Nonparametric clutter rejection in Doppler ultrasound using principal component analysis

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ABSTRACT

We propose a new nonparametric technique for clutter rejection. We consider the Doppler data sampled using a sufficiently large dynamic range to allow for the clutter rejection to be implemented on the digital side. The Doppler signal is modeled as the summation of the true velocity signal, a clutter component, and a random noise component. To simplify the analysis, the first two components are assumed as deterministic yet unknown signals. The Doppler data are collected from the sample volume of interest as well as from several sample volumes in its neighborhood. Given that the shape of the clutter component will be similar in all these signals and given its relatively higher magnitude, it is possible to separate this component using principal component analysis (PCA). In particular, the clutter component appears as the first eigenvector (principal component) in PCA. Given this principal component, the projection of the Doppler signal of interest onto this component is removed and the remaining signal is subsequently used to derive the Doppler spectrogram. We describe an efficient implementation methodology that allows the added computational complexity of the new system to be reasonable.

Keywords: Doppler, clutter rejection, principal component analysis, ultrasound imaging

1. INTRODUCTION

Even though the theory and methodologies used in the area of color flow mapping (CFM) have been the center of focus of Doppler research in the past two decades, it is not straightforward to implement such techniques on clinical systems. The main reason for that is the difficulty in characterization and suppression of nuisance components within the received signal and in particular the colored noise (clutter) component. Given an ultrasound system with the necessary acquisition and computational requirements for CFM, the computed CFM images may not yield useful information results in many cases as a result of signal contamination with both random and large colored noise components. The solution most implementations resort to is to fine-tune the filtration processes until satisfying results are obtained. This requires a lot of effort with the disappointing result that many such implementations are considered not robust by users. Therefore, a strategy that allows a more robust analysis of such information would be rather useful in making this technology more accessible.

We observe that the CFM data set used to generate a single instance of the CFM output bears similarity in many aspects to the data used in other medical imaging areas such as event-related studies performed using functional magnetic resonance imaging[3-6]. In such studies, the outcome of the experiment is in the form of a collection of temporal signals corresponding to different spatial positions that characterized by a very low signal-to-noise ratio (SNR). Given that a number of techniques have been proposed to handle such data adaptively while preserving the true signal part of the measured signal[3-6]. Among those approaches is the use of principal and independent component analyses in resolving the different sources that contribute to the measured signal[4]. Given the similarities with the CFM problem, it is of interest to investigate the use of such source separation techniques in this problem. In particular, we would like to be able to compute the different sources that contribute to the CFM data and use only those which contain the true signal in calculating the CFM images. Once this is possible, it is possible to compute more accurate maps and suppress artifacts resulting from other unwanted sources.

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The filtration technique used for clutter rejection has a direct influence on the accuracy of velocity estimation as described by the bias in the computed mean frequency. Several studies have been performed to investigate this effect as well as to propose methodologies to reduce its effect as a source of error in computing the Doppler velocity estimate. Stationary echo canceling was also shown to introduce a velocity dependent filtering, which influences the probability of detecting the current velocity[1-3]. Step-initialized IIR filters were compared to regression filters and were shown to provide inferior performance to their predicted one and to depend heavily of the clutter-to-flow-signal ratio[4]. Some authors compared the performance of three types of clutter rejection filters including FIR, IIR and regression filters, with their variants and reached a conclusion that the best performance design from each of them offer similar performance to the others with slight advantage to regression filters and projection initialized IIR filters[5,6]. The performance of adaptive techniques such as the discrete Karhonen-Loeve expansion was also investigated. The authors concluded that the eigenvectors corresponding to clutter still contain a significant amount of Doppler signal besides its computational burden[7]. Adaptive updating of the clutter filter to track possible temporal variations was also investigated for FLIR imaging applications[8-11]. The comparison between the use of filtering based on linear and nonlinear techniques was addressed whereby the conclusion was generally that the performance of nonlinear techniques is generally better but at the cost of 5-fold increase in the computational complexity on the average[12]. Split spectrum techniques followed by nonlinear processing were also investigated[13]. The idea of using regional principal component analysis for clutter rejection was proposed for radar imaging whereby PCA is performed and the different components are compared to a codebook that contains signal and clutter feature representations[14,15]. Based on the result of this comparison, the clutter components are removed.

