Physiological measurement

Application of the ARMA method to acoustic detection of coronary artery disease

M. Akay[1] **W. Welkowitz**[1,2] **J. L. Semmlow**[1,2] **J. Kostis**[1,3]

[1]Biomedical Engineering Department, Rutgers University, NJ 08855, USA
[2]Department of Surgery (Bioengineering), UMDNJ-Robert Wood Johnson Medical School, NJ 08854, USA
[3]Department of Medicine, UMDNJ-Robert Wood Johnson Medical School, NJ 08854, USA

Abstract—*To further explore the application of advanced signal processing techniques to the noninvasive detection of coronary artery disease, 30 patients (10 angioplasty and 20 normal or abnormal) were tested using autoregressive moving average (ARMA) modelling of the disastolic heart sound data. It is during diastole that coronary blood flow is maximum and sounds associated with turbulent blood flow through partially occluded coronary arteries would be loudest. Model parameters (the power spectral density (PSD) functions and the poles of the ARMA method) were used to separate the normal patients from the abnormal patients in the normal/abnormal study, or to decide whether the recordings were made before or after angioplasty in the angioplasty study. The decisions were made 'blind', without knowledge of the actual disease states of the patients for the normal/abnormal study and without prior knowledge of whether a given recording was made before or after angioplasty for the angioplasty study. Results from the angioplasty and the normal/abnormal studies showed that pre- and post-angioplasty records were correctly distinguished in 8 out of 10 cases, and normal and abnormal records were correctly distinguished in 17 of 20 cases. These results also confirmed that high frequency energy above 400 Hz is probably associated with coronary stenosis.*

Keywords—*Coronary artery disease, Noninvasive detection, Sound*

Med. & Biol. Eng. & Comput., 1991, **29**, 365–372

1 Introduction

INITIAL STUDIES showed that coronary arterial stenosis may give rise to diastolic murmurs (DOCK and ZONERAICH, 1967; CHENG, 1970; SANGSTER and OAKLEY, 1973). Such diastolic murmurs are rarely heard but can be a sign of coronary stenosis. In 1967 it was first reported that coronary stenosis can cause a diastolic murmur (DOCK and ZONERAICH, 1967). Three years later, two patients were reported with diastolic murmurs associated with a severe, localised narrowing of the left anterior descending (LAD) coronary artery caused by coronary stenosis (CHENG, 1970). Still later, three cases with diastolic murmurs associated with coronary artery disease (CAD) were also reported. For these cases, stenosis at the site of the murmur was proven by catheterisation and the diastolic murmur was modified after surgery (SANGSTER and OAKLEY, 1973; KARTCHNER *et al.*, 1973).

Studies involving turbulent blood flow have been carried out for many components of the cardiovascular system and it has been widely reported that turbulence produced by stenoses produces sounds because of the vibration of the surrounding structures (KURTZ, 1984; GIDDENS *et al.*, 1976; LEES and DEWEY, 1970; DUNCAN *et al.*, 1975). These sounds have been detected and analysed, and results generally showed that the high frequency energy increased when the degree of stenosis was increased. However, for severe obstructions, above 95% occlusion, sounds may not be produced because of the very low blood flow. At the lower end, occlusions as small as 25% narrowing have been detected (KHALIFA and GIDDENS, 1981) and used as a noninvasive measure to assess arterial narrowing in vessels of the neck, thorax and abdomen (LEES and MYERS, 1982; KHALIFA and GIDDENS, 1981). The auditory component caused by coronary stenosis is similar to that found in partially occluded carotid arteries but it is much attenuated by the intervening tissue (SEMMLOW *et al.*, 1983). It is also masked by the comparatively loud valve sounds. These can be eliminated by isolating diastolic portions of the acoustic signal using a time window synchronised with the cardiac cycle (SEMMLOW *et al.*, 1983).

