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A Non-destructive Approach for Noise Reduction in Time Domain

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Abstract: In this paper a new time domain noise reduction approach is presented. In existing noise reduction techniques, the structure of the enhanced signal might be slightly changed compared to the original signal. In the proposed non-destructive approach, the noisy signal is initially represented in a Hankel Matrix. Then the Singular Value Decomposition (SVD) operator is applied on the matrix to divide the data into signal subspace and noise subspace. Reducing the effect of noise from the singular vectors and using them in reproducing the matrix, leads to significant enhancement of information embedded in the matrix. This matrix is finally used to obtain the time-series signal. There are several important parameters, such as size of the matrix and the degree of the filter, affecting the performance of the proposed approach. These parameters are optimally set using the genetic algorithm. The results of applying the proposed method on different synthetic noisy signals indicate its better efficiency in noise reduction compared to the other time series methods. The obtained results also indicate that using the proposed approach keeps the main structure of the original signal unchanged.

Key words: Time series . Noise reduction . SVD . Singular values . Singular vectors . Savitzky-golay filter . Genetic algorithm

INTRODUCTION

Signal enhancement and noise reduction have wide applications in signal processing. They are often employed as a pre-processing stage in various applications such as audio conferencing, hands-free mobile telephony, cellular mobile communication, computer-based speech recognition or speaker identification and etc. [1-7].

Since the nature and the characteristics of noise may significantly change from application to application, noise reduction is a very challenging problem. In addition, noise characteristics may vary in time. It is therefore very difficult to develop a versatile algorithm that works in diversified environments. Hence the objective of a noise reduction system may depend on the specific context and application.

Two points are often required to be considered in signal de-noising applications: eliminating the undesired noise from signal to improve the Signal-to-noise Ratio (SNR) and preserving the shape and characteristics of the original signal. The existing noise reduction methods reduce the noise by considering some prior assumptions. Hence they are suitable for specific applications and conditions [8, 9]. For example, in using a typical Low Pass Filter (LPF), it is assumed that the noise is placed at the high frequency regions of the noisy signal. This means that the frequency bands of noise and the clean signal are distinct. This assumption may not be acceptable in various conditions and may restrict its applications. In addition, as can be seen in Fig. 1, low pass filters such as those using the convolution operator, cause shifting the signal in time domain and changing the shape of the signal slightly [10].

Depending on the domain of analyses, the existing noise reduction techniques can be categorized into three groups: time, frequency and time-frequency/time-scale domains. In time-scale based approaches, the signal is sub-divided into several frequency bands using wavelet transform. The noise reduced sub signals are then used to reconstruct the enhanced signal. Extensive researches have been accomplished on the wavelet based methods with considerable results [11-13]. One of these methods is based on the Bionic Wavelet Transform (BWT), an adaptive wavelet transform based on a non-linear auditory model of the cochlear [14, 15]. In this approach, the enhancement is the result of thresholding on the adapted BWT coefficients. In [16], the author proposed a time-frequency based approach for noise reduction. In this approach, the Singular Value Decomposition (SVD) technique is applied on the

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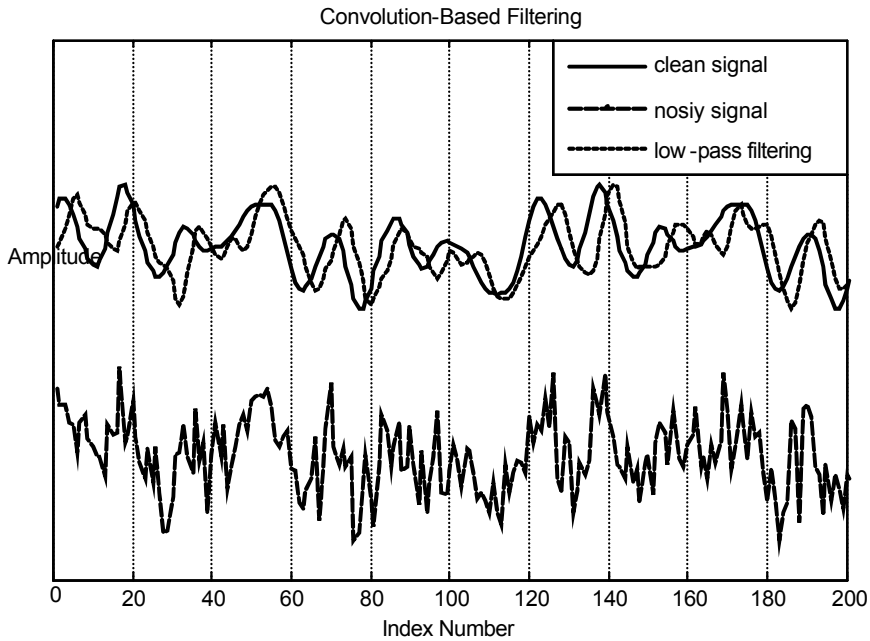


Fig. 1: The effect of convolution-based filtering on a noisy signal: A Butterworth LPF was applied on the noisy signal with SNR=1 (bottom dashed line). Although the noise was removed (dotted line), the shape of the enhanced signal is not the same as the original noise-free signal (the top solid line)