The blind source separation problem has received an increasing amount of interest in the past ten years in the area of signal analysis. This problem assumes the acquired signal to be composed of a weighted sum of a number of basic components corresponding to a number of limited sources. The solution of this problem consists of a set of basic components that correspond to an optimized basis set for the particular problem at hand. The advantages of using such components rather than any other arbitrary choice for the basis functions include the ability to reduce the number of features significantly in addition to separating the components that correspond to noise. This makes the use of such techniques desirable for biomedical signals.

Observing the correlation between the information in neighboring resolution cells, we propose a methodology to allow better analysis of Doppler ultrasound signals. A blind source separation problem is formulated to discern the different signal components for correct interpretation of the data using principal component analysis (PCA). The Doppler signal is modeled as the summation of the true velocity signal, clutter or baseline fluctuation, and random noise. The baseline fluctuation component can be considered as a deterministic yet unknown signal. A simple adaptive denoising technique is applied to reduce the effective dimension of the noise subspace. Then, given a region of interest, the temporal signals corresponding to all pixels within this region undergo the ICA iteration to compute a set of independent signals that most represent the actual components present within the data. Subsequently, a comparison of the temporal variations of these signals allows the user identify the components of the signals that correspond to baseline variation or random noise manually or using semi-automated techniques. The new technique shows large potential to alleviate some of the limitations in this demanding imaging mode as well as to make the interpretation of the results more robust.

2. SIGNAL MODEL

In color flow mapping, the image is constructed within the region of interest using estimates of some blood velocity measure in each pixel. Hence, to maintain the accuracy of the map, robust measures have been proposed in the literature to lower the sensitivity of estimates in the presence of noise. We propose a different strategy in this work that uses two steps; a modeling step and an analysis step. The advantage of this strategy is a more robust performance in the presence of different types and levels of random and colored noise.

The model of the data collected to reconstruct a single instance of the color flow map consists of a three dimensional complex array consisting of the quadrature samples collected from the 2-D region of interest along a specified time window. We consider now the time course signals of individual pixel. In conventional CFM techniques, each of these time courses is used to compute a single value to describe the velocity at this specific spatial position and time[2]. Here, we try to decompose this signal into its underlying components before we attempt to compute such estimate.

Each time course is assumed to contain contributions from four independent components: the true Doppler signal, the signal resulting from wall motion, clutter and baseline variation, and random noise[1,2]. The first three components are considered as deterministic yet unknown signals. The wall motion signal can be suppressed by using an analog wall motion filter before sampling of the signal. However, a residual contribution from this component usually remains with the filtered signal. In the more advanced Doppler system, wall motion filtering can be performed on the digital side using a high-resolution analog-to-digital converter to accommodate the required large dynamic range. This component is modeled as a large magnitude low frequency signal superimposed on the original signal. The third component is present as a result of the presence of stationary structures within each voxel. On the other hand, the fourth component is assumed to consist primarily of thermal noise that belongs to a zero-mean white Gaussian noise on both quadrature parts of the signal. The velocity estimate should be computed using only the first component.

Given that the contribution of each of the four components to the measured signal vary between different pixel locations, it is not generally possible to using simple averaging techniques to improve the accuracy of the map. The approach we propose here to improve the accuracy is to take advantage of the availability of time course signals from different spatial locations and the common origin and form of such signals as the wall motion signal and clutter signal among them. In particular, instead of filtering the individual signals using a rigid model for the deterministic and random nuisance sources, a nonparametric approach is used where the underlying sources of signal in the whole data set are estimated then used to remove nuisance from individual time courses. This approach relies on blind source separation methods such as principal component analysis or independent component analysis to perform the source localization from the data set at hand based on statistical criteria and without intervention from the user.

