Spectral Analysis of Heart Valve Sound for Detection of Prosthetic Heart Valve Diseases

Sang Hyun Kim[1], Hee Jong Lee[2], Jae Man Huh[1], and Byung Chul Chang[3]

The spectral analysis of heart valve sound is a noninvasive diagnostic method known to be useful in evaluating the state of the heart valve function. This may provide early detection of valve calcification, thrombus or destruction, since previous studies have shown that the dominant frequency peak moved to a high frequency area when natural heart valve leaflets were calcified, stiffened or destroyed. However, it is important for a heart valve sound diagnostic system to find a proper spectral analysis method on phonocardiography. Until now, conventional frequency analyses such as the Fourier transform or autoregressive spectral estimation technique have been used to estimate spectral components of a phonocardiogram, but they are inappropriate because the signal frequency is assumed to remain constant during the transform interval. To overcome this problem, in this study, FOS (Fast Orthogonal Search) & MUSIC (MUltiple SIgnal Classification), which both appeared suitable for the analysis of biological data, were applied to prosthetic heart valve sound as the new heart valve sound spectral analysis methods. Five subjects with normally functioning mechanical heart valves and a patient with a malfunctioning one were selected to collect the heart valve sound signals. As a result, the second dominant peak frequency proved to be important along with the first dominant peak frequency in identifying the valve function. This study showed that the new heart valve sound spectral analysis method presented in this paper may be an effective method in heart valve sound analysis. Further study using this system in a large population of patients will aid in providing a diagnostic method in the early detection of valve failure.

Key Words: Signal process, spectral analysis, heart valve sound, prosthetic heart valve

A number of patients who receive prosthetic heart valves are still subjected to replacement of the implanted valves or thrombolytic therapy because of

valvular malfunction. It is important, therefore, to clearly detect malfunction as soon as possible. Until now, phonocardiograpy, echocardiograpy, and cinefluoroscopy have been used as noninvasive procedures for evaluating valvular integrity. However, sometimes these methods may be sensitive only to malfunction of an advanced nature and as a result are not totally reliable for early detection.

Spectral analysis of a heart sound offers another means for diagnosis of valvular integrity. It is a noninvasive technique which has been found to be an effective method for monitoring the integrity of native and prosthetic heart valves, as well as for investigating the relationship between the sounds of

the heart and cardiovascular events. Since early detection of valve thrombosis is imperative, sound spectral analysis of prosthetic heart valves has been studied extensively (Joo *et al.* 1983; Durand *et al.* 1986; Durand *et al.* 1990; Sava and McDonnell., 1996). These studies demonstrated that sound spectral analysis is an extremely useful diagnostic tool for early detection of thrombosis in prosthetic heart valves. Finding an appropriate spectral algorithm for the early detection of valve failure is the most important thing in spectral analysis of a heart valve. However, standard frequency analyses such as the Fourier transform or autoregressive spectral estimation technique are inappropriate because the signal frequency is assumed to remain constant during the transform interval.

Recently, the MUSIC (MUltiple SIgnal Classification) method (Korenberg, 1985; Korenberg, 1989) and FOS (Fast Orthogonal Search) method (Kaveh and Barabell, 1986) have been used for spectral analysis, in which both appeared suitable for the analysis of biological data. The earlier studies reported that these methods were effective with short data records and could cope with noisy, missing and unequally-spaced data. But until now, these methods have not been used in estimating spectral components of a phonocardiogram. Therefore, in this study, these methods were applied to prosthetic heart valve sound as the new spectral analysis methods to overcome the limits of conventional methods.

MATERIALS AND METHODS

Five patients with normally functioning heart valves and one patient with a malfunctioning valve were selected to collect heart valve sound signals. The abnormal patient had a thrombus formation on the mechanical heart valve and was subjected to thrombolytic therapy. All patients had mitral valve replacement and Table 1 shows the list of patients.

