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Adaptive filtering noisy transcranial Doppler signal by using artificial bee colony algorithm

Nurhan Karaboga [a], Fatma Latifoglu [b,*]

[a] Erciyes University Engineering Faculty, Electrical & Electronics Eng. Dept., Kayseri, Turkey
[b] Erciyes University, Engineering Faculty, Biomedical Eng. Dept., Kayseri, Turkey

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ABSTRACT

Computerized processes are supportive in the new age of medical treatment. Biomedical signals which are collected from the human body supply or important useful data that are related with the biological actions of human body organs. However, these signals may also contain some noise. Heart waves are commonly classified as biomedical signals and are non-stationary due to their statistical specifications. The probability distributions of the noise are very different, and for this reason there is no common method to remove the noise. In this study, adaptive filters are used for noise elimination and the transcranial Doppler signal is analyzed. The artificial bee colony algorithm was employed to design the adaptive IIR filters for noise elimination on the transcranial Doppler signal and the results were compared to those obtained by the methods based on popular and recently introduced evolutionary algorithms and conventional methods.

1. Introduction

The Doppler ultrasound device provides non-invasive measurement of blood flow velocity with the aim of diagnosing vascular diseases. The Doppler shifts from red blood cells are used for computing blood velocity. In the computing of blood velocity, the Doppler-shift frequency and Doppler angle are used by the instrument. The Doppler signal displays a time-varying random character because the signal back scattered from the blood possesses a random spatial distribution (Evans, 1989). Doppler indices such as the resistance index (RI) or pulsatility index (PI) are ratios that are computed from various points on the spectrum which are computed to analyze the Doppler signals (Diniz, 2008). Traditionally, the short time Fourier transform (STFT) method has been found to be suitable for the application of the spectrogram (Diniz, 2008; Brody and Meindl, 1974; Shung et al., 1984; Leeuwen et al., 1986). Doppler spectrogram indices are determined from the maximum frequency waveform of the Doppler spectrogram (Haykin, 2002; Krusienski and Jenkins, 2005). The estimation resolution of the maximum frequency waveform is affected by the inner or outer noise in the system causing extra frequency. Hence, this is a significant stage which includes the denoising of the Doppler ultrasound signal for further processing (Liu et al., 1997, 1999).

When the system parameters or signal conditions change, adaptive filters are generally used and they are to be adjusted to balance this change (Behbahani, 2007). It is known that all adaptive filters capable of adapting at real-time rates experience losses in performance because their adjustments are based on statistical averages taken with limited sample sizes (Widrow, 1971). In the adaptive filtering case, the parameters of the filter which were evaluated a few moments before are used to automatically tune the parameters of the filter which are determined at the present moment, to adapt to the changing situation due to the achievement of the optimal filtering (He et al., 2008). The adaptive filter has the most important properties, because it can be effectively applied in unpredictable situations and the input signal the characteristics of which vary with time, may be tracked by using it. The adaptive filter has been applied mainly in signal processing, control, communications and many other systems for noise cancellation. The gradient based algorithms move in the negative gradient direction. So, they aim to obtain the global minimum on the error surface. However, the filter design approaches which are based on the gradient algorithms may lead to suboptimal IIR filter designs when the error surface is multimodal (Ng et al., 1996; Karaboga, D., 2005; Karaboga, N., 2005; Karaboga and Cetinkaya, 2011; Karaboga, 2009).

The artificial bee colony (ABC) algorithm is a relatively new swarm intelligence based algorithm which can be used to find optimal or near optimal solutions to numerical and discrete problems. The ABC algorithm was first introduced by Karaboga in 2005, inspired by the foraging behavior of honeybees (Karaboga, D., 2005; Karaboga, N., 2005). It is simple and robust

* Corresponding author. Tel.: +90 352 4374901x32977; fax: +90 352 4375784.
E-mail addresses: nurhan_k@erciyes.edu.tr (N. Karaboga), flatifoglu@erciyes.edu.tr (F. Latifoglu).

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optimization algorithm which can be easily implemented in widely used programming languages and has proven to be both very effective and quick for a diverse set of optimization problems (Karaboga et al., in press). Because of the nonstationary character of Doppler signals, the practical issues related to this signal must be solved using adaptive filters (Kaluzynski, 1987). In this work, a novel approach based on the ABC algorithm is proposed to denoise the Doppler signal by using adaptive IIR filter structures and also, its performance is compared to the popular algorithms such as particle swarm optimization (PSO) and differential evolution (DE), and conventional wavelet transform techniques. The paper is organized as follows. Section 2 describes the proposed artificial bee colony based adaptive noise cancellation system. Section 3 presents the application of the proposed method to the noise cancellation problem. The simulation study is outlined in Section 4 and the simulation results are discussed in Section 5.