3. PRINCIPAL COMPONENT ANALYSIS (PCA)

Principal component analysis is analogous to Fourier analysis in that the data is described in terms of the coefficients of a predetermined orthogonal set. Rather than using complex exponentials, the orthogonal set in PCA is determined adaptively based on the analyzed data set. In particular, PCA derives the directions of a set of orthogonal vectors that point into the direction of the highest variance of the data. The principal components are calculated as the eigenvectors of the covariance matrix of the data [11]. The eigenvalues denote the variances corresponding to these eigenvectors. Hence, PCA is an efficient technique for dimensionality reduction in multivariate statistical analysis.
Given a data matrix X of size m×n composed of m n-point sample windows, let a centered matrix Z be computed as $Z = (X - E\{X\})$, where E{X} is the matrix of mean vectors. Then, PCA is defined as [11],

$$Y = B^T Z \quad \text{and} \quad K_x = B \Lambda B^T \quad , \tag{1}$$

where Λ is a diagonal matrix with eigenvalues of the covariance matrix K_x on the diagonal (with eigenvalues ranked such that $\lambda_1 \geq \lambda_2 \geq \cdots \geq \lambda_n$) and the columns of B are the corresponding eigenvectors. The output of the PCA transform is uncorrelated vectors. The covariance matrix of the output Y is $K_y = E\{YY^T\} = \Lambda$. Due to the orthogonality of the matrix B, Eq. (1) can be rewritten as, *Z=B Y*, where the matrices are m×n, m×m, and m×n, respectively. In general, principal components analysis can be used for dimensionality reduction by truncating the signal components corresponding to the smallest eigenvalues. This is can be described as $Z' = B'Y'$, where the matrices are m×n, m×q, and q×n, respectively with q<n. In this case, the selection of the number of eigenvalues allows the inclusion of as much of the variability of the original data as needed. The efficiency of this approximation is estimated by the ratio between the chosen variance to the total system variance as,

$$E = \sum_{i=1}^{q} \lambda_i \Big/ \sum_{i=1}^{n} \lambda_i \, . \tag{2}$$

For feature extraction, each centered sample is represented by its projections on the q principal components computed as the inner product between the centered sample and each of the computed eigenvectors.

4. SIGNAL DENOISING

Since the basic assumption of PCA is that the number of uncorrelated components is less than the number of signals and given that each signal contains an independent white Gaussian noise component, the result from PCA is expected to exhibit mixing of sources in the principal components[16]. This is undesired because of the possibility of mixing of signal and clutter. Therefore, it is necessary to reduce the dimensionality of the sources before PCA is attempted. This can be done by a preprocessing denoising step[17]. This will be summarized as follows.

Consider a signal model that is composed of the sum of one deterministic component *d(t)* incorporating both the true Doppler, wall motion and clutter signals and an uncorrelated stochastic random noise component *n(t)*. That is,

$$s(t) = d(t) + n(t) \quad . \tag{3}$$

Since these two component are assumed independent, the corresponding power spectrums are related by,

$$P_{ss}(\omega) = P_{dd}(\omega) + P_{nn}(\omega) \quad , \tag{4}$$

where cross-terms vanish because the two components are assumed uncorrelated. Hence, an estimate of the power spectrum of the deterministic component takes the form[9],

$$P_{dd}(\omega) = P_{ss}(\omega) - P_{nn}(\omega) \quad . \tag{5}$$

That is, the signal power spectrum is obtained by spectrum subtraction of the noisy signal and noise power spectra. In order to compute the deterministic signal component from its power spectrum, the magnitude of the Fourier transform can be obtained as the square root of the power spectrum. The problem now becomes that of reconstructing the signal using magnitude only information about its Fourier transform. Several techniques can be used to do that. The one used for this work relies on an estimate obtained from the phase of the Fourier transform of the original signal $S(\omega)$. Hence, the Fourier transform of the processed signal $S_d(\omega)$ can be expressed as,

$$S_d(\omega) = \sqrt{P_{dd}(\omega)} \cdot \mathrm{e}^{j\,\mathrm{Phase}(S(\omega))} \quad . \tag{6}$$

The enhanced deterministic signal $s_d(t)$ is then computed as the real part of the inverse Fourier transformation of this expression.

