Determination of aorta failure with the application of FFT, AR and wavelet methods to Doppler technique

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Abstract

In this study, Doppler signals recorded from the output of aorta valve of 24 patients were transferred to a personal computer (PC) by using a 16-bit sound card. Doppler difference frequencies were recorded from each of the patients, and then analyzed using fast Fourier transform, autoregressive and wavelet transform analyzer to obtain their sonograms. These sonograms are then used to compare with the applied methods in terms of medical evaluation. © 2001 Elsevier Science Ltd. All rights reserved.

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1. Introduction

In the last three decades, Doppler blood flow methods have been widely used in medical practice. As a result, both pulse wave and continuous wave Doppler devices have been commonly used. Both of these devices transmit ultrasonic waves into blood and receive some part of them which are reflected by red blood cells. There is a direct relationship between the flow velocity of the blood and Doppler difference frequency which is obtained after the demodulation of transmitted signal with reflected signal. Some spectral analysis methods are applied to the Doppler signal in order to obtain medical information by taking into consideration the relationship between the Doppler signal and flow velocity of the blood. For this reason, the sonograms that show the change of Doppler spectrum by time are obtained [1,2].

Heart consists of four cardiac chambers, namely two atriums and two ventricles. The aorta valve, examined in this study, is in the beginning of aorta that comes out from the left atrium. Aorta valve is the part of heart which prevents blood from flowing backward during diastole, acting passively...
Some people may have anatomic abnormalities in their hearts. For instance, the abnormality named as the aorta failure is a result of anatomic disorder of aorta valve. This abnormality causes heart valve not to open and close properly. As a result, the volume of blood that is pumped to the extremities decreases and it causes some other problems to occur. Works up to date about the aorta valve blood flow sonograms have not been studied as the comparison of three spectral analysis methods.

In this paper, Doppler signals obtained from 24 patients, 18 of them have aorta failure, are examined by taking into consideration formation of their sonograms. Since the resolution of sonograms are high and also in good quality, they do not have misleading frequency components. fast fourier transform (FFT), autoregressive (AR) and wavelet transform (WT) methods are used for spectrum analysis of Doppler signal. These methods are compared in terms of their frequency resolution and the effects of clinical diagnosis.

2. Materials and method

The block diagram of the measurement system is shown in Fig 1. The system consists of five blocks. These are 2 and 7 MHz ultrasonic transducers, analog Doppler unit (Toshiba sonolayer 140 A-Echo Device), analog/digital interface card (sound Blaster Pro-16 bit), one PC and one printer [1]. Since the distance from the skin to aorta valve is too long, two different probes are used to obtain returned signal.

The echo device also contains an ultrasonic display unit that enables the sample volume to be placed anywhere in the heart valve. In this study, the device is used in pulse mode and the reverse flow of blood in the entrance of aorta valve is analyzed. MATLAB software package is used to form the spectrum functions of Doppler signals recorded in the PC and to obtain the sonograms. Doppler signals were recorded from each of the patients by placing sample volume of the device just over the aorta valves for 2 s. Three different kinds of spectral analysis methods were used to obtain sonograms which represent the changes in Doppler frequency with respect to time. In sonograms, horizontal axis represents time \((t)\) and the vertical axis represents the frequency \((f)\). The grey scale of the diagrams shows the power of frequency component of the graph \(P(f)\). As the grey scale turns into black it means that the power of related frequency component is increasing, otherwise it is decreasing [4–6].

In order to complete the spectral analysis, signals sampled in 5 kHz were framed by equal time intervals. The rate of change of signal spectra is an important factor to determine the optimum frame length. When there is an aorta failure, it is said that there is a fluctuated flow (i.e. turbulence). The frame length is chosen as 128 samples per frame in order to capture all signals arising from abnormalities [5]. In the signal analysis process, spectrum concept is essential. Fourier series are used to examine the spectrum of periodic analog signals. Fourier series can be defined as a general...
orthogonal expansion for periodic signals. On the other hand, Fourier integral is the limit position acquired by taking the Fourier series to infinity [7].

2.1. Fast fourier transform method

In order to take the FFT of a finite Doppler signal, it must be framed with the powers of 2, such as 64, 128, 256. Windowing technique is used to evaluate the frequency spectrum for the corresponding frame. By using windowing, the non-existing frequency components appearing in the spectrum is prevented. In addition, zero padding is applied to the same signal after windowing process. This entails certain overhead on the process although it increases the readability of spectrum [7].