The principal objective of this study is to continue to improve signal processing techniques which can be used to identify the additional signal components found in the heart sounds of patients with coronary artery disease. These added components form the basis of our approach to the noninvasive detection of coronary artery disease. In

First received 9th February and in final form 16th August 1990

earlier studies, the average power spectrum of diastolic heart sounds was estimated using traditional FFT methods (SEMMLOW *et al.*, 1983). Although some success was achieved in distinguishing normal from abnormal patients, this signal processing technique was not pursued for further studies as the method was sensitive to the effects of noise on the desired diastolic signal (SEMMLOW *et al.*, 1983).

The application of parametric modelling methods to signal identification problems results in a better estimation of spectral features, and so, particularly for low signal-to-noise ratios (SNR), model-based methods were employed to analyse the recordings of diastolic heart sounds and to detect features associated with coronary stenosis (AKAY *et al.*, 1988*a*; 1988*b*; 1990*a*; 1990*b*). Among the many model-based methods, the adaptive AR method was chosen to represent the diastolic signal source because it does not require prior knowledge of signal characteristics and it can track changes in signal characteristics. Initial analyses were carried out on 15 patients (10 abnormal, 5 normal) using two fast adaptive AR methods; the recursive least square lattice (RLSL) and the gradient adaptive lattice (GAL) methods (AKAY *et al.*, 1988*a*; 1990*a*). Spectra obtained from individual diastolic cycles showed some variations. To obtain representative frequency information, averages were calculated from an ensemble of 20–30 individual diastolic spectra. Results showed that the percentage of spectral energy above 400 Hz is greater in diseased patients than in normal patients. The poles of the AR model were also calculated and used as a discriminant criterion. In all subjects, the second and usually the third poles were further from the unit circle in normal patients than in diseased patients (AKAY *et al.*, 1988*a*; 1990*a*).

As the diastolic sound components associated with occlusive coronary stenosis contain narrow frequency bands, eigenvector methods were also applied to six angioplasty patients (AKAY *et al.*, 1988*b*; 1990*b*). In this application, diastolic heart sounds were represented as a number of sinusoids along with background noise. Frequency peaks were first identified and then the power level of each peak was calculated. The relative power of the second, or in some patients the third, peak was found to change in a consistent manner when the coronary stenosis was modified by angioplastic surgery (AKAY *et al.*, 1988*b*; 1990*b*).

Both of the applications of advanced signal processing techniques mentioned above demonstrated good performance in identifying diastolic heart sounds associated with coronary occlusion. The results also showed that the diastolic heart sounds can be assumed to be a stationary process and to contain narrow band signal components (AKAY *et al.*, 1989).

In the present paper, we apply the modified Yule-Walker (MYW) ARMA method to the diastolic heart sounds taken from patients before and after angioplasty, as well as from a ground of normal and diseased patients, to confirm our basic assumption that CAD has associated auditory components. The analysis was carried out on 10 angioplasty and 20 normal/abnormal patients using a 'blind' protocol (the people analysing the data were 'blind' in that they had no knowledge of the actual disease states of the patients for the normal/abnormal study and had no prior knowledge of whether a given recording was made before or after angioplasty for the angioplasty study). The MYW ARMA method was chosen because it is less sensitive to noise when compared to the usual AR methods and shows better performance (KAY and MARPLE, 1981; KAVEH and BRUZZONE, 1981) when the poles of the ARMA model are very close to the unit circle.

2 Method

Some discrete-time random processes can be modelled using the ARMA method when the signal is corrupted by heavy observation noise. The output sequence $y(n)$ can be modelled by assuming an input driving sequence $v(n)$ as follows (KAY and MARPLE, 1981):

$$y(n) = -\sum_{p=1}^{m} a_p y(n-p) + \sum_{p=0}^{q} b_p v(n-p) \quad (1)$$

where a_p represents the AR coefficients of the AR process at the pth stage, b_p represents the MA coefficients of the MA process at the pth stage, m represents the AR model order and q represents the MA model order.

The key point here is to separate the driving force $v(n)$ from any observation noise. The transfer function of the ARMA process $H(z)$ can be given in terms of the transfer functions of the AR and MA processes as follows:

$$H(z) = \frac{B(z)}{A(z)} \quad (2)$$

where $B(z)$ represents the transfer function of the MA portion of $H(z)$ and $A(z)$ represents the transfer function of the AR portion of $H(z)$.

