RESEARCH ARTICLE

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Clutter Rejection for Doppler Ultrasound Based on Blind Source Separation

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Doppler ultrasound is widely used diagnostic tool for measuring and detecting blood flow. To get a Doppler ultrasound spectrum image with a good quality, the clutter signals generated from stationary and slowly moving tissue must be removed completely. Without enough clutter rejection, low velocity blood flow cannot be measured, and estimates of higher velocities will have a large bias. In most cases it is very difficult to a chive a complete suppression without affecting the Doppler signal. Usually finite impulse response FIR, infinite impulse response IIR and polynomial regression PR filters were used for cluttering. In this paper we proposed a new method for clutter rejection in Doppler ultrasound to subtract all the clutter so as to achieve more accurate flow estimation. We proposed a new clutter rejection based on blind source separation using principal component analysis (PCA) and independent component analysis (ICA) methods. The proposed clutter was implanted to reduce the clutter originated from moving structure and backscattered flow, beside FIR, IIR and PR. The proposed clutter rejection method presentation is quantified in simulated FR Doppler data beside real Doppler data (heart data). The result shows that the proposed method gives better clutter rejection over other present types of clutters.

Keywords: Doppler Ultrasound Signal, Blood Flow, Spectrum, Clutter Rejection Filter, Independent Component Analysis and Principal Component Analysis.

1. INTRODUCTION

Doppler ultrasound is an important technique for non-invasive detecting and measuring the velocity of moving structures, such as blood flow within the body. Developments in Doppler ultrasound technology have led to a vast increase in the number of non-invasive blood velocity investigations carried out in all areas of medicine. There are now many types of Doppler ultrasound device available for detecting, measuring and imaging blood flow and other measurement within the body.[1–2]

The Doppler signal generated from a moving object contain not only great information about flow, but also backscatter signal contain clutter originated from surrounding tissue or slowly moving vessels. This clutter signal is typically 40 to 60 dB stronger than the Doppler shift signal originated from blood.[3–7] Thus an accurate clutter rejection is needed to estimate the flow accurately, by decreasing the bias in flow estimation. Clutter suppression is very important step in the processing of Doppler signal. A high pass filter is commonly used to remove the clutter signal from the Doppler shift signal. A high pass filter is used to suppress signal from stationary or slow moving tissue or any other organs, clutter filtering illustrated Figure 1. Signals originated from a slow moving object and tissues are low-frequency signals, generally they may have amplitude much stronger than high frequency signals generated from the faster blood flow. Thus, for separating the signals from blood and tissue, high pass filter with a sharp transition band is necessary.

Various types of static filter have been proposed to remove the clutter from the backscattered signals originated from moving object or surrounding tissue, such as finite impulse response (FIR) filter with a short impulse response, infinite impulse response (IIR) filter with special initialization so as to reduce the ring-down time and polynomial regression (PR) filter.[8–13] The clutter from tissue often changes through space and time due to changes in physiology and tissue structure,[14] and due to a limited number of data samples available (less than 20 sample volume[4]), in addition, if the clutter filter not appropriate selected the signal-to-noise ratio would be corrupted.[6] Due to all this, high pass filter can't effectively suppress the clutter without affecting the desired flow signal.[15] To remove the clutter with high performance we proposed more advance clutter methods that can overcome these drawbacks of the high pass filter.

In this work a new method for clutter suppression have been proposed, to remove the clutter originated from moving objects and surrounding tissue. The proposed method analyzes the Doppler data using blind source separation techniques within

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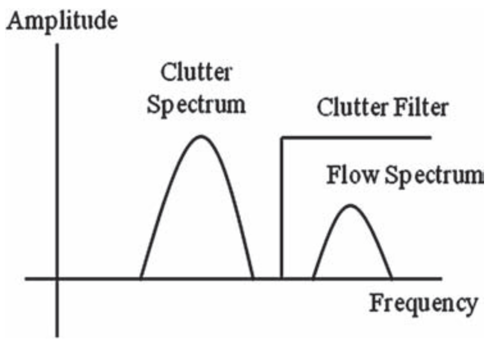

Fig. 1. Clutter filtering.

the framework of principal component analysis (PCA) using covariance and independent component analysis (ICA). PCA and ICA proposed in Refs. [16–18].

The RF Doppler data is the sum of the signals from blood flow and backscatter signal contains clutter originated from surrounding tissue or slowly moving vessels. The data prepared to satisfy ICA and PCA by doing some preprocess steps, then small window was considered. Both PCA and ICA applied to the original data set (the data after windowing), so as to re-expressed the data into a new coordinate system such that the clutter and echo signal separated along different bases. Filtering is then achieved by rejecting the bases describing the clutter signal from moving tissue and returning the signal containing information regarding blood flow. The output can be used to generate Doppler spectra with high performance.

The proposed techniques can improve the image quality in a Doppler ultrasound spectrum by removing the clutter signal with high performance without affecting the blood flow (Doppler shift) signal. The performance of the techniques is quantified by using Rf data collected from the URI-OPT (URID mode) beside real Doppler data (heart data) from Torp.[19] In addition, the performance of the proposed method evaluated with minimum phase FIR, projection initialization IIR and PR filters.