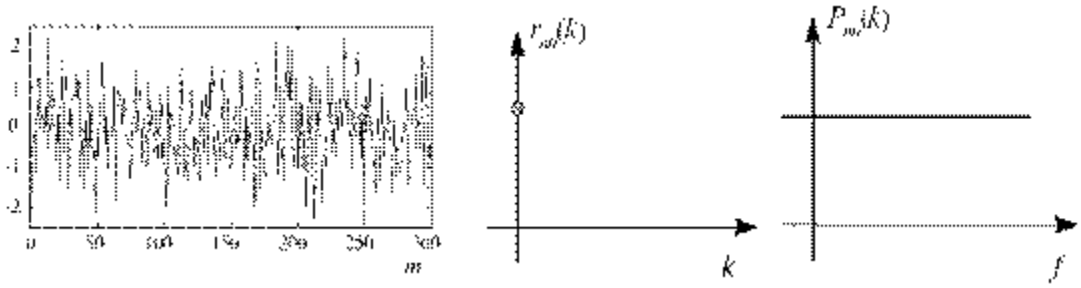
matrix of the time-frequency representation of the signal. This technique separates noise subspace and signal subspace using singular values of data matrix as criteria for subspace division. This time-frequency based technique has a good performance in reducing noise from both stationary and nonstationary signals. However, there are two deficiencies in the time-frequency based approach for noise reduction. A high computational time is required for representing signal in the time-frequency domain. In addition, some time-frequency distributions, such as B-distribution [17], cannot be synthesized to the time series.

There are a number of frequency domain based approaches that use spectral subtraction for noise reduction [18-23]. These approaches are only suitable for specific applications. For example, in [19] the noise is considered to be stationary. In practice, however, the noise is usually nonstationary. In another approach [23], the high frequency region of the signal is used to estimate the noise. This approach can be used to enhance speech signals, as the high frequency region has no signal of human speech. It was reported that this approach needs a high sampling rate (higher than 30 KHz).

The Wiener filter is a well-known noise reduction technique among the time domain based approaches [24]. In this method, the noisy signal is passed through a Finite Impulse Response (FIR) filter whose coefficients are estimated by minimizing the Mean Square Error (MSE) between the clean signal and its estimation to restore the desired signal. This filter is one of the most fundamental approaches for noise reduction, which can be formulated in the time and also in the frequency domains.

The Wiener filter is usually able to reduce noise in a signal. However, the amount of noise reduction is often accompanied by signal degradation. In other words, Wiener filter can be used to reduce noise in a signal if the SNR is high enough (usually higher than 4 dB). When SNR for a signal is low, using Wiener filter may not be a suitable solution and may just transform the noise from one form to another [10, 24]. This is a discouraging factor in choosing Wiener filter for noise reduction.

Recently, time domain based approaches for noise reduction have received considerable attention among scientific researches [25-27]. These techniques construct a time data matrix of noisy signal. The structures of these data matrices usually have the Hankel or Toeplitz forms, which have been introduced in [28-30]. In this paper, we utilize the Hankel matrix to construct the data matrix. This data matrix is subdivided into signal subspace and noise subspace using the SVD-based approach introduced in [27]. In this article the Savitzky-Golay low pass filter [31] is utilized to reduce noise from the singular vectors. The noise reduced singular vectors with the singular values of the signal subspace are used to reconstruct the matrix. Subsequently, this noise-reduced matrix is used to extract the time series, representing the



(a) (b) (c)

Fig. 2: Illustration of (a) an arbitrary white noise, (b) its autocorrelation and (c) its power spectrum

noise-attenuated signal. Some specific parameters which are determined using the genetic algorithm, such as size of the matrix and the degree of the filter, may affect the performance of our noise reduction approach.

The organization of present paper is as follows: Section 2 describes the proposed SVD-based noise reduction technique. The noise subspace subtraction is outlined in this section after a brief preliminary description of the SVD operator. We propose the utilization of the Savitzky-Golay filter to enhance the noisy singular vectors and show how applying the genetic algorithm can be useful in the optimal setting of the parameters. In Section 3, the proposed noise reduction method is applied on stationary and non-stationary signals and the results are compared with those obtained using other time-domain noise reduction methods. Finally, the conclusions are drawn in section 4.

SVD-BASED NOISE REDUCTION TECHNIQUE

Preliminaries: In many noisy acoustic environments such as a moving car or train, or over a noisy telephone channel, the signal is considered to be infected by an additive random noise [1]. In this paper, we suppose that the clean signal has been corrupted by an additive white Gaussian noise:

$$X_n = X_s + W_n \tag{1}$$

where X_n, X_s and W_n denote noisy signal, clean signal and white Gaussian noise, respectively. The white noise is defined as an uncorrelated process with equal power at all frequencies (Fig. 2).