Discrete Fourier transform of a discrete time periodic signal is defined as follows:

$$X_k = \sum_{n=0}^{N-1} x(n) \exp\left(-j\frac{2\pi kn}{N}\right),$$  

(1)

where \(X_k\) is expressed as discrete Fourier coefficient, \(N\) is the frame size and \(x(n)\) is the input signal on time domain. To obtain the frequency spectrum of this signal, logarithmic values of the squares of absolute values of \(X_k\) are found as shown below.

$$P(k) = 10 \log |X_k|^2.$$  

(2)

However, the performance of FFT method becomes insufficient for recording blood flow in the stenosis where the speed of blood is high thus causing turbulences. It is also observed that the spectrum becomes wider and frequency resolution decreases in these areas.

Modern spectral analysis methods like AR and WT are more powerful than the FFT spectral analysis method [7]. The correct estimation of the coefficients that depend on the modelling degree is necessary for the AR modelling method. By using these coefficients, the signal’s power density function is established. These models are the ones that are applied to the time series like AR. It is convenient to use the least-numbered parametric method to get a fine modelling of a time series.

2.2. Autoregressive modelling method

AR modelling method is suitable for time series that have sudden peaks but not deep hallows in their frequency spectrum [7–9].

An AR process \(x\) of order \(p\) is defined as

$$x(n) = -\sum_{m=1}^{p} a_m x(n-m) + e(n),$$  

(3)

where \(x(n)\) is the array of samples, \(a_m\) are the model coefficients and \(e(n)\) is the driving white noise which represents the error term. The model contains \(p + 2\) parameters which have to be estimated from the data: the coefficients, the mean of the samples and the variance of the white noise. The problem of estimation of these parameters corresponds to evaluation of linear equations which are computationally easy to implement.

In the following equations, \(a_{ki}\) stands for the \(i\)th coefficient of an AR model of order \(k\). The first-order AR process is described by

$$a_{11} = -R_{xx}(1)/R_{xx}(0)$$  

(4)
and
\[ \sigma_1^2 = [1 - a_{11}^2]R_{xx}(0), \] (5)
where \( \sigma^2 \) is the variance of the driving white noise and \( R_{xx}(0) \) is the estimate of the autocorrelation function of the process. Next, the Levinson algorithm is used to compute consecutive superior orders from \( k = 2 \) to \( p \):
\[ a_{kk} = \frac{R_{xx}(k) + \sum_{m=1}^{k-1} a_{k-1,m} R_{xx}(k-m)}{\sigma_k^2}, \] (6)
\[ a_{ki} = a_{k-1,j} + a_{kk} a_{k-1,k-i}, \quad i = 1, 2, \ldots, k - 1, \] (7)
\[ a_k^2 = [1 - a_{kk}^2] \sigma_k^2. \] (8)

Once the desired order, \( p \), is achieved, the power spectral density estimation of the data is given by
\[ P(f) = \frac{\sigma_p^2 \Delta t}{|1 + \sum_{m=0}^{p} a_{pm} e^{-j2\pi f m \Delta t}|^2}, \] (9)
where \( a_{p0} = 1 \). Obviously Eq. (9) refers to a continuous function \( P(f) \), computed from a finite-discrete series of parameters \( a_{pm} \) and \( \sigma_p \). In order to make the task feasible in a digital computer, the power spectrum is computed for a finite set of frequencies \( k \):
\[ P(k) = \frac{\sigma_p^2 \Delta t}{|1 + \sum_{m=0}^{p} a_{pm} e^{-j2\pi k m \Delta t}|^2}, \] (10)
where \( a_{p0} = 1 \).