ICA and PCA have been proposed for different applications in biomedical field such as, their application in analysis of electroencephalographic (EEG) data and event-related potential (ERP) data,[20–21] in the analysis of functional magnetic resonance imaging,[22] in Doppler ultrasound[23] and in clutter rejection in color flow mapping.[24]

The paper organized as follows: In Section 2 the methods used to implement our proposed adaptive clutter rejection filter and analyze its performance are presented. In Section 3 the result and discussion of the simulation data with proposed methods and present methods was discussed, beside the result of real Doppler data and the performance of the proposed methods compared to the present methods was discussed. Finally, a brief summary conclusion of the work was presented in Section 4.

2. METHODS

2.1. Simulation Data (URI)

To quantify the performance of a new clutter for rejecting the clutter, the Doppler data from URI downloaded and generate Doppler IQ using MATLAB (MathWorks, Inc., Natick, MA). Ultrasound research interface (URI) and Ultrasound research interface offline processing tools (URI–OPT) are software and sample data. In this work we will concentrate on URI–OPT. URI–OPT are a Matlab based program for reading and processing the RF data acquired from a URI-equipped Antares system. URI-OPT can be used to display different Doppler imaging mode. One of the most important modes that we are interested in is spectral Doppler mode, which is used to display the Doppler spectrum of RF data. The speed of flow information within the Doppler range gate is displayed as gray scale intensities at a time versus velocity plot.

The data used are data of Doppler spectrum collected from URIDmode. The data tested first on the program to display the spectrum, and then the data extracted and stored in Matlab. Matlab program was developed to read the saved data and then generate Doppler In-phase/Quadrature (IQ) data, which is used to test our proposed clutters rejection filter and comparison between different types of clutters filters. The parameters used to generate the Doppler IQ data illustrated in Table I. The generated Doppler IQ data is a complex matrix X in 100×7923.

The complex data matrix X obtained can be expressed as:

$$X = \begin{bmatrix} x_{11} & x_{12} & \cdots & x_{1N} \\ x_{21} & x_{22} & & x_{2N} \\ \vdots & \vdots & \ddots & \vdots \\ x_{M1} & x_{M2} & \cdots & x_{MN} \end{bmatrix} \tag{1}$$

Where M is the number of pulses and N is the axial sample volume. Each column in the matrix X represents a vector with length M.

The input sample vector to clutter rejection filter with index depth equal to n, can be represented by the following expression:

$$x_n = [x_{1,n}, x_{2,n}, \ldots, x_{M,n}]^T, n = 1, \ldots, N \tag{2}$$

2.2. A Signal Model

The generated Doppler signal data originated not only from blood flow, but also it originated from different tissue regions with different motion patterns, the clutter Doppler signal is a sum of contributions from different regions. We assume that the resulting signal consists of a blood signal component b originated from the reflected echo from the moving red blood cells, a clutter component c originated from surrounding and moving tissue and white noise n originated from electronics or any other component. The signal can be modeled as:

$$X = b + c + n \tag{3}$$

The signal characterized by the correlation matrix.[3] The correlation matrix Rx given by:

$$R_x = E\{xx^{*T}\} \tag{4}$$

Table I. Paramerters used to genarate doppler IQ.

Data parameters	Values
First value	1
Last value	7923
Range gate start	1100
Range gate size	100
Vector group	0
Real group	1000
Frequency	7.2727
PRF	2441

In our case the correlation matrix expressed as:

$$R_x = R_c + \sigma_n I + R_b \tag{5}$$

Where, R_c is the clutter correlation matrix, σ_n is the noise variance, R_b is the blood correlation matrix and I is the identity matrix.

The three components originated from different source and are statistically independent. Thus with the proposed methods we can easily determine the basis vectors that are statistically independent.[25]

The Doppler IQ data prepared to satisfy our proposed clutter rejection method based on ICA and PCA by doing some preprocess steps, such as applying discrete Fourier transform (FFT) and the absolute value to the data so as to remove the imaginary values. Assume that our input signal $f(x, y)$ is a function of 2-D space define over an x–y plane. The two-dimensional FFT takes a complex array and expressed by using the following form:

$$f(u, v) = \frac{1}{MN}\sum_{i=1}^{M}\sum_{j=1}^{N} f(x, y)e^{-2j\pi(ux/M+vy/N)} \tag{6}$$

A small window has taken for testing our clutter rejection filters. The result Doppler IQ signal illustrated in Figure 2, only 8 signals were shown.

2.3. Real Doppler Data (Heart Spectrum Data)

Our proposed clutter method applied to real Doppler data (heart data). The data downloaded from.[19] Software programs written in MATLAB (MathWorks, Inc., Natick, MA) were developed and used to generate an original Doppler ultrasound spectrogram, using different cluttering filters beside our proposed clutter rejection. Hamming window with a size of 32, 0.25 overlap, dynamic range 40 and the gain is −35 were used to generate the spectrum. The clutter rejection filter which removes clutter with high performance, gives spectrum image with a good quality.