The coefficients of the AR and MA models can be calculated accurately and efficiently using the MYW method (KAVEH, 1979; BRUZZONE and KAVEH, 1984; FRIEDLANDER and PORAT, 1984; IZRAELEVITZ and LIM, 1983). Although the ARMA process can be modelled by maximum likelihood techniques that minimise a nonlinear function, it has been shown that this is not the best method in practical applications (KAY and MARPLE 1981). As an alternative to the maximum likelihood realisation of the ARMA technique, we chose the easily implementable MYW ARMA method (FRIEDLANDER and PORAT, 1984). The over-determined YW ARMA method also gives better performance than the maximum likelihood realisation of the ARMA process when the poles of $A(z)$ are sufficiently close to the unit circle (BRUZZONE and KAVEH, 1984; FRIEDLANDER and PORAT, 1984). The first step in the procedure is to calculate the estimated autocorrelation functions. The MYW method calculates the AR coefficients using a set of linear equations of the autocorrelation function (ACF) recursively. After calculating the AR coefficients, the signal is filtered using $A(z)$ as a prediction filter. This filtered signal is then used to calculate the MA coefficients using the Durbin method (KAY and MARPLE, 1981).

The AR coefficients R_{yy} can be calculated using the following equation:

$$R_{yy}(k) = \sum_{p=1}^{m} a(p) R_{yy}(k-p) \quad (3)$$

where $p = 1, \ldots, m$, $k = q+1, q+2, \ldots, q+m$, where k represents the highest order of the ACF and q represents the highest order of the MA process.

To get the most accurate results, it has been proven that the higher order samples of the ACF (autocorrelation function) should be used. Another key point to note is the requirement that the AR filter $A(z)$ has all of its zeros within the unit circle to guarantee the stability of $H(z)$.

The power spectral density (PSD) term S_{ARMA} obtained from the ARMA method can be calculated as follows:

$$S_{ARMA}(w) = \sigma_e^2 \left[\frac{B(w)}{A(w)}\right] \quad (4)$$

where σ_e^2 represents the noise variance from the ARMA method. The method described is called the 'pole-zero' method. For the initial estimation, $a(0) = b(0) = 1$ is chosen.

Instead of $L = m + q$ ACF (L is the highest order of the samples of the ACF), $L \geqslant m + q$ can be used to obtain an accurate estimate of the AR coefficients. By using this inequality, more equations will be available than unknowns. The extraction of AR parameters can be carried out in general by solving the equation

$$\begin{vmatrix} R_{yy}(q) & R_{yy}(q-1) & \cdots & R_{yy}(q-m+1) \\ \vdots & \cdots & \cdots & \vdots \\ R_{yy}(L-1) & & & R_{yy}(L-p) \end{vmatrix} \times \begin{vmatrix} a(0) \\ \vdots \\ a(m) \end{vmatrix} = \begin{vmatrix} R_{yy}(q+1) \\ \vdots \\ R_{yy}(L) \end{vmatrix} \quad (5)$$

This equation can be solved by using either the Levinson recursion technique, or the least squares algorithm (KAY and MARPLE, 1981).

3 Model order selection

The Akaike criterion can be used to determine the order of the ARMA coefficients (KAY and MARPLE, 1981). The model order which minimises eqn. 6 below is the correct order for the ARMA model (KAY and MARPLE, 1981; KAVEH and BRUZZONE, 1981):

$$AIC(i, j) = N \ln \sigma_{ij}^2 + 2(i + j) \quad (6)$$

where i represents the order of the AR model, j represents the order of the MA model, N represents the number of the samples in the input signal and σ_{ij}^2 represents the noise of ARMA (i, j) at the ith and jth stage.

Another approach is filtering $y(n)$ with the estimated inverse filter $1/H(z)$ to generate an estimate of the white noise sequence $v(n)$. If the correct order is chosen, the estimated ACF will be zero after the first lag since the output power is white noise (BOX and PIERCE, 1970).

