of DRS depend on the filtered signals, the rule is simple better the noise reduction better the classification and accuracy rate.
Classification rate for 50 snicks of each category (a) Gaussian lowpass filter (b) Blind deconvolution (c) MISO Wiener filter (d) PCA blind signal separation in Table1

Table 1 clearly shows PCA blind signal separation is beast of all because signal filtered by this technique have very least missing rate when cricket DRS apply on these signals.

Checked Classification rate for 50 Snicks of Each Category	Ball-Bat	Ball-Pad	Ball-Ground	Ball-Glove	Ball-Bat-Pad
Gaussian low pass filter	45	46	43	44	42
Blind deconvolution	45	47	42	41	43
MISO Wiener filter	46	45	46	45	46
PCA blind signal separation	48	49	47	45	48

Gaussian low pass filter and blind deconvolution were also good as other techniques but in Bat-Pad mix category, the accuracy rate was not satisfactory. MISO Wiener filter was one of the best technique according to classification rate achieved by cricket DRS because the signals were extremely denoised; hence the signals passed through PCA blind signal separation were noiseless.

5. CONCLUSION

The research was able to denoise the signals clearly by using the PCA BSS. Other schemes were good but were not able to get better denoising. The classification rate for low pass filter and by deconvolution was also satisfactory but in the case of MISO Wiener filter was more better as compare to other two schemes. The classification rate for the denoised nicks passed by PCA BSS was best in all the schemas. Future work involves using wavelet based denoising. Combining these approaches with our proposed remixing procedure may help better address the intra-source ambiguity problem.

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