Linear prediction is based upon an extrapolation of the known values of an autocorrelation function using the autoregressive model as the basis for extrapolation [7]. Supposing that \( p + 1 \) values of an autocorrelation function \( R_{xx}(0) \) to \( R_{xx}(p) \) are known, the linear prediction extrapolation of the autocorrelation is
\[ r_{xx}(n) = - \sum_{m=1}^{p} a_{pm} r_{xx}(n-m) \quad \text{for } |n| > p. \] (11)

This approach maximizes the randomness of the unknown time series, producing the flattest spectrum for all of the alternatives for which the autocorrelation function in the interval \( R_{xx}(0) \) to \( R_{xx}(p) \). When the linear prediction extrapolation is used, it is convenient to choose an alternative representation for the power spectrum density as given below:
\[ P(k) = \Delta t \sum_{m=1}^{K-1} r_{xx}(m) e^{j2\pi km \Delta t}, \] (12)
where \( K \) can be chosen as a power of 2, in order to enable the computation using the FFT algorithm. This method does not yield satisfactory results when one wants to observe the effects of sudden fluctuations despite the fact that a good spectral resolution was obtained, and misleading frequency components can be found in sonogram. For this reason, wavelet method was found to be necessary.
2.3. Wavelet transform method

According to the principle of uncertainty, increasing the resolution on the time axis decreases the resolution on the frequency axis and vice versa. To solve this problem, there is a need to use narrow windows for higher frequencies and wide windows for lower frequencies. WT method provides the window length to get wider and narrower when it is required. The goal of this model is to catch a spectral resolution balance and reduce the number of samples. The WT is being increasingly applied to analyze signals with nonstationary components. Nonstationary means that the frequency content of the signal may change over time and the onset of changes in the signal cannot be predicted in advance. Doppler blood flow signals in the aorta valve, which are transient-like and of very short duration, fit the definition of nonstationary signals. Like FFT-based time-frequency representation, a complete WT process creates a two or three-dimensional representation with description of time, wavelet scale (1/frequency), and amplitude of the WT coefficients. The WT decomposes a time series into time-scale space and enables one to determine both dominant modes of variability and how those modes vary in time. The continuous wavelet transform (CWT) is performed by projecting a signal \( s(t) \) onto a family of zero-mean functions (the wavelets) deduced from an elementary function (the mother wavelet) by translations and dilations. It is given by [10]

\[
W(a, b) = \frac{1}{\sqrt{|a|}} \int_{-\infty}^{\infty} s(t) \Psi^*(\frac{t - b}{a}) \, dt, \quad a \in R^+ - \{0\}, \quad b \in R, \tag{13}
\]

where \(^*\) denotes the complex conjugate and \( \Psi^*(t) \) is the analyzing wavelet. The variable \( a(>0) \) is the scale factor and controls the scale wavelet, so that taking \( |a| > 1 \) dilates the wavelet \( \Psi \) and taking \( |a| < 1 \) compresses \( \Psi \). The variable \( b \) is the time translation factor and controls the position of the wavelet. The wavelet transform is characterized by the following properties:

1. it is a linear transformation,
2. it is covariant under translations:

\[
s(t) \rightarrow s(t - u) \quad W(a, b) \rightarrow W(a, b - u), \tag{14}
\]

and

3. it is covariant under dilations:

\[
S(t) \rightarrow S(kt) \quad W(a, b) \rightarrow \frac{1}{\sqrt{k}} W(ka, kb). \tag{15}
\]

The basic difference between the WT and the FFT is that when the scale factor \( a \) is changed, the duration and the bandwidth of the wavelet are both changed, but its shape remains the same. The CTW uses short windows at high frequencies and long windows at low frequencies, in contrast to the FFT, which uses a single analysis window. This partially overcomes the time-resolution limitation of the FFT. The bandwidth \( B \) is proportional to the frequency \( f \). The CWT can also be assumed as a filter bank analysis composed of band-pass filters with constant relative bandwidth.

If \( W(a, b) \) is the WT of a signal \( s(t) \), then \( s(t) \) can be restored using the formula:

\[
S(t) = \frac{1}{C_\Psi} = \int_{-\infty}^{\infty} \int_{-\infty}^{\infty} W(a, b) \Psi \left( \frac{t - b}{a} \right) \, \frac{dadb}{a^2} \tag{16}
\]
provided the Fourier transform of wavelet $\Psi(t)$, denoted $\Psi(f)$, satisfies the following admissibility condition:
\[ C_\Psi = \int_{-\infty}^{\infty} \frac{|\Psi(f)|^2}{f} \, df < \infty. \]

3. Results and discussion

It is convenient to think of the interpretation of the Doppler waveform shapes as a process of pattern recognition. The object of waveform analysis is to recognize those waveforms that are abnormal even if the details of why a particular physiological or pathological change gives rise to a particular change in waveform shape is not fully understood.