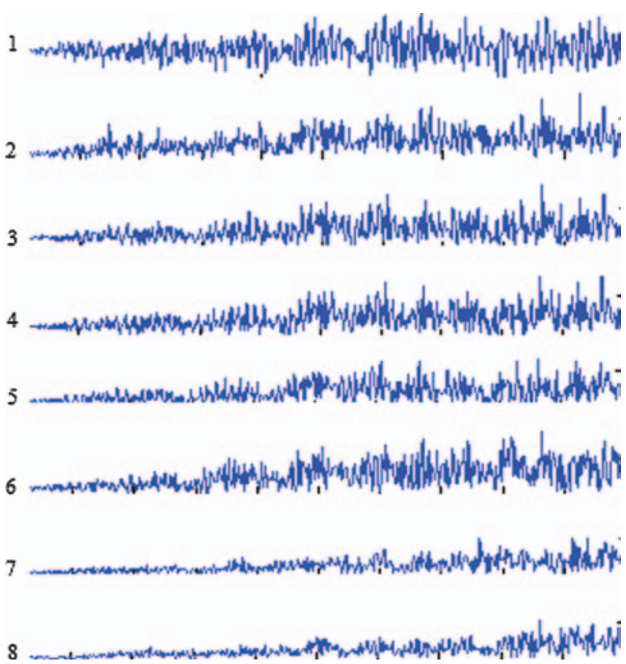

Fig. 2. The doppler IQ signal used in simulation.

2.4. Principal Component Analysis

Principal component analysis (PCA) is the techniques that based on sophisticated mathematical principle to transform correlated variables into smaller numbers of variables known as principle components (PCs). The PCs are calculated as the eigenvectors of the covariance matrix of the data.[24] The variance corresponding to these eigenvectors are denoted as the eigenvalues. PCA is one of the most useful tools in modern data analysis, because it is simple and non-parametric methods for extracting useful information from perplexing data set. PCA uses a vector space transform to achieve the reduction and de-noising of the large number of data set. This is particularly useful in application of PCA if a set of data used has many variables lies in actuality, close to two-dimensional plane.[16,26] Using PCA will help to identify the most meaning full basis to re-represent the desired data set. This new basis filters out the noise and reveals hidden structure.

The input data X is a matrix represented in term of the M-by-N with observation (samples) in columns and variables in its rows. The main approach to analysis the data is to use the data averaging strategies to expose the hidden input intrinsic nature of the data. The error due to noise will be canceled out when a mean of data is calculated. The mean of the data matrix calculated by:

$$\hat{X} = \frac{1}{n-1}\sum_{m=1}^{n} X_i^m \tag{7}$$

The mean of each of the measurements, subtracted from original input data matrix X, each entry in the matrix is replaced by its difference with mean. This produces a data with zero mean. Then the covariance was calculated from the resulting matrix, so as to measure the degree of linear relationship between a pair of variables. A large positive value indicates positive correlation and large negative value indicate negative correlations. Since the resulting matrix from subtracting the mean of the data consist of a row vector for each variable, each vector contains all samples for one particular variable. The covariance expressed as a dot product matrix,[27] and given by:

$$Cx = \frac{1}{n-1}DD^T \tag{8}$$

Where, D is the matrix resulting from subtracting the mean from the original data and T is transpose.

The result is a square symmetric matrix in term of the M-by-M. The diagonal terms of the resulting matrix are the variance of exacting measurement. The off diagonal terms of the matrix are the covariance between the measurements.

Since the covariance matrix is a square in term of the M-by-M, this matrix can be used to calculate the eigenvector and eigenvalue. The eigenvector and eigenvalue give quite different values for eigenvalues. So the eigenvector with highest eigenvalue represent the principal components of the data set.

After getting the eigenvectors of the covariance matrix, they ordered by eigenvalues, highest to lowest. If the lesser significant component ignored this lead to losing some information, but if the eigenvalues are small, there have no much lost in information. Leave out some information lead to reduction in data set dimension.

Considering some of eigenvectors from the list of eigenvectors, and forming a matrix with these eigenvectors in term of columns, gives a matrix of vector (feature vector). Finally to get the PCA filtered of the data set X, the data mean-adjusted matrix of each axial line was projected onto the selected basis function, as described by:

$$Y = P * X \tag{9}$$

Where, Y represent the final filtered data set, P is the matrix with eigenvectors in columns transposed so that the eigenvectors are now in the rows, with the most significant eigenvector at the top and X is the mean-adjusted data transposed.

2.5. Independent Component Analysis

There are several transformation methods proposed for data analysis and finding a suitable representation of the multivariable data such as PCA. A recent developed transform method is independent component analysis (ICA), which is used to minimize the statistical dependent of the component of the representation. Our goal is to use ICA to estimate the original data set of mixed data with clutter noise. In other words separate the clutter from the blood flow data. This is referred to as the blind source separation (BSS) problem.[28–30]

ICA technique based on non-Gaussinanity and use higher order statistics rather than second order to separate the signal from the clutter.[28,31] Beside the non-Gaussian, ICA assumes the components to be independent.[32] This is powerful and attractively set of assumption that make ICA very aggressive tasks, however, ICA treat the observed signal as a set of random variables without considering the dependency of adjacent time point.