The Hankel matrix is a square matrix, in which all the elements are the same along any northeast to southwest diagonal. In mathematical terms each element of this matrix can be expressed as $a_{i,j} = a_{i-1,j+1}$. For $X_n(i)$, I = 1,…,N representing the noisy signal, the Hankel matrix is constructed as follows:

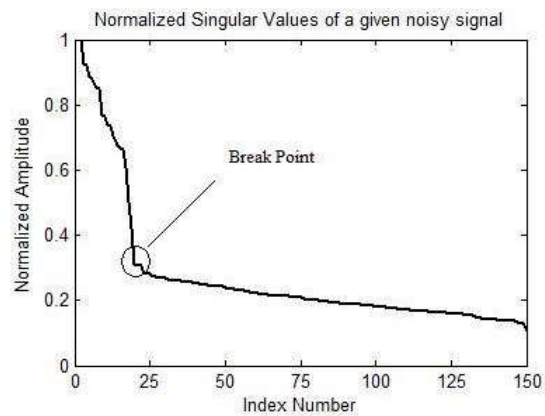


Fig. 3: Normalized singular values of the Hankel matrix constructed from a given noisy signal

$$H = \begin{bmatrix} X_n(1) & X_n(2) & \dots & X_n(K) \\ X_n(2) & X_n(3) & & X_n(K+1) \\ \vdots & \vdots & & \vdots \\ X_n(L) & X_n(L+1) & \dots & X_n(N) \end{bmatrix} \tag{2}$$

Generally, the singular value decomposition of matrix H with size P×Q is of the form:

$$H = U\Sigma V^T \tag{3}$$

where $U_{P\times r}$ and $V_{r\times Q}$ are orthogonal matrices and Σ is a r×r diagonal matrix of singular values with components $\sigma_{ij=0}$ if $i\neq j$ and $\sigma_{ij}>0$ and $\sigma_{ij}>0$ Furthermore, it can be shown that $\sigma_{11}\geq\sigma_{22}\geq\ldots\geq 0$. The columns of the orthogonal matrices U and V are called the left and right singular vectors respectively.

Noise subspace subtraction: Subspace filtering is a technique that has been proven very effective in the area of signal enhancement [4]. Hence, to enhance information embedded in the Hankel matrix, we propose dividing the data matrix into signal subspace and noise subspace using the singular values. Since singular vectors are the span bases of the matrix,

reducing the effect of noise from the singular vectors and using them in reproducing the matrix, leads to further enhancement of information embedded in the matrix.

Mathematically, the subspace separation can be expressed as below:

$$H = U\Sigma V^T = \begin{pmatrix} U_s & U_n \end{pmatrix} \begin{bmatrix} \Sigma_s & 0 \\ 0 & \Sigma_n \end{bmatrix} \begin{pmatrix} V_s^T \\ V_n^T \end{pmatrix} \quad (4)$$

$$X_s = U_s U_s^T H = H V_s V_s^T \quad (5)$$

$$W_n = U_n U_n^T H = H V_n V_n^T \quad (6)$$

where Σ_s and Σ_n represent the clean signal subspace and noise subspace, respectively. As can be seen from equation (4), we must determine a threshold point in the Σ matrix where lower singular values from that point can be categorized as noise subspace and therefore should be set to zero. To determine this point, the singular values of Σ matrix for a given simple noisy signal are plotted, respect to their indices (Fig. 3). A break point can clearly be seen in this figure. Considering this break point as the threshold and setting the lower singular values to zero leads to considerable noise reduction. However, for more complicated signals, determining this threshold point is very challenging and needs more attention. We have recently developed an approach to obtain this threshold point, see [10]. In that study, we had utilized the maximum slope of changes in the singular values curve. But in the proposed method we use the genetic algorithm to find this value as well as other important parameters. The procedure of this technique will be explained in the following subsections. As mentioned above, our research indicates that the noise subspace is mainly related to those singular values that are lower than the threshold point. Thus, we suggest setting these singular values to zero for space division.

To clarify the proposing method, the concept of matrix rank is described briefly. The rank of a matrix can be directly determined by the number of nonzero singular values from its SVD. For example, when the clean data matrix is symmetric (Toeplitz) or per symmetric (Hankel) and the data are sinusoidal or complex exponential, with no additive noise, then the rank is equal to twice the number of real sinusoid or the number of complex exponentials presented in data [32]. But a noisy signal has much more nonzero singular values which belong to the noise subspace. Hence, they must be set to zero for noise reduction.

Enhancing the singular vectors: We have inferred from our experiments that by merely filtering the singular values, some noisy data will still be available in the signal subspace. Thus besides the noise subspace subtraction, we must filter the singular vectors (SVs) for further noise reduction. Figure 4, illustrates the effect of noise on the U matrix (left singular vectors). In this experiment, an arbitrary stationary signal is infected by the 0dB white Gaussian noise. Then, the first, third and fifth columns of U matrix associated with the clean and noisy signals are plotted. As it can clearly be seen in this figure, the noise has affected the original signal's left singular vectors (Fig. 4).

In this study, SVs are treated as time-series. To reduce the effect of noise on SVs, we utilize the Savitzky-Golay filter. This low-pass filter is suitable for smoothing data in time series as well as calculating the first up to the fifth derivatives. In the Savitzky-Golay approach, each value of the series is replaced with a new value which is obtained from a polynomial fit to 2k+1 neighboring points. The parameter k is equal to, or greater than the order of the polynomial. The main advantage of this approach in comparison with other adjacent averaging techniques is that it tends to preserve the features of the time series distribution. To further studies, refer to [31].

In this approach a polynomial of degree d is fit on n_w consecutive data points from the time-series, in which n_w is the frame or window size. Filtered singular vectors can be obtained as follows:

$$U_{Se}^i = F\left(U_S^i\right), \quad i = 1,..., P \quad (7)$$

$$V_{Se}^i = F\left(V_S^i\right), \quad i = 1,\ldots,Q \quad (8)$$

In the proposed approach, the amount of noise reduction depends on the degree and frame size of the Savitzky-Golay filter. As illustrated in Fig. 6 and 7, choosing various frame sizes and polynomial degrees for Savitzky-Golay filter leads to achieving different results.

