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A New Clutter Rejection Technique for Doppler Ultrasound Signal Based on Principal and Independent Component Analyses

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Abstract—**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. 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 clutter rejection based on principal component analysis (PCA) and independent component analysis (ICA). The proposed clutter rejection method presentation is quantified in simulated FR Doppler data beside real Doppler data. The result shows that the proposed method gives better clutter rejection.**

Index Terms—Doppler ultrasound signal; blood flow; spectrum; clutter rejection filter; Independent component analysis and principal component analysis.

I. 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. There are now many types of Doppler ultrasound device available for detecting and measuring blood flow 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 [3-5]. 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. 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, infinite impulse response (IIR) filter and polynomial regression (PR) filter [6 - 8]. The clutter from tissue often changes through space and time due to changes in physiology and tissue structure, and due to a limited number of data samples available (less than 20 sample volume [3]), in addition, if the clutter filter not appropriate selected the signal-to-noise ratio would be corrupted [4]. Due to all this, high pass filter can't effectively suppress the clutter without affecting the desired flow signal [9].

In this work a new cluttering methods have been proposed, to remove the clutter originated from moving objects and surrounding tissue. The proposed method based on principal component analysis (PCA) [10] and independent component analysis (ICA) [11].

. Both PCA and ICA applied to the original data set, 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 proposed techniques remove the clutter signal with high performance without affecting the blood flow signal. The performance of the techniques is quantified by using simulated RF data and real Doppler data [12].

ICA and PCA have been proposed for different applications such as, their application in analysis of EEG data [13], event-related potential (ERP) data [14] and in clutter rejection in color flow mapping [15].

II. Methods

A. 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. URI-OPT are a Matlab based program for reading and processing the RF data acquired from a URI-equipped Antares system.

The data used are data of Doppler spectrum collected from URIDmode. 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 x 7923. 100 is the number of pulses and 7923 is the axial sample volume

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

The complex data matrix X obtained can be expressed as:

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

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

$$x_n = \left[x_{1,n}, x_{2,n}, \ldots, x_{M,n}\right]^T, n = 1, \ldots, N \quad (2)$$

B. 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 $\boldsymbol{b}$, a clutter component $\boldsymbol{c}$ and white noise $\boldsymbol{n}$. The signal can be modeled as:

$$X = \boldsymbol{b} + \boldsymbol{c} + \boldsymbol{n} \quad (3)$$

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.

A small window has taken for testing our clutter rejection filters. The result Doppler IQ signal illustrated in figure 1, only first signal was shown for simplicity.

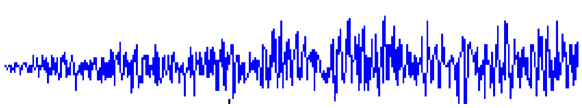

Fig. 1. The Doppler IQ signal used in simulation

C. Real Doppler Data (Heart Spectrum Data)

Our proposed clutter method applied to real Doppler data (heart data). The data downloaded from [12]. 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.

D. 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 [15]. The variance corresponding to these eigenvectors are denoted as the eigenvalues. 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 [10]. 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 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 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 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.

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. 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.

E. Independent Component Analysis

A recent developed transform method for data analysis and finding a suitable representation 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 separate the clutter from the blood flow data.

ICA technique based on non-Gaussianity and use higher order statistics rather than second order to separate the signal from the clutter [16]. Beside the non-Gaussian, ICA assumes the components to be independent.

Since ICA uses higher order statistics rather than second order moments to determine the basis vectors that are statistically independent as possible. 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 [17].

The proposed method for cluttering rejection compared with other three methods proposed for clutter rejection in [3]. The parameters used for designing the filters illustrated in table II to achieve filters with the same frequency response. 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. The accuracy of each method was computed and compared with others.

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	-	-	-

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.

III. RESULT AND DISCUSSION

A. Simulation Results

In this section we want to describe the simulation result of our proposed clutter rejection filter, 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. The result of the simulation shows that, the clutter suppressed from the Doppler signal more effectively, an example of result signal illustrated in figure 2 and the spectrum of the signal shown in figure 3, we only display the first two signals.

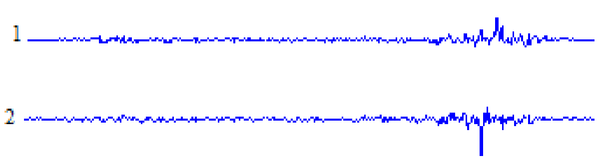

Fig. 2. An example of the filtered signal

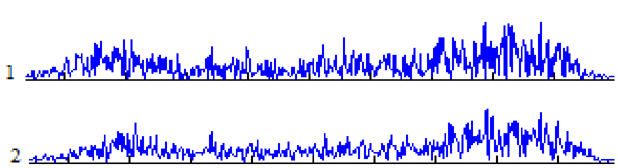

Fig. 3. An example of the spectrum of the signal filtered

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 4.