Recording procedure of heart sound

Fig. 1 schematically describes the recording procedure of the system. Heart sounds were recorded during quiet respiration with the patient in a supine

Table 1. List of patients

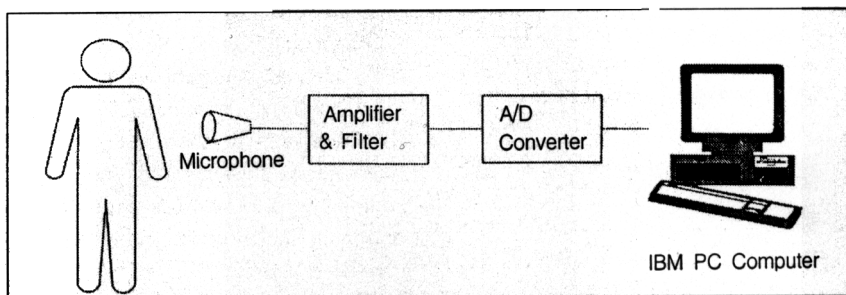| Patient No.	Birth year	Sex	Valve type	Size	Condition
	1950	F	Hancock	29 mm	normal
2	1961	F	St-Jude	29 mm	normal
3	1963	M	St-Jude	27 mm	normal
4	1934	M	St-Jude	29 mm	normal
5	1952	F	Carbomedics	33 mm	normal
6	1929	F	Carbomedics	29 mm	abnormal

Fig. 1. Process of recording the heart valve sounds

position using a microphone transducer (E′ for M, White Plains, New York, USA). The microphone was placed at the second left intercostal space. The sound signals were amplified, filtered via a multi-channel photographic recorder (E for M, White Plains, New York, USA). The signals were filtered out below 50 Hz and above 500 Hz. The frequency response of the sound amplifier and microphone combination was flat (within 1 db), between 80 and 300 hertz. The analog sound signal was then processed through a 12-bit data translation analog-to-digital converter board (Data Translation, Marlboro, Massachusetts, USA) contained in an IBM-PC/386 personal computer. The digital signal was filtered out using a Butterworth filter below 50 Hz and above 950 Hz. Recordings were made over a 10-second interval at a sampling rate of 2 kHz. Each data collection was stored on a computer hard disk. In this study, a closing sound component of the shape which occurred most frequently during recording was selected. The average difference between two components selected at random in terms of the dominant peak frequency was less than 10%.

Algorithms of sound spectral analysis

MUltiple SIgnal Classification (MUSIC) method: In the MUSIC method, the signals are divided into two subspaces, corresponding to the signal subspace and the noise subspace. With the MUSIC method, a correlation matrix of $N \times N$ is formed and its eigenvalues and eigenvectors are found. While the Pisarenko method involves projection of the signal vectors onto a single noise eigenvector, the MUSIC method involves projection of the signal onto the entire noise subspace.

If P_{noise} is defined as the projection of signal subspace onto the noise subspace, E_{noise}, the MUSIC pseudospectrum is defined as

$$\widehat{P_{\text{MUSIC}}}(e^{jw}) = \frac{1}{\overrightarrow{w}^{*T} \overrightarrow{P_{noise}} \overrightarrow{w}}$$

$$= \frac{1}{\overrightarrow{w}^{*T} \overrightarrow{E_{noise}} \overrightarrow{E_{noise}^{*T}} \overrightarrow{w}} \quad (1)$$

where

$$\overrightarrow{w} = \begin{bmatrix} 1 \\ e^{jw} \\ \vdots \\ e^{j(N-1)w} \end{bmatrix}$$

An alternative root-finding variation of the method called "root MUSIC" can be developed as follows. Define the eigenfilter

$$E_i(z) = e_i[0] + e_i[1]z^{-1} + \cdots + e_i[N-1]z^{-(N-1)} \quad (2)$$

where the $e_i[n]$ are components of the eigenvectors $\overrightarrow{e_i}$. The denominator of (1) can then be written as

$$\overrightarrow{E_{noise}} = [\overrightarrow{e_{M+1}} \quad \overrightarrow{e_{M+2}} \quad \cdots \quad \overrightarrow{e_N}] \quad (3)$$

The MUSIC pseudospectrum can therefore be expressed as

$$\widehat{P_{\text{MUSIC}}}(e^{jw}) = \frac{1}{\sum_{i=M+1}^{N} E_i(z) E_i^*(1/z^*)} \Bigg|_{z = e^{jw}} \quad (4)$$

Since the denominator goes to zero at $z = e^{jw_i}$ ($i=1,2,\cdots,M$), the denominator polynomial has M roots lying on the unit circle. Those M roots correspond to the signal frequencies. Note that since each eigenfilter $E_i(z)$ is an $(N-1)^{th}$ degree polynomial, it has a total of N-1 roots. M of these roots correspond to the e^{jw_i} and lie on the unit circle. The other N-M-1 roots not on the unit circle are called "spurious" roots and play no particular role in locating the spectral lines. In theory these roots are not a problem, but in practice some of them may lie close to the unit circle and could be mistakenly attributed to signals. The polynomial $\widehat{P_{\text{MUSIC}}}(z)$ used in root MUSIC also has spurious roots. However, the effect of adding the eigenfilter terms in (2) is to move these spurious roots away from the unit circle. Only roots of the eigenfilters lying on the unit circle become roots of the polynomial $\widehat{P_{\text{MUSIC}}}(z)$.