Since ICA uses higher order statistics rather than second order moments to determine the basis vectors that are statistically independent as possible, ICA can consider as an extension of PCA.[31,33] This made ICA gives a better separation result in most applications. A fast fixed-point algorithm (FastICA) for Matlab is a program package used for implementing ICA.[28,34] The first step in ICA is whitening (sphere) the data. Before applying the ICA to the data and after centering, the observed vector transformed linearly so as to obtain a new vector that is white, its component un-correlated and their variance equal to unity (the covariance of a new vector equals the identity matrix). The covariance matrix expressed as:

$$E\{\hat{x}\hat{x}^T\} = 1 \tag{10}$$

Several methods proposed for whitening, the most popular used is eigenvalue decomposition (EVD) of the covariance matrix

$$E\{xx^T\} = EDE^T \tag{11}$$

Where, x is the observed vector, $\hat{x}$ is a new vector, E is the orthogonal matrix of eigenvectors of $E\{xx^T\}$ and D is the diagonal matrix of its eigenvalues. The whitening expressed by:

$$\overline{x} = ED^{-1/2}E^T x \tag{12}$$

Dimension reduction was performed, besides whitening the data, the reduction done by discarding the small eigenvalues, which perform in statistical technique of PCA. Three conventional methods can be used for utilizing the high-order information. The projection pursuit technique was used to find linear combinations of maximum non-Gaussianity. The central limit theory shows that the distribution of a sum of independent random variables tends toward a Gaussian distribution. Thus, a sum of two independent random variables usually has a distribution that is closer to Gaussian than any of the two original random variables. The non-Gaussianity was measured for solving the ICA problem, several methods proposed for measuring non-Gaussianity. The classical measure of non-Gaussianity is kurtosis or fourth-order cumulant. Kurtosis is zero for Gaussian random vector and nonzero for non-Gaussian random vector. Kurtosis can be positive or negative. The Kurtosis principle is maximized by applying the FastICA algorithm, to estimate the independent component.

The proposed method for cluttering rejection compared with other three methods proposed for clutter rejection in Ref. [4] the methods are FIR, IIR and PR filters. The parameters used for designing the filters illustrated in Table II to achieve filters with the same frequency response. Root mean square deviation (RMSD) or root mean square error (RMSE) and error are frequently used measure of the differences between values predicted by a model or an estimator and the values actually observed. RMSD and error are a good measure of accuracy. The accuracy of each method was computed and compared to that calculated from our proposed cluttering method.

The error was calculated by subtracting the output of clutter filter signal from input to clutter signal. The error calculated using the following expression:

$$\text{Error} = f(i,j) - g(i,j) \tag{13}$$

RMSD was computed using the following expression:

$$\text{MSE}(f,g) = \frac{1}{mn}\sum_{i=0}^{m-1}\sum_{j=0}^{n-1}[f(i,j), g(i,j)]^2$$

$$\text{RMSD}(f,g) = \sqrt{\text{MSE}(f,g)} \tag{14}$$

Where, f is the input matrix to the clutter filter, g is the output from the clutter filter and mean square error (MSE) is the square of the difference.

After preprocess, the clutter rejection filter applied to the Doppler IQ data which consists of blood flow signal and clutter signal to remove unwanted signal and remain the blood flow signal only. Then the spectrum of the filtered signal calculated to see wither the clutter was removed or not. Preprocess and clutter rejection filtering process steps were illustrated in Figure 3.

3. RESULT AND DISCUSSION

3.1. Simulation Results

In this section we want to describe the simulation result of our proposed clutter rejection filter based on ICA and PCA, beside the present cluttering algorithms. The Doppler IQ data consist of blood flow signal and clutter signal. The clutter filter applied to this signal so as to remove unwanted signal and remain the blood flow signal only. Our proposed clutter method applied to the data. The result of the simulation shows that, when the proposed clutter with ICA and PCA used, the clutter suppressed from the Doppler

Table II. FIR, IIR and PR filters design paramerters.

Filter type	Order	Cutoff frequency	Maximum d_P	Minimum d_S
FIR	5	0.09 π	0.5	−80
IIR	3	0.2 π	0.5	
PR	2			

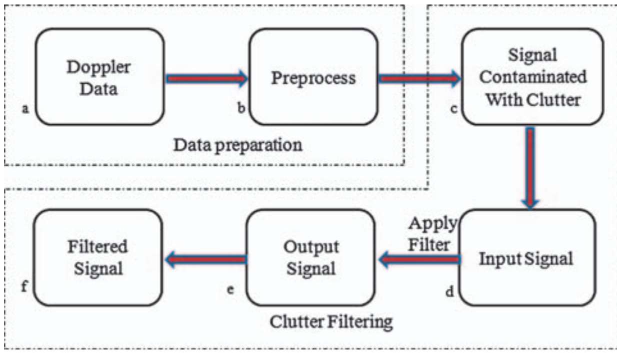

Fig. 3. The data preparation and clutter filtering process, (a) Doppler data collected. (b) Prepare the data for filtering. (c) Spectrum of doppler signal contaminated with clutter, generated from projection of input doppler IQ signal into filtered signal. (d) Doppler IQ input signal after preprocess. (e) Filtered signal. (f) Spectrum of filtered signal.

signal more effectively, result signal illustrated in Figures 4 and 5 respectively, we only display the first four signals.