In this study, we have distinguished four crucial parameters affecting the performance of proposed noise reduction method. They are the number of rows l (in the data matrix), the optimum threshold point P_{cut} needed for space subdivision, the degree d and the window size n_w of Savitzky-Golay filter. To set these parameters properly, we define a cost function and use the genetic algorithm to minimize the cost.

Once a filter is applied on a signal, the level of sudden changes in successive samples is reduced. On the other hand, the enhanced signal should still be similar to the noisy signal after filtering since this is the

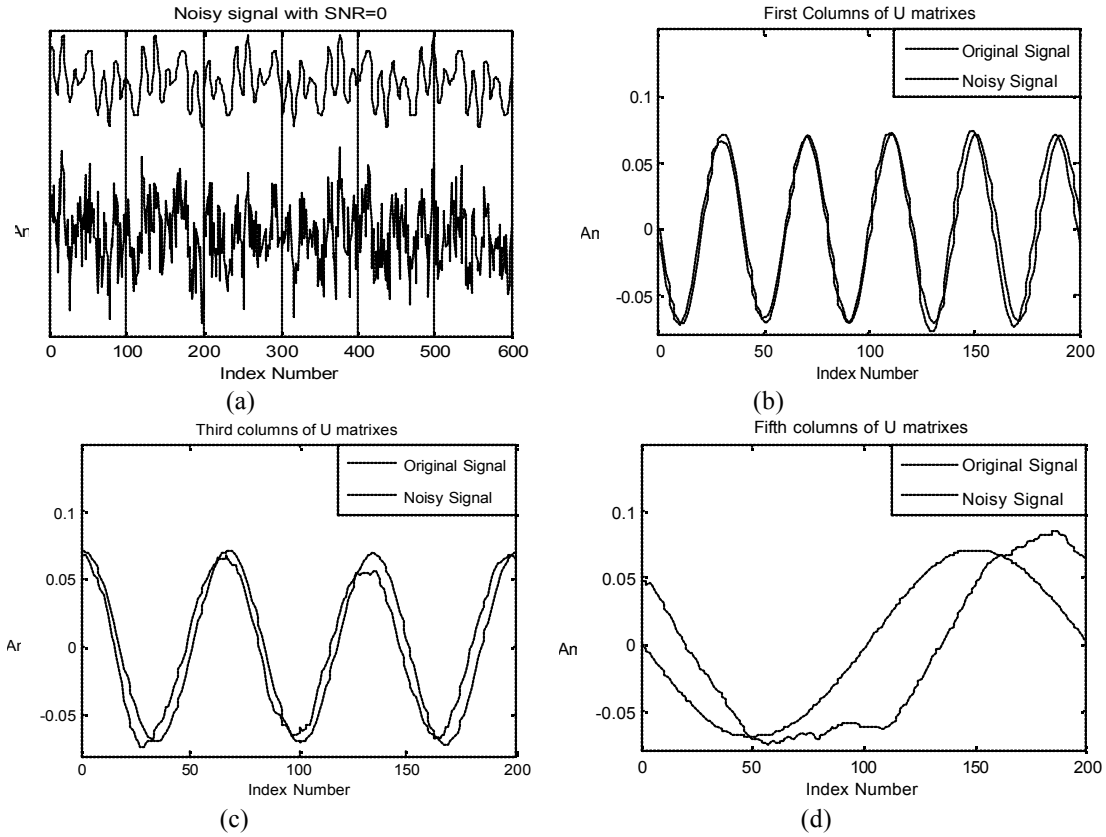


Fig. 4: Effect of noise on the columns of U matrix: (a) original arbitrary signal and its noisy version with SNR=0 dB; (b), (f) and (d): The effect of noise on the first, third and fifth columns of the U matrix, respectively

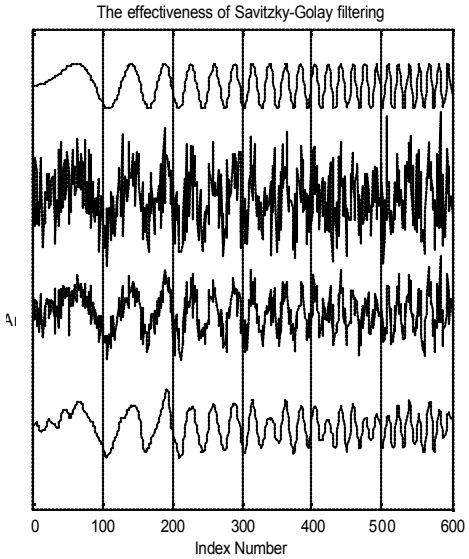


Fig. 5: The result of applying Savitzky-Golay filter on singular vectors of the noisy signal. From top to bottom: clean signal, noisy signal with SNR=0dB, the result of subtracting the noise subspace per se, the result of filtering the singular vectors as well as noise subspace subtraction