Fast Orthogonal Search (FOS) method: The FOS method is capable of higher resolution than is obtainable by conventional Fourier series analysis. It is effective with short data records, and can cope with noisy, missing and unequally-spaced data. It enables a parsimonious sinusoidal series representation or model to be systematically developed for the time series.

Consider approximating a nonlinear system by the difference equation model.

$$y(n) = F[y(n-1), \quad \cdots \quad , y(n-k), \ldots, x(n), \\ \cdots \quad , x(n-L)] + e(n) \quad (5)$$

Equation (5) can be expressed more concisely as

$$y(n) = \sum_{m=0}^{M} a_m p_m(n) + e(n) \quad (6)$$

Here the a_m are the difference equation coefficients.

$$p_0(n) = 1 \quad (7)$$

and the remaining $p_m(n)$ are chosen from the x and y terms on the right side of (5) and cross-products thereof(including powers):

$$p_m(n) = y(n-k_1) \cdots y(n-k_i) x(n-l_1) \\ \cdots x(n-l_j)$$

$$\quad (8)$$

$$m \geq 1, \quad i \geq 0, \quad 1 \leq k_1 \leq K, \quad \cdots \quad , 1 \leq k_i \leq K$$
$$j \geq 0, \quad 0 \leq l_1 \leq L, \quad \cdots \quad , 0 \leq l_j \leq L$$

An orthogonal search method was developed for efficiently obtaining the different equation models of nonlinear systems with unknown structure. Using this method, we can build up an economical series representation

$$y(n) = \sum_{m=0}^{M} g_m w_m(n) + e(n) \quad (9)$$

where the $w_m(n)$ are orthogonal over the data record, and the g_m are the orthogonal expansion coefficients (achieving a least-squares fit). However, the creation of the orthogonal functions $w_m(n)$ in (9) is expansive in computing time and memory, and is avoided if model terms are selected by the fast orthogonal search. This method uses a Cholesky decomposition as follows. The orthogonal expansion coefficients in (9) are given by

$$g_m = \frac{C(m)}{D(m, m)} \quad (10)$$

where

$$D(0, 0) = 1 \quad (11)$$

$$D(m, 0) = \overline{p_m(n)}, \quad m = 1, \quad \cdots \quad , M \quad (12)$$

$$D(m, r) = \overline{p_m(n) p_r(n)} \\ - \sum_{i=0}^{r-1} a_{ri} D(m, i), \quad a_{ri} = \frac{D(r, i)}{D(i, i)} \quad (13)$$

$$m = 1, \quad \cdots \quad , M \quad ; \quad r = 1, \quad \cdots \quad , m$$

$$C(0) = \overline{y(n)} \quad (14)$$

$$C(m) = \overline{y(n) p_m(n)} - \sum_{r=0}^{m-1} a_{mr} C(r), \, a_{mr} \\ = \frac{D(m, r)}{D(r, r)} \quad (15)$$

$$m = 1, \quad \cdots \quad , M$$

If the g_m and a_{mr} were known, the coefficients a_m in (6) could be obtained by the following formula.

$$a_m = \sum_{i=m}^{M} g_i v_i \quad (16)$$

Suppose that the model terms $p_m(n)$ had already been selected. Then, the a_{mr} could be calculated from (15). The g_m follow from (10). Finally, the required coefficients a_m in (16) could be obtained from (16). It can be shown that the mean square error of the model fit is equivalently

$$m.s.e = \overline{y^2(n)} - \sum_{m=0}^{M} g_m^2 D(m, m) \quad (17)$$

Suppose that $a_M p_M(n)$ was the last term added to the model of (6). Then the addition of this term reduced the mean-square error by the amount

$$Q(M) = g_m^2 D(M, M) \quad (18)$$

Equation (17) makes it possible to rapidly assess the benefit from adding any given candidate term to the model, without requiring the creation of the orthogonal functions $w_m(n)$. Then the candidate with the largest Q value is selected (optionally, subject to exceeding a specified positive threshold level).