The spectrum of the signal was calculated from the filtered signal by using both ICA and PCA, the result signal shown in Figures 6 and 7 respectively.

Beside our proposed method we applied the data to the present clutter rejection methods FIR, IIR and PR filters for comparison. The present cluttering filter applied to our simulated data the result shows that all types of clutter filters are able to remove the clutter from the Doppler IQ data, the results illustrated in Figure 8.

The spectrum of the signal was calculated from the output of the three types of filters, the result shown in Figure 9.

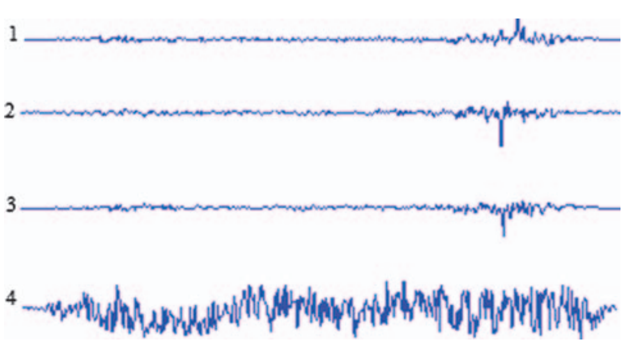

Fig. 4. The filtered signal using ICA.

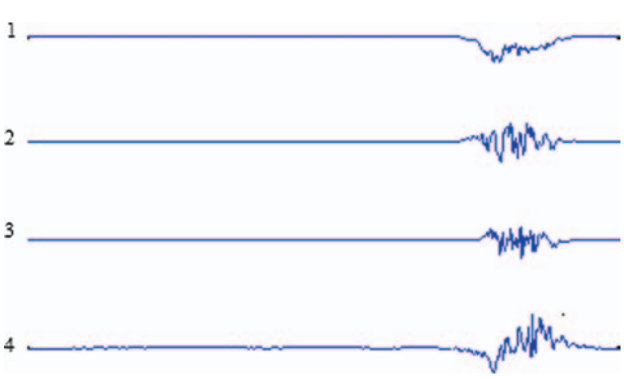

Fig. 5. The filtered signal using PCA.

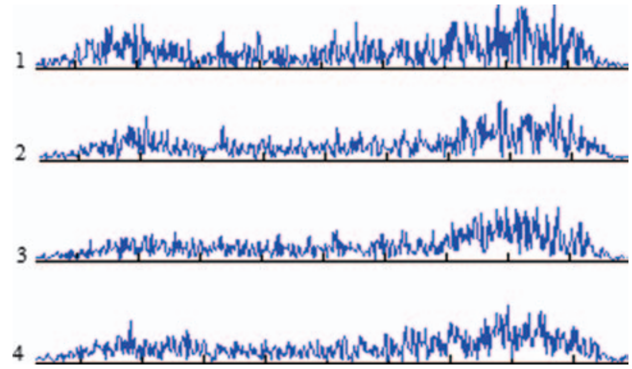

Fig. 6. The spectrum of the signal filtered using ICA.

To make sure that the clutter signal was removed from our Doppler IQ data by using all five clutter rejection filters. The original Doppler IQ data was projected into the filter output data. The inner product results show that the blood signal contaminated with clutter, the result shown in Figure 10.

To compare the propose clutter method using ICA and PCA with present clutter rejection methods, FIR, IIR and PR, root mean square deviation and error for each was computed. Since the clutter rejection characteristics differ from each other, performance of the clutter rejection methods also varies according to the clutter filter. The result shows that the proposed clutter based on ICA gives lower error values, while the proposed clutter based on PCA, gives error higher than that from ICA. The resulting error of PR using clutter space dimension given in Table II is lower than FIR. FIR gives highest error value among all the clutters, the result of RMSE and error for different clutters illustrated in Table III. The table shows that there is an improvement on the error and the RMSE when the signal cluttered with the proposed clutter rejection filter. The performance categorized from 1 to 5, the clutter filter with highest performance has lower error and the clutter filter with lower performance has highest error value. Figure 11 shows the performance of the clutter filters, the better clutter rejection obtained by using ICA. The PR clutter filter gives the same performance as ICA when the filter designed with space dimension equal to 20, which is needed more calculations. When PCA used for filtering, the clutter was removed with performance lower than that obtained by using ICA. IIR give comparable clutter rejection. FIR gives a lower performance