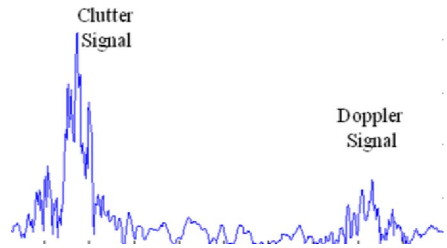

Figure 4. Doppler signal contaminated with clutter

To compare the propose clutter method with present clutter rejection methods, root mean square error 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 RMSE and error for different clutters illustrated in table III. 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 5 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. IIR give comparable clutter rejection and lower than PCA. FIR gives a lower performance among all types of clutters. The ICA and PCA give better performance when used for Doppler signal cluttering

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

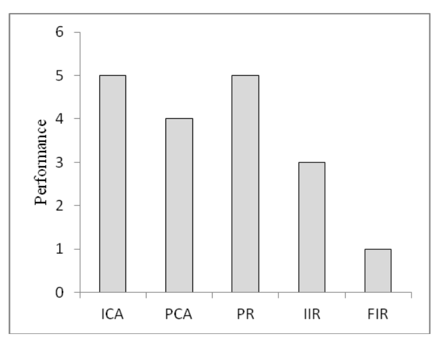

Fig. 5. The performance of different clutter rejection

B. Real Doppler Data Results

The experiments with the real Doppler data illustrated in figure 6 Figure 6 (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 6 (b) illustrates the Doppler spectrogram from data filtered via Butterworth IIR filter where the clutter line is significantly reduced. PR gives an image with a clutter line down the center narrower than that from IIR filter, figure 6 (c) shows the result spectrogram image. When PCA and ICA used for cluttering the result image illustrated in figure 6 (d, 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 with a performance better than other types of clutter rejection filters, and gives the Doppler spectrogram image with good quality.

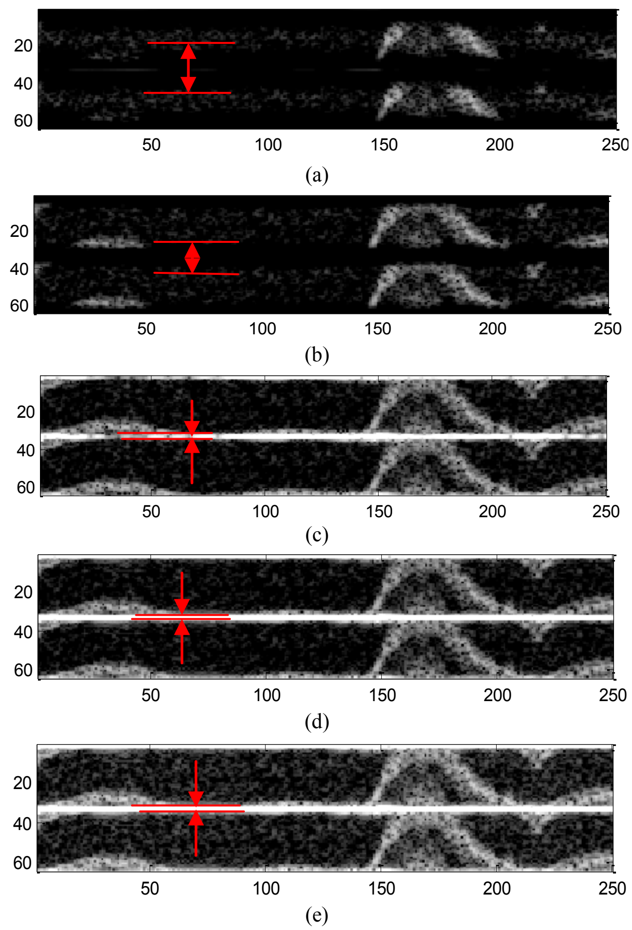

Fig. 12. The resulting Doppler sonogram images of heart for different types of clutter rejection filters (a) The Doppler sonogram using FIR clutter (b) The Doppler sonogram using IIR clutter (c) The Doppler sonogram using PR clutter (d) The Doppler sonogram using PCA clutter (e) The Doppler sonogram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

IV. Conclusion

The nonlinear adaptive clutter filter technique, based on ICA and PCA 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. 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 gives error less than FIR and IIR and comparable result with PR. The proposed methods with ICA gives better clutter rejection than the PCA. PCA removes the clutter with performance better than FIR and IIR filters. For the real Doppler data, the result Doppler image shows that the Doppler spectrogram image, changed adaptively depending on the type and characteristics of clutter. The result shows that the proposed clutter suppress the clutter more effectively than the present clutter rejection filters. 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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