2. Proposed adaptive noise cancellation system

Widrow and Glover proposed adaptive noise cancellation in 1975 (Widrow and Glover, 1975). Noise cancellation is a key problem of filter design. This filter design can be applied when the reference noise signal is achieved. In many applications, e.g. speech processing, echo cancellation and enhancement, antenna array processing, biomedical signal and image processing, the noise cancellation technique has been used (Widrow and Walach, 1996; Haykin, 1996; Feder et al., 1989; Billings and Fung, 1995). In standard noise elimination methods, only one primary signal is used (Widrow and Walach, 1996). However, especially in biomedical signal processing, several primary signals can be measured. Usually this advantage can be used to improve the performance of the noise elimination process. To allow doctors to view the best signal that can be obtained, we need to develop an adaptive filter to remove the contaminating signal in order to better obtain and interpret the transcranial Doppler signal (Behbahani, 2007).

Fig. 1 shows that the noisy signal $d(n)$ which is collected by the biomedical sensors, carries the meaningful signal $s(n)$. To eliminate noise from the noisy signal, the reference sensors remove environmental noise and this noise $x(n)$ is used for the input of the adaptive filter. The filter can only adjust the reference noise to generate a similar signal to $y(n)$, because $s(n)$ is not suitable. Then, to remove the noise signal $y(n)$ in the noisy signal, the error signal $e(n)$ converges by stages to the noiseless signal $s(n)$ of the approximate signal. The adaptive filter can be adapted to the environmental set by these signals using this method.

An adaptive IIR filter can be formulated in the transfer function equation. It is denoted as

$$H(z)=\frac{\sum_{i=0}^{M} b_i z^{-i}}{1+\sum_{i=1}^{N} a_i z^{-i}} \tag{1}$$

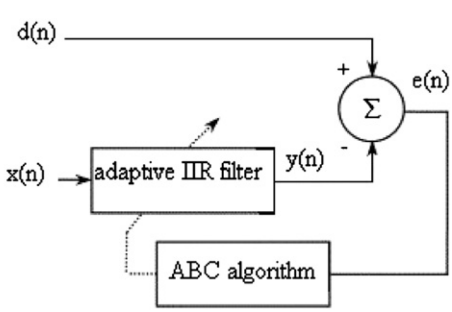

Fig. 1. Block diagram of the proposed adaptive noise cancellation system.

where b_i and a_i represent the zeros and poles of the transfer function, respectively, and the filter order is $N\ (\geq M)$. The coefficients are presented in the following vector form:

$$w=[b_0\ b_1\ \ldots\ b_M\ a_1\ a_2\ \ldots\ a_N]^T \tag{2}$$

To guarantee the stability condition of the designed adaptive IIR filter, the unit circle must contain all the poles of the adaptive filter. In the simulation, a noise signal is chosen as an additive white Gaussian noise (AWGN) due to the specification of the power spectrum. AWGN is an uncorrelated noise with constant power spectral density. In theoretical study, it has an infinite power which lies in the infinite frequency range.

The error signal $e(n)$ is calculated by the difference between the noisy signal $d(n)$ and the adaptive filter output $y(n)$. The error signal is re-entered into the adaptation algorithm, then the coefficients of the adaptive filter are adjusted so that a given cost function is minimized. The cost function used is the Mean Squared Error (MSE) which is defined as

$$J(w)=\frac{1}{N}\sum_{n=1}^{N}\left[d(n)-y(n)\right]^2=E\left[\left|e(n)\right|^2\right] \tag{3}$$

where E represents the expected value. Minimizing $J(w)$ results in a filter error that is the best least squares estimate of the signal. The adaptive IIR filter extracts the signal, or eliminates noise, by iteratively minimizing the MSE between the primary and the reference inputs. In the population, the quality of the solution i is evaluated by

$$fit_i(w)=\frac{1}{1+J_i(w)} \tag{4}$$

where $J_i(w)$ is the cost function value when the parameter set w_i is used for the adaptive filter. In order to compute $J(w)$, a moving scheme is employed by using a block of N samples. After each cycle, the block is moved by one sample.

3. Artificial bee colony algorithm

Swarm intelligence is a popular area in the field of optimization and researchers have developed various algorithms by modeling the behaviors of different swarms of animals and insects such as ants, termites, bees, birds and fish (Karaboga and Akay, 2009). Some classical kinds of swarms include a colony of ants; a bee colony swarming around their hive; a swarm of cells is an immune system, a crowd which is a swarm of people; and a flock of birds.

The artificial bee colony algorithm was introduced by Karaboga for numerical optimization problems in 2005; the performance of ABC was also compared by Basturk and Karaboga with that of other algorithms such as Particle Swarm Optimization (PSO) or Differential Evolution (DE) (Karaboga and Basturk, 2007, 2008). In the ABC algorithm, there are three types of bees in the colony: employed, onlooker and scout bees. In this algorithm, it is supposed that the number of employed bees is also equal to the number of food sources in the colony. There is only one employed bee for each food source. Therefore, the number of employed bees is equal to the number of food sources. In the ABC algorithm, the search process is divided into three steps after the initialization stage. Basic steps of the ABC are presented below.

3.1. Initialization

3.1.1. Repeat

Step 1: Locate the employed bees on their food sources and evaluate their nectar amounts