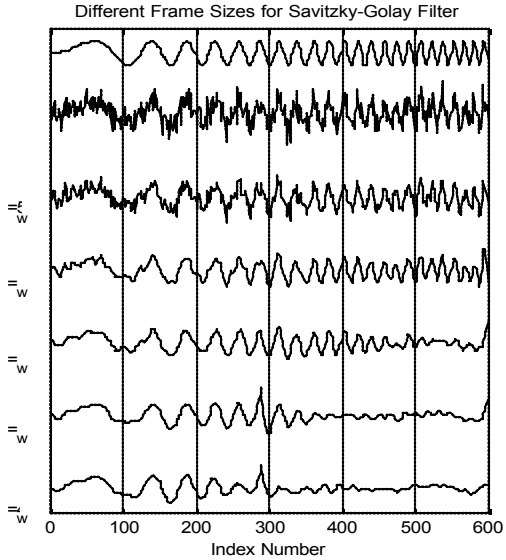


Fig. 6: The effect of using different values as Savitzky-Golay window size. From top to bottom: clean signal, noisy signal and the enhanced signals after applying $n_w = 5$, $n_w = 15$, $n_w = 25$, $n_w = 35$ and $n_w = 45$, as the window sizes of the Savitzky-Golay filter

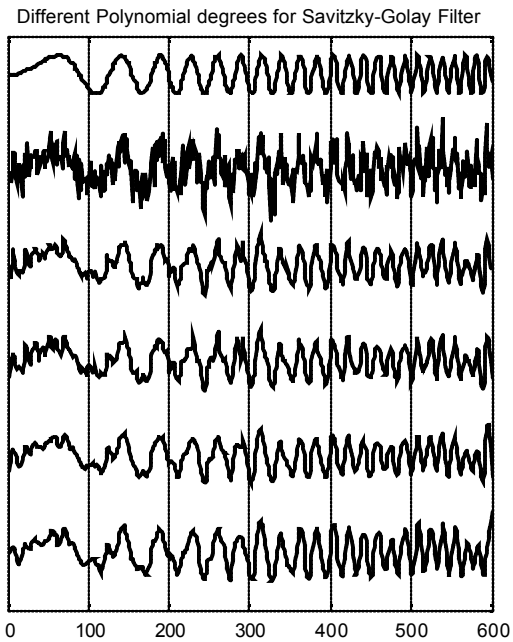


Fig. 7: The effect of using different values as Savitzky-Golay polynomial degree. From top to bottom: clean signal, noisy signal and the enhanced signals using d=5, d=4, d=3 and d=2, as the degrees of the Savitzky-Golay filter. The window size was set to 15

only thing we know about the shape of the original signal. Hence, we offer the following cost function for optimally tuning parameters of the filter:

$$J(l,p_{cut},d,n_w) = (1-\alpha)\left(\sum_k |x_e(k) - x_n(k)|\right) + \alpha\sum_k |x_e(k+1) - x_e(k)| \quad (9)$$

where x_n, x_k and k represent the noisy signal, enhanced signal and their sample number respectively. In this equation, α is a factor determining smoothness of the enhanced signal and must be chosen between 0 and 1. At the right side of the above equation, the first term indicates the distance between the enhanced signal and the noisy signal; and the second term indicates the smoothness of the enhanced signal.

We minimize this cost function using genetic algorithm. The genetic algorithm is an iterative algorithm which randomly chooses some values from the search space in each repetition. In this algorithm, the enhanced signal is initially computed using samples of these four parameters and then the cost function in (9) is calculated. In each repetition, the parameters are optimally chosen to minimize the cost. After several iterations, the final optimal parameters are achieved. For more detailed information about the genetic algorithm refer to reference [33].

The enhanced data matrix is then obtained using:

$$H_e = U_e \Sigma_s V_e^T \quad (10)$$

where U_e and V_e are the enhanced versions of left and right singular vectors and Σ_s represents the matrix containing the signal subspace singular values.

Finally, the enhanced signal X_e is extracted as follows:

$$X_e = [H_e(1,1)\ldots H_e(1,Q), H_e(2,Q)\ldots H_e(P,Q)] \quad (11)$$

PERFORMANCE EVALUATION

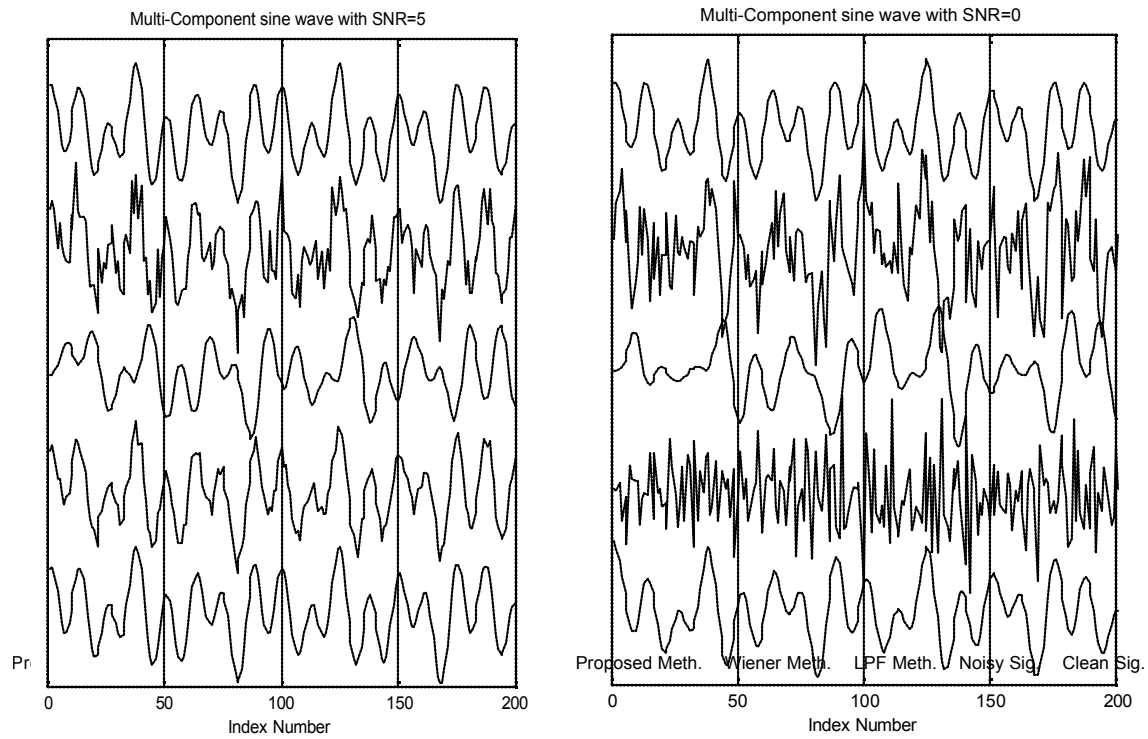
To evaluate performance of the proposed approach, several experiments have been carried out on multi-component periodic signals as well as linear FM (LFM) signals corrupted by additive white Gaussian noise. The results of each experiment are described in the following subsections.

Multi-component periodic signals: Let

$$x(t) = 0.2\sin(2\pi ft) + \sin(2\pi(3f)t) + 0.5\cos(2\pi(5f)t) + 1.5\cos(2\pi(7f)t) + \eta(t) \quad (12)$$

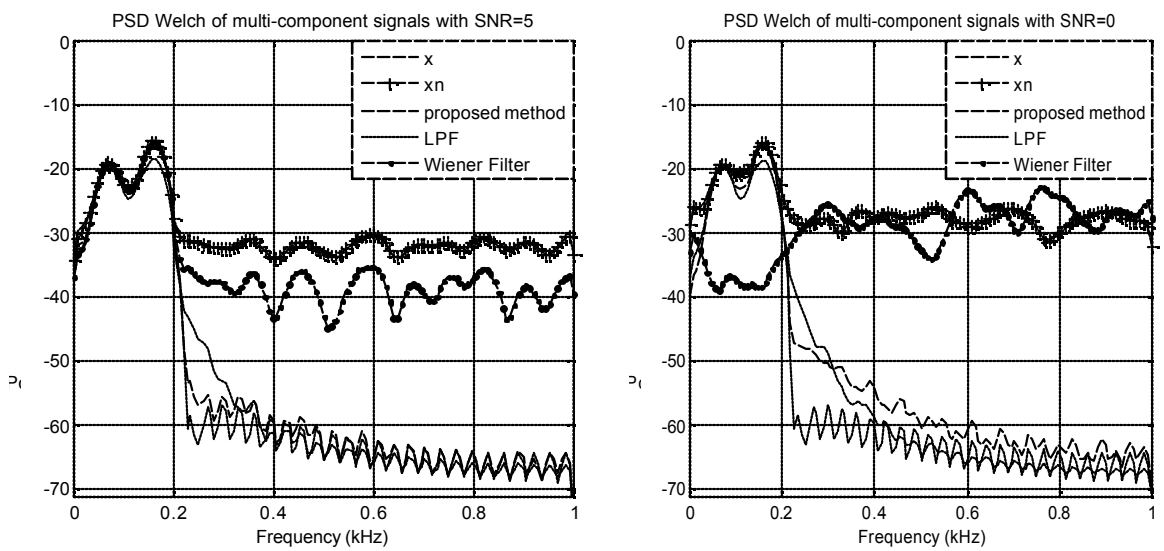
represent a multi-component signal infected by noise η (t). In this experiment, we use this signal with *f=25* Hz and the sampling frequency f_s is set to 2kHz. Performance of the proposed method is compared with that of Butterworth LPF and Wiener filter, which are considered as time series approaches.

The signal in equation (12) was filtered using the three different approaches and the time domain representations of the clean, noisy and enhanced signals are shown in Fig. 8 for 5dB and 0dB signal-to-noise ratio (SNR). As the figures show, the convolution-based filter (the low pass filter) can reduce the noise, but with the cost of shifting and slightly changing the shape of the signal. This deformation is proportional to the filter window length. Although there are no such deficiencies in using the Wiener filter, the noise attenuation level is less than the proposed method. In addition, Wiener filter is not able to reduce noise in a signal with a low SNR. On the other hand, not only is the proposed method able to reduce the noise from signal without any considerable distortion or deformation, but is able to reduce noise even where the SNR value is very low. In this experiment, utilizing the



(a) (b)

Fig. 8: Comparing the performance of the three different noise reduction techniques on multi-component signals corrupted by white Gaussian noise with SNR=5 dB (a) and SNR=0 dB (b). In each sub-plot, from top to bottom: clean signal, noisy signal, output of LPF, Wiener filter and the proposed approach



(a) (b)

Fig. 9: Considering PSD of the signals on 100 realizations to compare the performance of the three different noise reduction techniques on multi-component signals with SNR=5 dB (a) and SNR=0 dB (b)

genetic algorithm leads to achieving the following optimum parameters. In the case of 5dB noisy signal, the number of rows (l), the optimum threshold point (P_{cut}), the degree (d) and window size (n_w) of the Savitzky-Golay filter are equal to 352, 0.1523, 3 and 5, respectively. On the other hand, in the case of 0dB noisy signal, the above parameters obtain 370, 0.2392, 3 and 13, respectively.