We concentrated on obtaining parsimonious sinusoidal series representations of time-series data. In what follows, (6) represents a sinusoidal series representation which systemically constructed for the time-series data $y(n)$, $n = 0, \ldots, N$. Equation (7) still holds and for $i = 1, 2, \cdots$

$$p_{2i-1}(n) = \cos w_i n, \, p_{2i}(n) = \sin w_i n \quad (19)$$

The w_2 are determined successively by searching

through a set of candidate frequencies $\dot{w}_A, w_B, \cdots$ which need not be commensurate. It can be shown that adding the i-th term pair

$$T_i = a_{2i-1} p_{2i-1}(n) + a_{2i} p_{2i}(n) \qquad (20)$$

In (20), a_{2i-1} and a_{2i} are respectively the cosine and sine amplitude.

Thus, begin by introducing a constant into the sinusoidal series and obtaining the coefficients, $a_1, a_2, a_3, \cdots$, we can calculate the magnitude of the frequency at each frequency range.

RESULTS

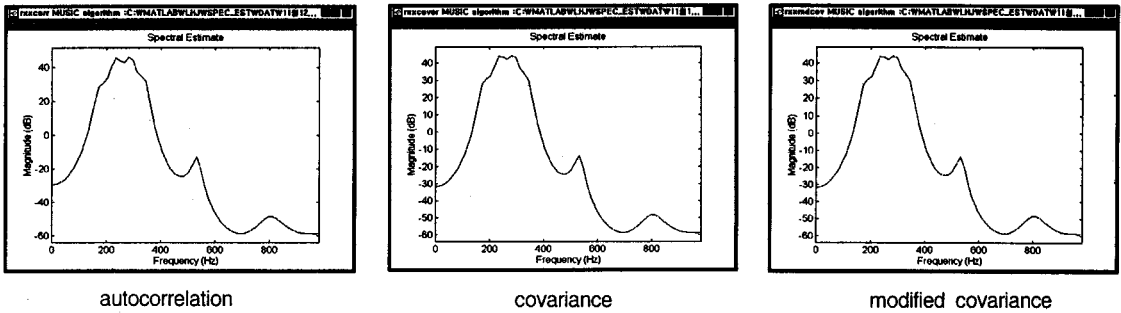To calculate a correlation matrix used in the MUSIC method, we tested three correlation estimate

autocorrelation   covariance   modified covariance

Fig. 2. Spectrum for patient 1 calculated by 3 correlation methods

patient 2 peak-218.8Hz   patient 3 peak-234.4Hz   patient 4 peak-234.4Hz

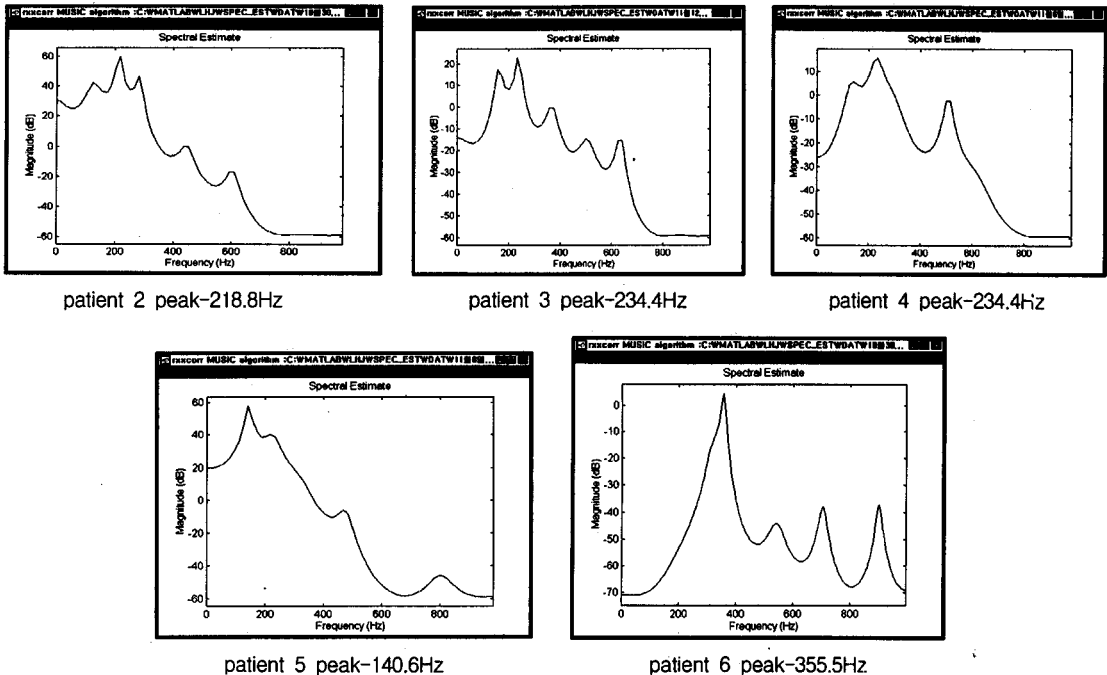patient 5 peak-140.6Hz   patient 6 peak-355.5Hz