4 Results and discussion

Patients were selected from those undergoing catheterisation and/or angioplasty at the Cardiodynamics Laboratory of Robert Wood Johnson University Hospital. Diastolic heart sounds were recorded from the 4th intercostal space on the chest of patients using a specially designed high sensitivity accelerometer (PADMANABHAN *et al.*, 1989). These sounds were recorded while the patients held their breath and were supine. Diastolic heart sounds taken from patients with mild aortic regurtation, mild mitral stenosis or other audible murmurs present in diastole were not used in the analysis. The normal population was comparable to the abnormal population in terms of age (almost all of them were above 50 years old) and the majority were males.

The objective of the angioplasty study was to evaluate acoustical detection of coronary artery disease. The angioplasty study was carried out in a blind fashion without knowledge of whether a given recording was made before or after angioplastic surgery. For each patient 10 cardiac cycles were digitised (sampling frequency = 4kHz) and an average spectrum was constructed. The spectra were obtained using the ARMA method described above.

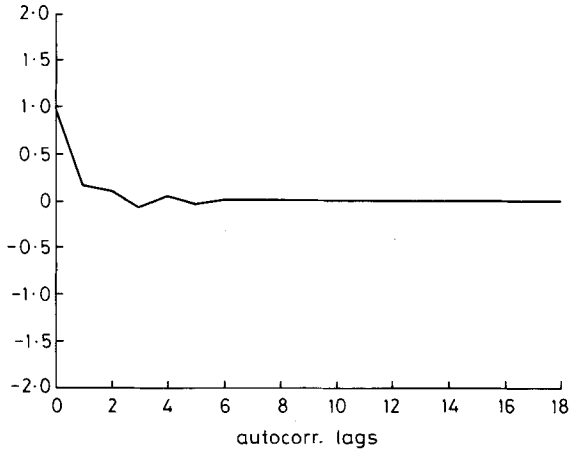


Fig. 1 *Autocorrelation lags*

Before the analysis, the DC component from each record was eliminated (period-by-period). As detailed elsewhere (SEMMLOW *et al.*, 1983), the diastolic heart sounds passed through an anti-aliasing filter set for a cut-off frequency of 1200 Hz and a highpass filter set for a cut-off frequency of 200 Hz. We selected filter orders $m = 7$ (the AR order), $q = 5$ (the MA order) and $L = 15$ (the ACF order) to be adequate to produce an estimate of the white noise process after filtering $y(n)$ with the estimated inverse transfer function of the ARMA method (BOX and PIERCE, 1970) (see Fig. 1).

Table 1 Angioplasty patients database

Patient	Pre-condition (per cent)	Number of les.	Post-condition (per cent)	Number of les.
1	LAD 90, RCA 30, 30 RCA 40	4	LAD 20, RCA 30, 30 RCA 40	4
2	CFX 99, 90, 90 LAD 55	4	CFX 20, 40, 40 LAD 55	4
3	LAD 95	1	LAD 50	1
4	CFX 90	1	CFX 20	1
5	RCA 90, 55, 35 CFX 35	4	RCA 20, 70, 20 CFX 35	4
6	CFX 95, 40 RCA 100, 95	4	CFX 40, 40 RCA 100, 95	4
7	LAD 99, 70 RCA 95, 25, 60	5	LAD 20, 20 RCA 95, 25, 60	5
8	normal	—	normal	—
9	LAD 20, 40, RCA 50 CFX 25, 25, RCA 75	6	LAD 20, 40, RCA 50 CFX 25, 25, RCA 35	6
10	RCA 90, 90, 35 LAD 40, CFX 20	5	RCA 10, 35 LAD 40, CFX 25	4
11	CFX 99, 75 LAD 20, 20	4	CFX 30, 75 LAD 20, 20	4

LAD is the left anterior descending artery
RCA is the right coronary artery
CFX is the circumflex artery

From a combination of the parameters obtained from the ARMA method, a subjective judgment was made of which record in a pair was recorded before, and which was recorded after, angioplasty. The parameters used included the amplitude of the second (high frequency) spectrum peak ($p2$) and the movement of the dominant poles (the pair with the highest amplitude, usually the second pole pair). The estimate of which record was made before angioplasty was correct in 8 of the 10 angioplasty patients. In the angioplasty study a normal patient was also included in the database to add complexity to the blind study. This patient was correctly assessed as normal. As analysis was of only a pair of readings no statistical analysis was carried out after unblinding.