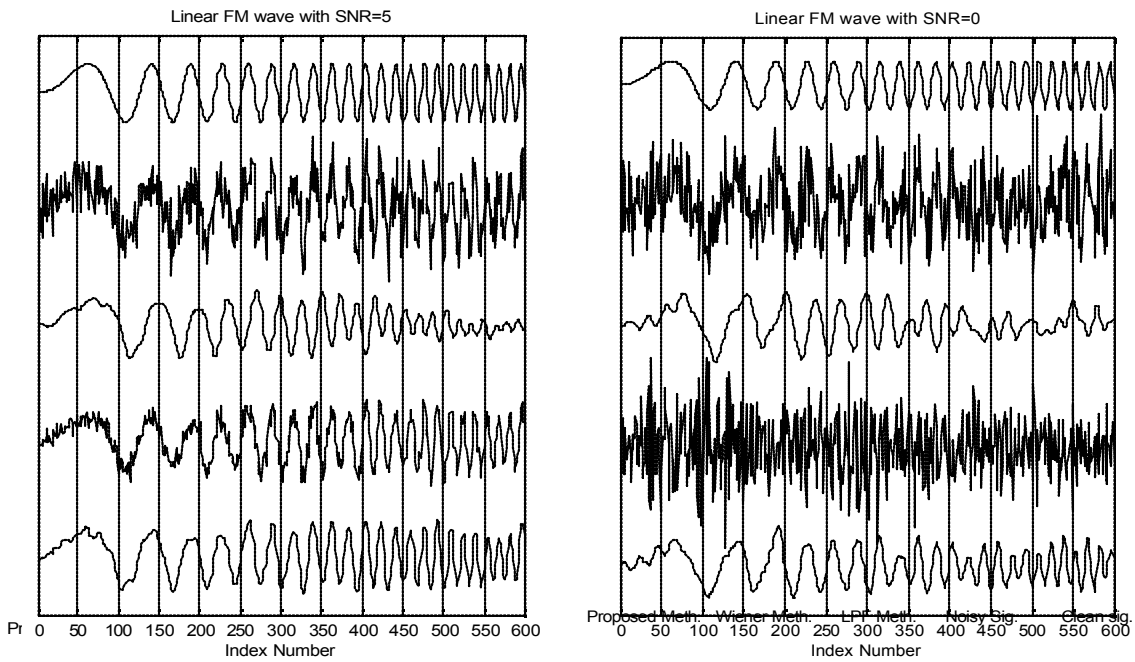


Fig. 10: Comparing the performance of the three different noise reduction techniques on LFM signals with SNR=5 dB (a) and SNR=0 dB (b) In each sub-plot, from top to bottom: clean signal, noisy signal, output of LPF, Wiener filter and the proposed approach

To further evaluate performance of the three different de-noising approaches, it is desired to compare Power Spectrum Density (PSD) of the clean and the enhanced signals. Hence, we have computed the PSDs of these signals using the Welch type estimation methods on 100 realizations and the results are shown in Fig. 9. As the figure shows, the proposed method is able to retrieve the frequency information of the signal better than either Wiener or LPF methods, especially where the SNR is very low.

LFM signals: The three approaches in the previous experiment have been applied on linear FM signals considered as nonstationary signals. In this experiment, the LFM signal's frequency begins from 1 Hz and terminates at 150 Hz. The sampling frequency is f_s = 4kHz and the number of samples is N = 6000.