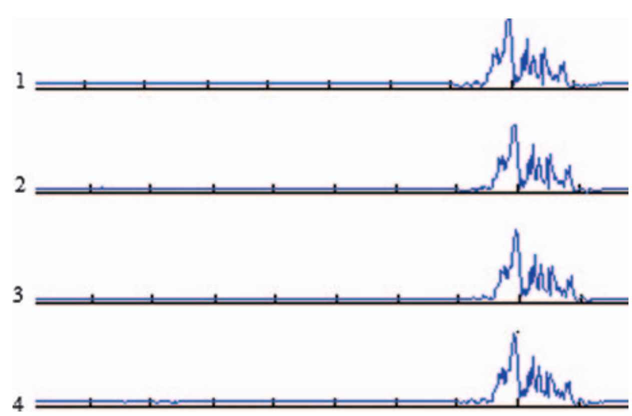

Fig. 7. The spectrum of the signal filtered using PCA.

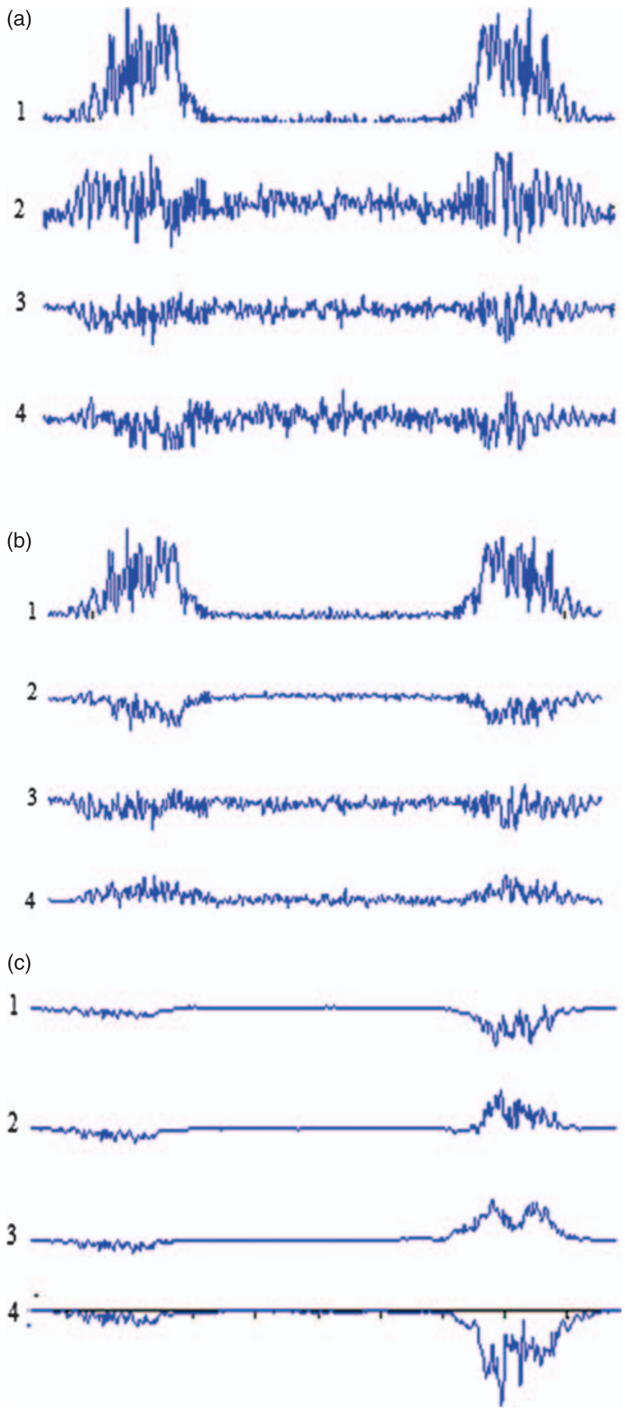

Fig. 8. The signal filtered using present clutters, (a) the signal filtered using FIR. (b) the signal filtered using IIR. (c) the signal filtered using PR.