5. METHODS

We start with a basic set of assumptions as follows:

a. The flow signal component is uncorrelated with the present clutter component.
b. The signals from neighboring flow mapping resolution cells contain clutter signals that are correlated.
c. The flow signal components from neighboring resolution cells are uncorrelated.

Then, we propose a regional PCA approach that works by including signals from a local area in addition to an external "navigator" area away from the region of interest. The reason for including an external area is to account for any scanner instabilities as a part of the unwanted part of the signal. By choosing pixels along on same lines as the region of interest, we can measure any temporal variations of the transmitted power, receiver gain, or any fluctuations from cross-talk between the different components of the system. We also include in this analysis a length of the signal that is significantly larger than the one used for CFM velocity estimation (for example, 128 points instead of the 8-16 samples used for CFM computations). We call this length the "PCA window". The CFM velocity estimate can still be computed from the smaller length after the clutter is removed bearing in mind the added shift in the timing of this computation (i.e., a velocity estimate has to wait for the time needed to acquire the longer record and for the PCA computation before it can be performed). Since the clutter component is present in all signals and that it is usually stronger than the flow signal, the outcome of PCA will always have the clutter signal as the first principal component. By suppressing this component from all points in the region of interest, a clutter free signal record is generated and can be divided into smaller windows for CFM estimates to be computed. The process is repeated using either overlapping or non-overlapping PCA windows. Given that the process depends only on the data to calculate and remove the clutter component, it adapts well under different conditions of flow signal, random noise and clutter. Therefore, its performance should be robust enough for practical purposes. A block diagram of the proposed methodology is shown in Fig. 1.

In order to apply the signal denoising preprocessing step, we need to obtain an estimate of the present noise power in the system. According to the above derivation, we need to compute the variance of the data in order to obtain the noise power spectrum model using the empirical formula. The simplest way to do that is to estimate the variance of background areas within the available data set. Background areas correspond to stationary tissues within the region of interest or can be estimated separately as the signal when the receiver multiplexer is turned off.

6. RESULTS

The proposed method was implemented to compute the PCA of simulated signals consisting of a Doppler shift signals (assumed to include a range between 300 Hz and 3 kHz), a clutter component (assumed to be in the range 1-300Hz), and a random white Gaussian noise component. The real and imaginary parts of the signal were preprocessing using the denoising method and then analyzed using PCA. The preliminary results from analyzing the original signal using PCA show a good separation of flow signal from clutter. Moreover, the analysis results from the PCA technique were rather robust to detect the clutter signal as the first component.

The computational complexity of the proposed technique is obviously high for full featured PCA compared to the requirements of real-time display of CFM information. However, observing that we need only the first principal component, the actual time needed to obtain this component is significantly smaller than that needed to compute full PCA results. Therefore, we believe that this methodology can be implemented on current ultrasound imaging systems.

7. CONCLUSIONS

A new clutter rejection method for ultrasound CFM applications is developed. The idea is to examine the signals from a neighborhood as well as from navigator locations in the field of view to extract information about the clutter signal characteristics. The new method is nonparametric and therefore adapts to the present noise components and distributions within the region of interest. It also takes into account the nuisance components from random noise as well as temporal instabilities in the imaging system. Given that we need only the first component of PCA to identify clutter, the computational complexity of the proposed system is significantly less than full PCA and therefore is more suitable for practical implementation.