Fig. 3. Sound spectrum by MUSIC method

methods of autocorrelation, covariance, and modified covariance for patient 1. Fig. 2 shows the results of the spectrum for patient 1 from these three methods.

As we can see in Fig. 2, it does not have any significant effect on finding the second dominant frequency peak, even though the differences in curve patterns of the spectrum between each method exist. Thus we selected the autocorrelation method to calculate the correlation matrix in this study. Fig. 3 shows the results of the spectrum by the MUSIC method. Fig. 4 shows the results of the spectrum by the FOS method. Each frequency spectrum contains two or more frequency peaks.

Table 2 shows the first dominant frequency peak of all patients calculated by each spectral estimation method. Patients 1 to 5 were normal prosthetic heart implantation patients, and patient 6 had a defective heart valve. Both methods indicated similar first dominant frequency peaks for all the normal patients. The defective valve patient showed a higher peak than the normal patients.

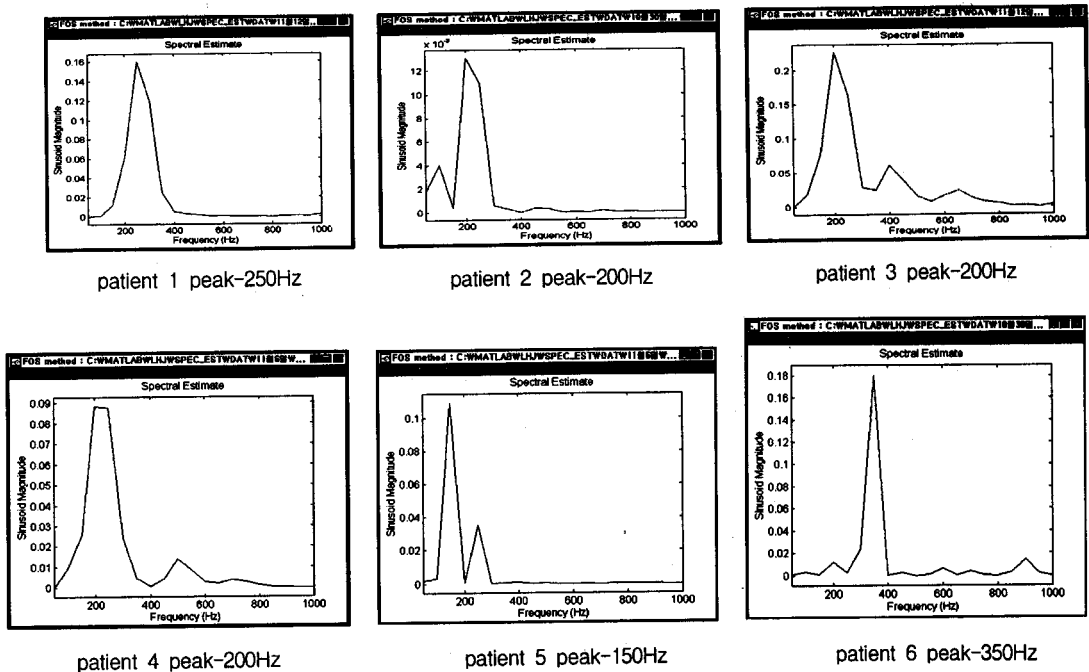Table 3 shows the second dominant frequency peak of all patients calculated by each spectral esti-

patient 1 peak-250Hz   patient 2 peak-200Hz   patient 3 peak-200Hz

patient 4 peak-200Hz   patient 5 peak-150Hz   patient 6 peak-350Hz

Fig. 4. Sound spectrum by FOS method

Table 2. First dominant frequency peak by each method (unit: Hz)