In order to verify the aorta failure during the inspection on echo-cardiographic monitoring, it might be observed the following symptoms: widening in the left ventricle, disordered flow in the aorta entrance and vibration in the mitral valve. In order to get a good diagnosis, spectral resolutions of the sonograms must be clear and of high quality. Spectral curves must also be clear. In addition, the sonograms should not contain misleading frequency components.

In this work, sonograms obtained from 24 patients, six healthy subjects and 18 with aorta failure, were obtained. In Fig. 2, aorta flow sonograms recorded from a normal 32-year-old healthy subject are presented. The sonograms in Fig. 2(a), (b) and (c) are obtained using the FFT analyzer, AR modelling analyzer and the WT analyzer, consecutively. When inspecting of the sonograms, it is seen that there are some differences in the case of flow spectra. Since the blood flow at aorta valve is almost jet flow (i.e. speed of blood is high), the frequency distributions with time on sonograms are seen as broadness. This is true for healthy subject. In the FFT output, there are some misleading frequencies comparing with AR and WT. On the other hand, the envelope of the sonogram of AR method is not seen clearly in comparison with WT. The WT analyzer offers a good quality sonogram output in terms of frequency resolution and signal capturing.

In Fig. 3, aorta flow sonograms suffering from aorta failure recorded from 65-year-old woman with 80% insufficiency in her aorta valve. In the case of aorta insufficiency, the blood is released backward although the aorta valve is closed. Since this blood flow is towards ultrasound probe, transit time of sonograms from systole to diastole is more longer. The sonogram in (a) is obtained using the FFT analyzer, in (b) using AR modelling analyzer and in (c) using the WT analyzer. When inspecting sonograms, it is obviously seen that blood flow velocity decreases. On the other hand, there are not any broadening on the sonogram outputs. We can see that there are some misleading frequency on the FFT analyzer comparing with AR and WT. The WT analyzer offers a good quality sonogram output in terms of frequency resolution and signal capturing compared with AR and FFT.

Aorta and pulmonary valves (semilunar valves) in the beginning of aorta and pulmonary veins prevent the blood from flowing back to the ventricle. They work passively. If a patient has an aorta failure, the backward flow of blood cannot be avoided. This increases the frequency difference between the systole and diastole. On the other hand, fluctuated flow occurs in the aorta at the same time. This fluctuated flow in the 2000–50,000 Hz frequency limit causes sudden changes in very short time interval as shown in Fig. 4. In Fig. 4, spectral decompositions of FFT, AR, and WT are shown. This figure again shows that WT is superior in the case of spectral resolution and capturing of all frequency components. In the case of sudden changes, WT method gives better performance...
for spectral resolution than FFT and AR methods. Because of fluctuated flow and backward flow of blood, the frequency difference between systole and diastole is quite high. When the measurement period is short (i.e. short frame length), FFT and AR methods do not give a good performance in the case of frequency resolution as shown in Figs. 2 and 3. On the other hand, the areas of systole

Fig. 2. Doppler sonogram recorded from a 32-year-old healthy person: (a) FFT; (b) AR; (c) WT.
and diastole are not clear for FFT and AR method in the case of frequency resolution in Figs. 2 and 3. By widening or narrowing the window length in the WT method, the sonograms can be obtained more clear and higher spectral resolution compared with AR and FFT methods at those areas where the flow speed of blood is high, fluctuated or insufficient, as shown in Figs. 2 and 3.
Fig. 4. Spectral decompositions of FFT, AR and WT.

Fig. 5. 3-D Doppler sonogram recorded from a 65-year-old patient: (a) FFT; (b) AR; (c) WT.
On the other hand, if there is a need to observe sudden changes in frequency, three-dimensional sonograms can be obtained. Fig. 5 shows three-dimensional sonograms of Fig. 3. As it is seen in Fig. 5, a three-dimensional WT sonogram can provide a good spectral resolution. It also provides short-frequency responses in a wide angular mode, giving an opportunity for better diagnosis compared with FFT and AR method. As a result, WT method gives better performance for nonstationary signals. It also provides better results to observe the effects of sudden changes using window size.

4. Conclusion

Doppler aorta valve blood flow signals are processed using three different signal processing analyzers. WT method offers best advantages to the FFT and AR method in the case of misleading frequency, signal capturing and clinical evaluation. Since blood flow signal is nonstationary, WT method is suitable for processing this type of signal.

References


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