Table 2 Normal/abnormal patients database

Patient	Condition (per cent)	Number of occlusion
1	LAD 40, RCA 35, 90, 90, CFX 13	5
2	CFX 30, 80	2
3	CFX 90	1
4	CFX 70	1
5	LAD 90	1
6	LAD 100, CFX 40, 40	3
7	LAD 35, 25, RCA 90, 55, 35 CFX 35, 35	7
8	LAD 45, 80	2
9	normal	—
10	LAD 20, 40, RCA 60, 75, CFX 25 CFX 25	5
11	LAD 99, 70, RCA 60, 95, 25	5
12	normal	—
13	normal	—
14	normal	—
15	normal	—
16	normal	—
17	normal	—
18	normal	—
19	normal	—
20	normal	—

The same procedure and decision parameters of the ARMA method were used to analyse diastolic heart sounds obtained from normal and abnormal patients in the normal/abnormal study. Results showed that 85 per cent of all records were correctly classified. In this study, patients with occlusions of less than 30 per cent were considered to be normal. All of these patients were cath-proven as normal or diseased.

Table 1 shows a description of the stenoses for patients used in the angioplasty study and Table 2 provides the same information for patients in the normal/abnormal study. Figs. 2 and 3 show the PSD function and poles obtained from the ARMA model applied to a typical period of the isolated heart sounds of angioplasty patient 6.

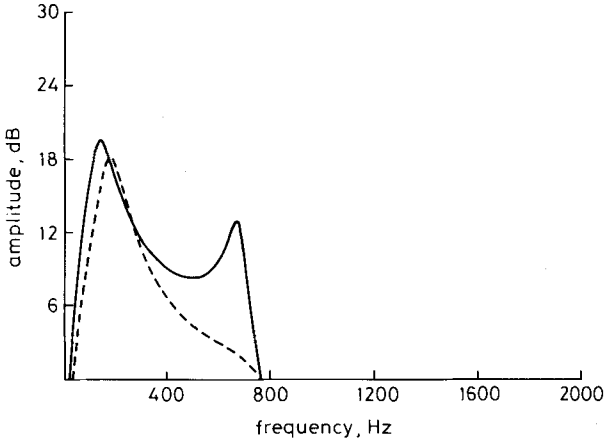


Fig. 2 *ARMA spectrum for angioplasty patient 6*
——— *pre-angioplasty*
– – – – *postangioplasty*

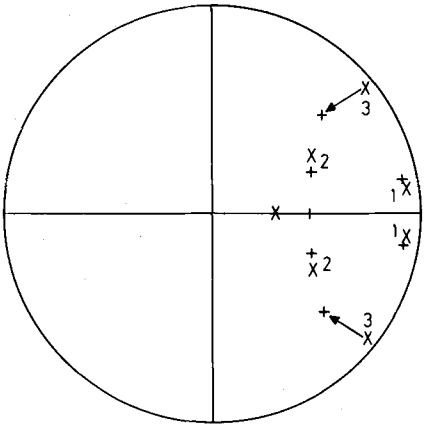


Fig. 3 *Poles obtained from ARMA model applied to a typical period of the isolated heart sounds of angioplasty patient 6*
× *pre-angioplasty*
\+ *postangioplasty*