Patient No.	MUSIC	FOS
patient 1	281.2	250
patient 2	218.8	200
patient 3	234.4	200
patient 4	234.4	200
patient 5	140.6	150
patient 6	355.5	350

Table 3. Second dominant frequency peak by each method (unit: Hz)

Patient No.	MUSIC	FOS
patient 1	234.4	×
patient 2	281.2	100
patient 3	156.2	400
patient 4	140.6	250
patient 5	218.8	250
patient 6	902.3	900

mation method. As seen in Table 3, the normal subjects all showed similar second dominant frequency peaks with each other. The abnormal patient showed a higher peak than the normal patients. Both the first and second dominant frequency peaks for normal patients were seen below 300 Hz and for the abnormal patient it was above 300 Hz. Especially for the abnormal patient, the second dominant peak was much higher than for normal patients.

DISCUSSION

This study showed that both methods of spectral analysis of valvular sound could facilitate the diagnosis of prosthetic valve malfunction. For mechanical valves, a localized thrombosis causes progressive restriction of the disc motion, which may immobilize the disc in a semiclosed position. It affects the closing sound of the valve which results in an increase of the vibration frequency of the valve (Durand *et al.* 1986; Durand *et al.* 1990; Sava and McDonnell, 1996). Both estimated frequency spectra suggested that the signal processing algorithms in this study may be useful in determining the degree of valve failure. For the normal subjects, the first dominant frequency peaks occurred below 300 Hz. Apparent increases in the first and second dominant frequency peaks were noted for the abnormal patient. Moreover, the second dominant frequency peak revealed a significant difference in magnitude between normal and abnormal subjects, which proved to be an important parameter for diagnosing valvular malfunction. For patient 5, the first dominant frequency peak occurred near 150 Hz. It is thought that the extremely large valve size of this patient made the difference in the frequency spectra compared to the others. But it still showed a lower peak compared to the abnormal valve. Especially using the FOS method, it only displayed the dominant peaks because in this method, when adding terms, only a value over the threshold level was taken without obtaining the parameters below those values. Thus, the FOS method has an advantage when only one

or two of the dominant frequency peaks are important.

In this study two spectral estimation methods, MUSIC and FOS, were used to estimate the frequency spectrum of the prosthetic valve sound. These positive results would lead to further equivalent or related in vivo studies and to provide a preliminary databank. It is suspected that this method can detect somewhat different kinds of valve failure, like valve leaflet calcification or minor problems besides thrombosis formation. A large patient population will be needed to prove the effectiveness of this system. This system will be more useful when the whole system is operated through a notebook computer, which would make it possible to diagnose patients in the outpatient room.

REFERENCES

Durand LG, Blanchard M, Cloutier G, Sabbah HN, Stein PD: Comparison of pattern recognition methods for computer-assisted classification of spectra of heart sounds in patients with a porcine bioprosthetic valve implanted in the mitral position. *IEEE Trans Biomed Eng 37: 1121-1129, 1990*

Durand LG, Guise JD, Cloutier G, Guardo R, Brais M: Evaluation of FFT-based and modern parametric methods for the spectral analysis of bioprosthetic valve sounds. *IEEE Trans Biomed Eng 31: 572-578, 1986*

Joo, TH, McClellan JH, Foale RA, Myers GS, Lees RS: Pole-zero modeling and classification of phonocardiograms. *IEEE Trans Biomed Eng 30: 110-118, 1983*

Kaveh M, Barabell AJ: The statistical performance of the MUSIC and the minimum-norm algorithm for resolving plane waves in noise. *IEEE Trans Acoust Speech Signal Process ASSP-34: 331-341, 1986*

Korenberg MJ: Orthogonal identification of nonlinear difference equation models. *Proc Midwest Symp Circuit Sys 1: 90-95, 1985*

Korenberg MJ: A robust orthogonal algorithm for system identification and time-series analysis. *Biol Cybern 60: 267-276, 1989*

Sava HP, McDonnell JTE: Spectral composition of heart sounds before and after mechanical heart valve implantation using a modified forward-backward Prony's method. *IEEE Trans Biomed Eng 43: 734-742, 1996*