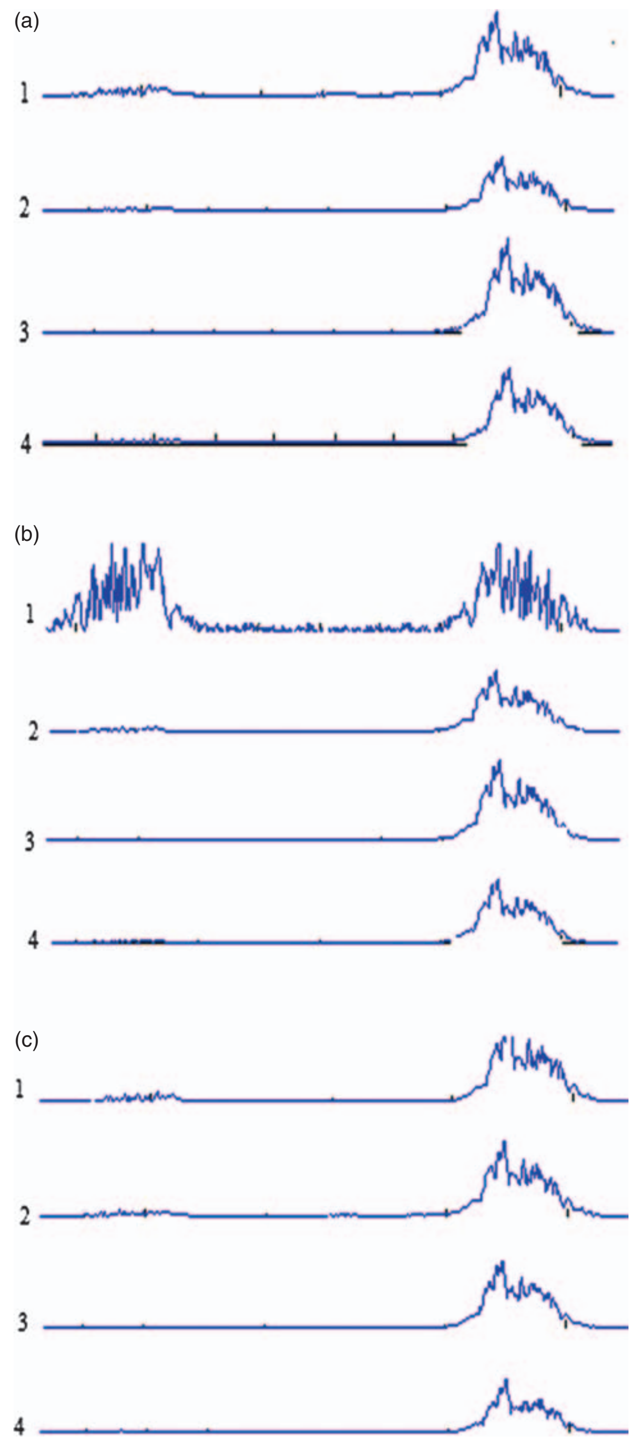

Fig. 9. The spectrum of filtered signal. (a) the spectrum of filtered signal using FIR. (b) the spectrum of filtered signal using IIR. (c) the spectrum of filtered signal using PR.

among all types of clutters. The propose clutter rejection method; suppress the clutter signal without altering the blood signal. The ICA and PCA give better performance when used for Doppler signal cluttering.

3.2. Real Doppler Data Results

The experiments with the real Doppler data illustrated in Figure 12(a) demonstrates Doppler spectrogram image generated from Doppler data filtered by using minimum phase FIR filters. Wide clutter line presented down the center of resulting Doppler image. Figure 12(b) illustrates the Doppler spectrogram from data filtered via Butterworth IIR filter where the clutter line is significantly reduced. PCA gives an image with a clutter line down the center narrower than that from IIR filter, Figure 12(c)

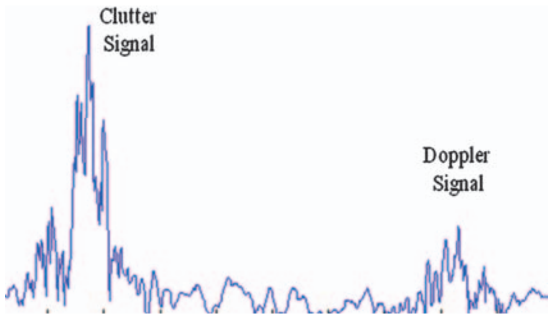

Fig. 10. Doppler signal contaminated with clutter.

Table III. **The performance of different clutters.**

Clutter type	Error	RMSD	Performance
FIR	$22.76*10^8$	80142.7	1
IIR	$10.5*10^8$	49578.5	3
PR	$4.97*10^8$	32038	5
PCA	$7.91*10^8$	43684.1	4
ICA	$4.97*10^8$	32038	5

shows the result spectrogram image. When ICA and PR used for cluttering the result image illustrated in Figures 12(d) and (e), the resulting image has very small clutter line around the image center. We can conclude that our proposed clutter rejection method can remove the clutter originated from stationary and slowly moving tissue with a performance better than other types of clutter rejection filters, and gives the Doppler spectrum image with a narrower clutter line around the center.

Beside the PSNR and RMSE used for clutter evaluation, the relative time for cluttering form each clutter was used. The cluttering time from each filter was calculated by running the program several times and calculates the average. The relative filtering time during cluttering the real Doppler data using current and proposed filters illustrated in Table 7.7. The result shows that the proposed clutter based on PCA gives lower cluttering time, while the proposed clutter based on ICA, gives relative time higher than that from PCA. PR gives the highest cluttering time among all the clutters types and FIR gives lower time than PR.