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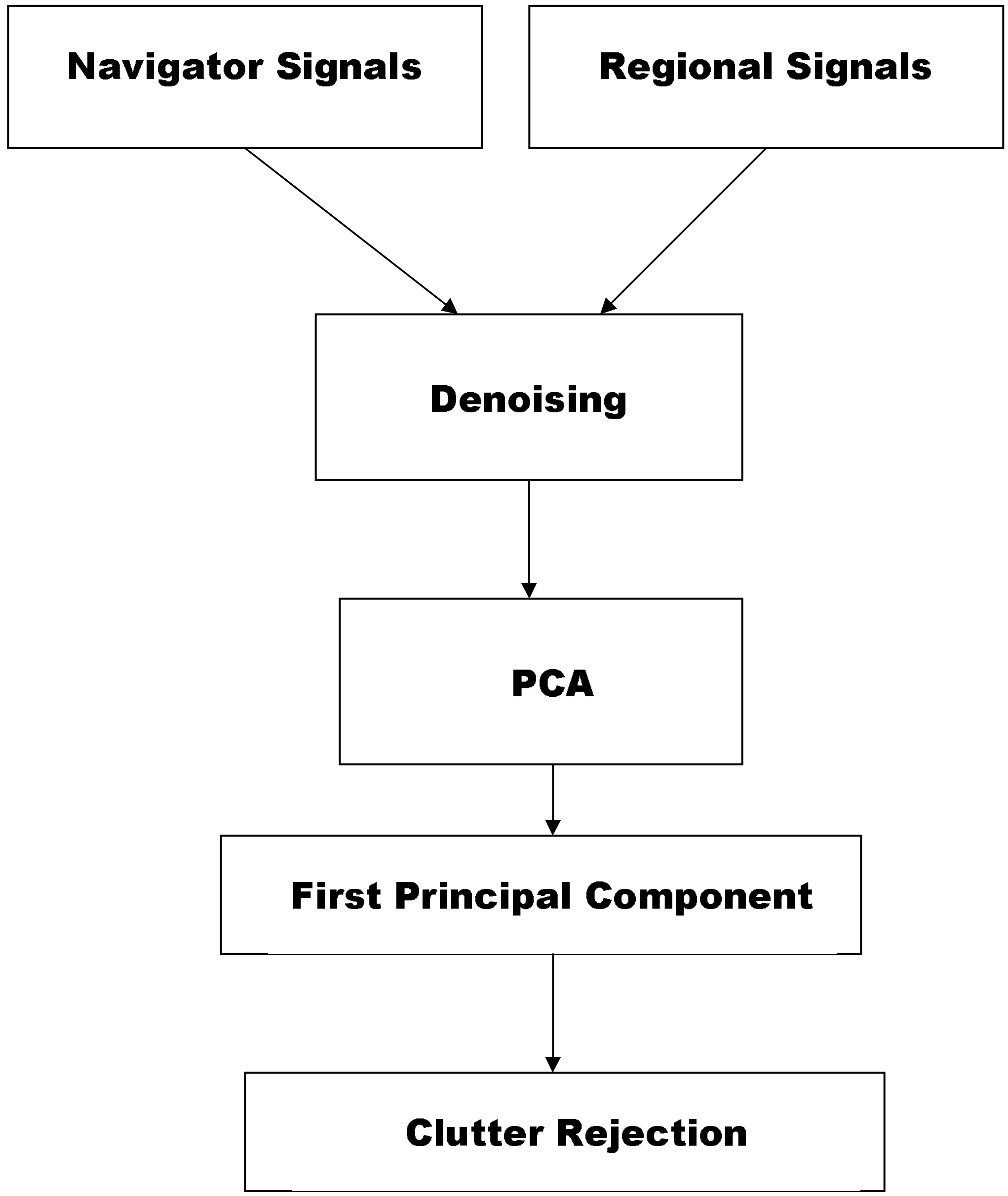

Figure 1. A block diagram of the proposed methodology. The principal component is computed and taken as the estimate of clutter in ultrasound CFM signal.