After unblinding, PSD and poles of the ARMA method were calculated. Table 3 shows specific spectral features including the absolute power between 400 and 800 Hz (AP), the absolute value of the second peak ($p2$), and the poles of the ARMA method ($z1$, $z2$, $z3$) before and after angioplastic surgery. From all these figures the most apparent spectral feature associated with coronary artery disease patients was high energy between 400 and 800 Hz when compared to normal patients as has been found in previous studies (AKAY *et al.*, 1988*a*; 1988*b*; 1989; 1990*a*; 1990*b*; SEMMLOW *et al.*, 1990; AKAY, 1990). Only poles of the ARMA method were used as the decision parameters because the diastolic heart sounds contain narrow band signal components (AKAY *et al.*, 1988*a*; 1988*b*; 1989; 1990*a*; 1990*b*; SEMMLOW *et al.*, 1990; AKAY, 1990). The poles were expressed in terms of magnitude and phase (in radians) for both studies. It can be seen from Table 3 that the absolute power above 400 Hz and the power level of the second peak decreased drastically after corrective surgery, except in patients 9 and 11. For these patients the high frequency energy after surgery was greater than before surgery. However, inspection of Table 1 shows that for patient 9, while one 75 per cent occlusion of the right coronary artery (RCA) was reduced to 35 per cent, there was no change in the other left anterior descending artery (LAD), circumflex (CFX) and RCA stenoses. In patient 11, surgery decreased the CFX occlusion from 99 per cent to 30 per cent, but did not change the 75 per cent CFX occlusion or either of the LAD occlusions. Thus these patients were still abnormal. In this study, the normal patient 8 was used as an additional 'control' and showed less power above 400 Hz and lower power levels in the second peak than any of the pre-angioplasty patients.

In addition to evaluating the PSD function, obtained using the ARMA method, the poles of the ARMA model, averaged over 10 cardiac cycles, were evaluated for their diagnostic capability. The AR filter order is seven, therefore three complex conjugate pole pairs and one real axis pole were obtained. Table 3 shows the averaged poles for the corresponding 10 angioplasty patients. It can be seen in Table 3 that the relatively low frequency (150–300 Hz) peak in the PSD function gives rise to a complex conjugate pair falling close to the unit circle. These are not useful for diagnosis because they do not shift with surgery (they are nearly the same before and after angioplastic surgery). However, surgery produced a consistent shift away from the unit circle in the second and third pole pairs, again with the exception of patients 9 and 11. For the normal patient 8, the second and third complex pair were far from

Table 3 Angioplasty patients database parameters

Patient	Condition	$p2$	ap	$z1$	$z2$	$z3$
1	pre	26·5	833·0	0·89/∓0·05	0·50/∓0·18	0·99/∓0·33
	post	11·3	511·0	0·95/∓0·08	0·92/∓0·30	0·62/∓0·36
2	pre	57·8	868·4	0·97/∓0·07	0·90/∓0·17	0·88/∓0·36
	post	13·6	546·9	0·98/∓0·08	0·87/∓0·21	0·66/∓0·48
3	pre	78·1	2094·0	0·97/∓0·07	0·86/∓0·20	0·84/∓0·42
	post	6·3	491·5	0·95/∓0·09	0·82/∓0·30	0·62/∓0·35
4	pre	309·8	3765·5	0·96/∓0·06	0·63/∓0·21	0·97/∓0·32
	post	193·7	2751·4	0·92/∓0·07	0·60/∓0·25	0·95/±0·32
5	pre	133·7	1904·6	0·95/∓0·05	0·39/∓0·16	0·97/∓0·32
	post	5·6	391·6	0·98/∓0·06	0·86/∓0·17	0·86/∓0·33
6	pre	215·7	2312·7	0·94/∓0·06	0·45/∓0·32	0·97/∓0·33
	post	156·2	2111·6	0·93/∓0·11	0·64/∓0·29	0·90/∓0·32
7	pre	45·2	765·3	0·93/∓0·08	0·93/∓0·31	0·99/∓0·33
	post	24·6	612·1	0·92/∓0·08	0·56/∓0·29	0·94/∓0·35
8	1.rec.	7·3	629·2	0·93/∓0·10	0·36/∓0·34	0·80/∓0·36
	2.rec.	7·1	654·2	0·95/∓0·09	0·37/∓0·29	0·81/∓0·38
9	pre	110·5	2673·8	0·94/∓0·06	0·80/∓0·29	0·95/∓0·32
	post	611·9	6799·6	0·74/∓0·07	0·97/∓0·31	0·96/∓0·35
10	pre	630·4	11569·8	0·95/∓0·05	0·67/∓0·20	0·96/∓0·32
	post	525·3	8826·9	0·80/∓0·10	0·97/∓0·33	0·57/∓0·43
11	pre	213·2	3244·6	0·86/∓0·16	0·53/∓0·22	0·97/∓0·32
	post	432·0	10256·4	0·90/∓0·12	0·98/∓0·32	0·78/∓0·39