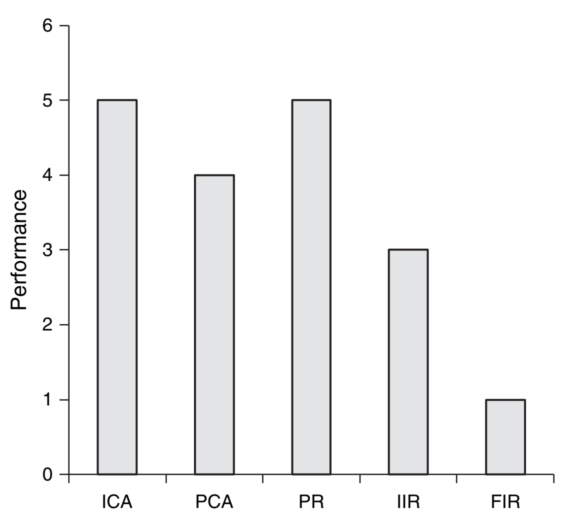

Fig. 11. The performance of different clutter rejection.

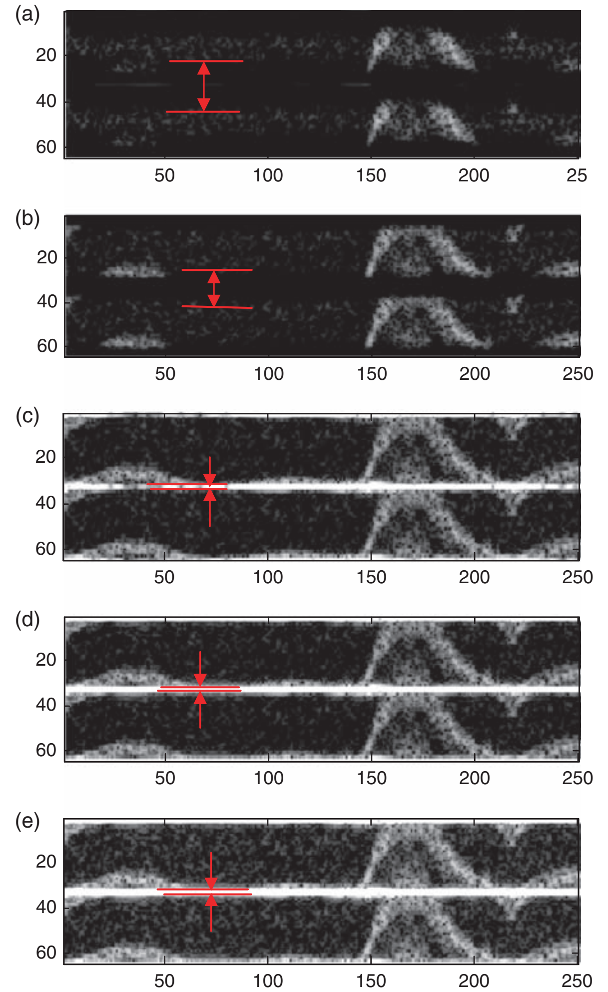

Fig. 12. The resulting Doppler sonogram images of heart for different types of clutter rejection filters (a) the doppler sonogram using FIR clutter (b) the doppler sonogram using IIR clutter (c) the doppler sonogram using PR clutter (d) the doppler sonogram using PCA clutter (e) the doppler sonogram using ICA clutter.

Table IV. **The relative time for different clutters.**

Filter type	IIR	FIR	PR	PCA	ICA
Relative time (S)	0.114	0.329	0.465	0.069	0.025

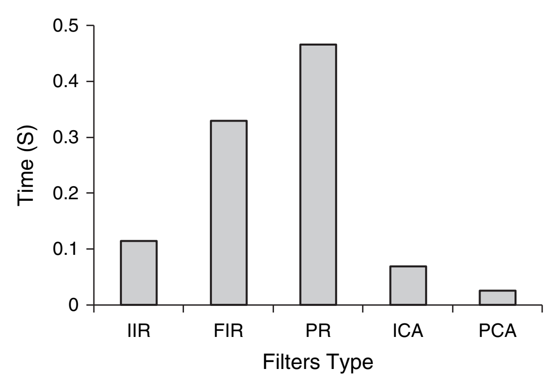

Fig. 13. Cluttering time for different filter.

The IIR gives lower time among the present cluttering methods. We can conclude that our proposed cluttering methods give lower cluttering time as shown in Figure 13.

4. CONCLUSION

The nonlinear adaptive clutter filter based on PCA and ICA has been demonstrated. The results show that the clutter filters reduce the clutter signal originate from stationary and slowly moving tissue. The methods were tested in a simulation Doppler IQ data and real Doppler heart data. The simulation result shows that the clutter filters are able to reduce the clutter signal from the echo signal. When the result of our proposed clutter rejection filter compared with other cluttering filter methods, the result shows that our proposed methods when ICA used gives error less than FIR and IIR and comparable result with PR. When proposed methods with PCA used the results show that ICA gives better clutter rejection than the PCA. PCA removes the clutter with better performance than FIR and IIR filters. For the real Doppler data, the result Doppler image shows that the Doppler spectrum image, changed adaptively depending on the type and characteristics of clutter. The result shows that the proposed clutter suppress the clutter more effectively than other clutter rejection algorithms. The resulting images from our proposed clutters are more accurate than that from present clutter algorithms. The proposed clutter suppression can be used clinically after more test and studies.

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