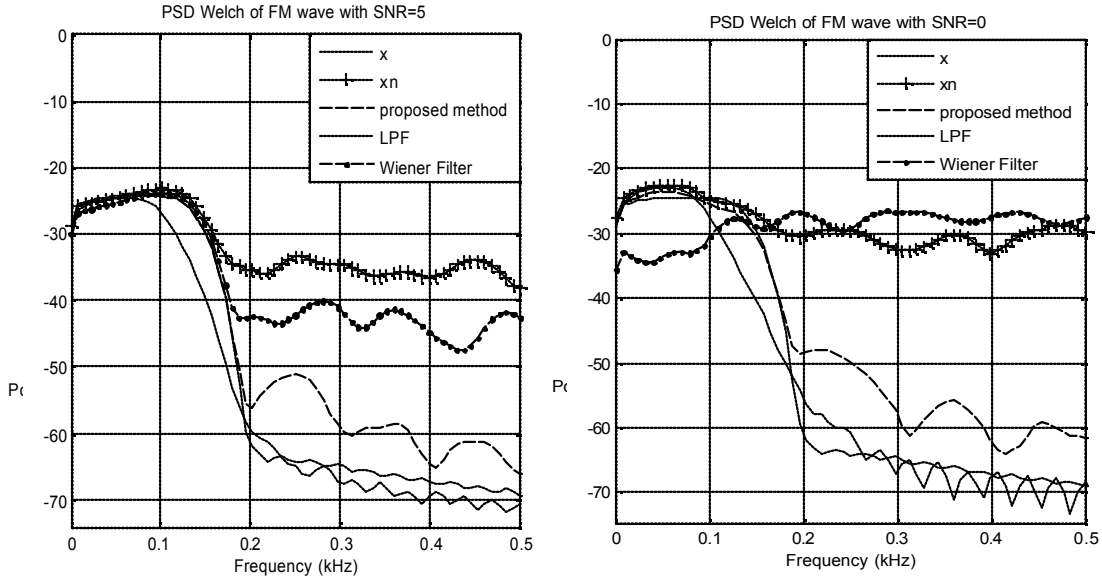
The time domain representations of the clean, noisy and enhanced signals are shown in Fig. 10. Similar to the previous Experiment, the LPF shifts and deforms the signal. But deformation amount is more considerable compared to the previous Experiment. This event seems reasonable, because the noise and the clean signal may have more overlap in frequency regions for a LFM signal. Hence by filtering the high frequency bands of noisy signal, some noise may still be present in the filtered signal. On the other hand, Wiener filter has a good performance when SNR is not less than about 4 dB. Indeed, where the energy of noise is significant and SNR is low, the performance of Wiener filter drops drastically. As can be seen in the figure, the proposed method is able to reduce the noise from the noisy nonstationary signal, even where the SNR is low and the frequency range of the signal is wide enough.

In this experiment, utilizing the genetic algorithm results in following optimum parameters: In the case of 5dB noisy signal, the number of rows (l), the optimum threshold point (P_{cut}), the degree (d) and window size (n_w) of the Savitzky-Golay filter are equal to 452, 0.1332,3 and 17, respectively; and for the case of 0dB noisy signal, the above parameters obtain the values of 473, 0.3489, 3 and 19, respectively.

The PSD of the linear FM signals on 100 realizations have been plotted in Fig. 11. It can be noticed that in the case of LFM signals, the PSD of the filtered signal using LPF may converge to the PSD of the clean signal at very low power/frequency magnitudes (in dB) as properly as the one obtained using the proposed method. But at higher power/frequency magnitudes, the proposed method clearly demonstrates its prominence in retrieving the frequency components of the clean signal in comparison with the other approaches.

Table 1: The Monte-carlo simulation on 100 realizations of different SNR values for the multi-component and LFM signals

Initial SNR (dB)	Method	Final SNR (dB) Multi-component	Final SNR (dB) LFM	Initial euclidean distance Multi-component	Initial euclidean distance LFM	Final euclidean distance Multi-component	Final euclidean distance LFM
5	Wiener	12.04	10.56	245	232	128	138
	LPF	7.22	7.05	245	232	231	186
	Proposed approach	18.56	13.94	245	232	76	102
2	Wiener	1.55	0.51	322	276	404	506
	LPF	5.41	4.05	322	276	239	226
	Proposed approach	13.4	10.84	322	276	114	134
1	Wiener	-5.81	-6.09	366	318	1088	1050
	LPF	2.20	2.29	366	318	314	290
	Proposed approach	9.65	8.23	366	318	140	167
0	Wiener	-28.30	-10.24	465	470	5628	1688
	LPF	2.08	1.68	465	470	325	313
	Proposed approach	8.13	6.56	465	470	156	190



(a) (b)

Fig. 11: Considering PSD of the signals on 100 realizations to compare the performance of the three different noise reduction techniques on LFM signals with SNR=5 dB (a) and SNR=0 dB (b)

Monte-carlo simulation: In this section, we have a performance comparison between the proposed method and the other approaches using the two most common criteria, SNR and Euclidean distance. In the first criterion, the SNR is computed in the enhanced signal and then compared with that of the noisy signal. In using the second criterion, the Euclidean distance between the clean and the noisy signal is computed and then compared with the distance between the clean and the enhanced signal. Whereas the convolution-based filtering of the signal causes shifting in time domain and this occurrence drastically affects the value of the Euclidean distance, the shifting effects of the filter is initially removed from the filtered signal before measuring the criterion.

The results of Monte-Carlo simulation on 100 realizations of different SNR values for the multi-component and the LFM signals are shown in Table 1. These results attest that the proposed approach has a better performance compared to the other existing approaches in noise reduction. The results in this table indicate that while SNR of the noisy signal highly affects performance of Wiener filter, the proposed method can enhance the signal even at the presence of

very energetic noise (SNR<2 dB). Since, noise (especially Gaussian noise) has a wide frequency activity; LPF cannot reduce noise at their pass-band frequency area.

CONCLUSIONS

The technique proposed in this paper is a new approach for signal enhancement in time domain. In this paper the noise subspace is initially eliminated from the signal subspace using the SVD-based technique. Then the singular vectors are filtered utilizing the Savitzky-Golay smoothing filter. The optimal number of Hankel matrix rows, the threshold point where the lower singular values must be set to zero, the polynomial degree and window size of the Savitzky-Golay filter are determined using the genetic algorithm. Results in this paper indicate the considerable advantages of the proposed approach over the existing approaches for noise reduction in time domain.

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