$p2$ is the amplitude of the second peak (pressure in dB)
ap is the absolute area between 400 and 800 Hz (units of pressure-Hz)
$z1$ is the first complex pair of poles from ARMA model
$z2$ is the second complex pair of poles from ARMA model
$z3$ is the third complex pair of poles from ARMA model

the unit circle for both the first and the second recording.

In the second part of this study, isolated diastolic heart sounds obtained from 20 (10 abnormal and 10 normal) patients were analysed using the ARMA methods. Table 4 shows the absolute power between 400 and 800 Hz (AP), the absolute value of the second peak ($p2$) and the complex conjugate pole pairs obtained with the ARMA method ($z1$, $z2$, $z3$) for the normal/abnormal patients.

Figs. 4 and 5 show the PSD function and poles obtained with the ARMA model applied to a typical period of the isolated heart sounds of diseased patient 2. Figs. 6 and 7 show the PSD function and the poles obtained with the ARMA method applied to a typical period of the isolated heart sounds of normal patient 17. The most apparent spectral feature associated with the coronary artery diseased patients is the very high energy between 400 and 800 Hz (Fig. 4) compared to normal patients (Fig. 6). An alternative decision criterion used an estimation of the poles (Figs. 5 and 7) obtained with the ARMA method for the normal/abnormal patient groups. In all patients a large, relatively low frequency peak was found, which gave rise to a complex conjugate pole pair falling close to the unit circle (Figs. 5 and 7). Again this pole pair and frequency peak were not relevant decision criteria because they were nearly the same in all patients. However, the second and the third complex conjugate pole pairs fell

Table 4 Normal/abnormal patients parameters

Patient	$p2$	ap	apr	$z1$	$z2$	$z3$
1	630·4	11569·2	0·1	0·95/∓0·05	0·67/∓0·20	0·96/∓0·32
2	326·5	2123·0	2·5	0·89/∓0·09	0·50/∓0·18	0·99/∓0·33
3	274·9	4818·0	2·1	0·97/∓0·07	0·58/∓0·29	0·96/∓0·32
4	151·0	6294·2	1·5	0·93/∓0·11	0·92/∓0·35	0·71/∓0·38
5	111·7	2329·9	1·6	0·95/∓0·07	0·96/∓0·32	0·71/∓0·33
6	111·2	1856·0	4·0	0·92/∓0·06	0·25/∓0·28	0·91/∓0·32
7	110·6	2673·8	0·7	0·94/∓0·06	0·80/∓0·29	0·96/∓0·32
8	99·0	1221·0	0·9	0·92/∓0·09	0·97/∓0·31	0·99/∓0·34
9*	96·3	754·8	1·2	0·93/∓0·09	0·56/∓0·24	0·95/∓0·29
10	96·2	1162·0	2·1	0·81/∓0·10	0·51/∓0·22	0·98/∓0·32
11	25·9	607·3	4·0	0·93/∓0·06	0·35/∓0·28	0·95/∓0·33
12*	12·0	766·6	16·2	0·95/∓0·09	0·67/∓0·29	0·85/∓0·43
13*	6·1	798·6	13·8	0·94/∓0·09	0·58/∓0·38	0·80/∓0·46
14*	4·0	520·2	0·8	0·85/∓0·10	0·77/∓0·37	0·92/∓0·46
15*	3·2	491·0	45·0	0·94/∓0·09	0·87/∓0·43	0·77/∓0·48
16*	2·8	361·7	17·0	0·96/∓0·09	0·37/∓0·20	0·71/∓0·27
17*	2·8	247·3	10·2	0·95/∓0·09	0·48/∓0·33	0·81/∓0·41
18*	2·5	331·2	5·9	0·95/∓0·08	0·55/∓0·20	0·75/∓0·47
19*	2·4	312·7	11·8	0·90/∓0·08	0·25/∓0·38	0·80/∓0·49
20*	1·8	705·8	0·2	0·78/∓0·11	0·79/∓0·43	0·70/∓0·47

$p2$ is the amplitude of the second peak (pressure in dB)
ap is the absolute area between 400 and 800 Hz (units of pressure-Hz)
apr is the ratio of ap below 400 Hz over ap above 400 Hz
$z1$ is the first complex pair of poles from the ARMA method
$z2$ is the second complex pair of poles from the ARMA method
$z3$ is the third complex pair of poles from the ARMA method
* normal patients

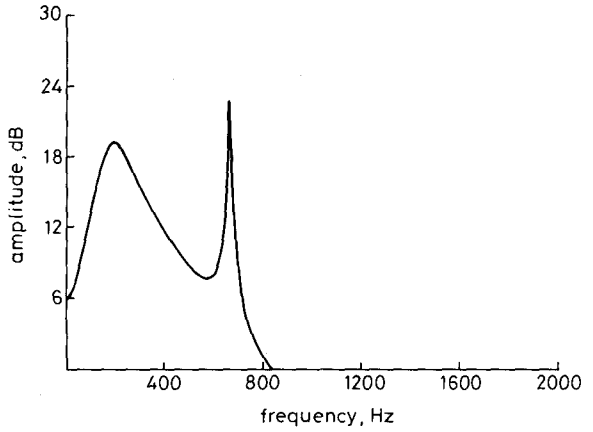


Fig. 4 *ARMA spectrum for diseased patient 2*

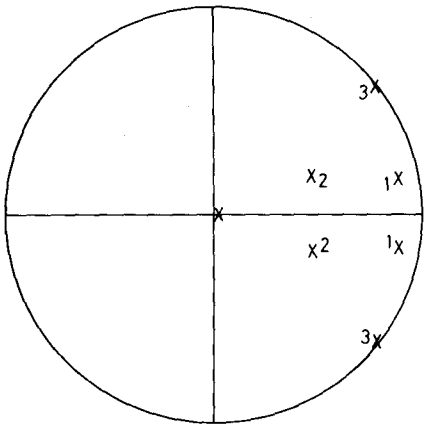


Fig. 5 *Poles obtained from ARMA model applied to a typical period of the isolated heart sounds of diseased patient 2*

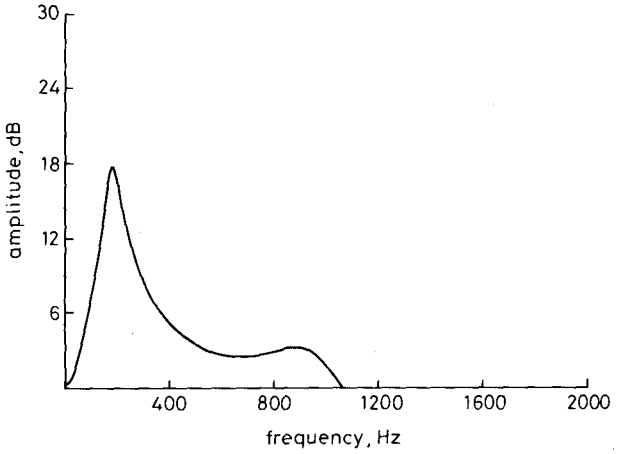


Fig. 6 *ARMA spectrum for normal patient 17*

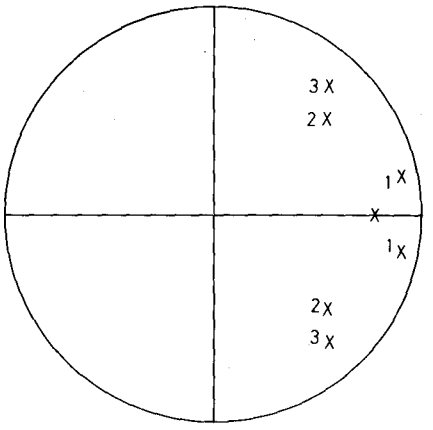


Fig. 7 *Poles obtained from ARMA model applied to a typical period of the isolated heart sounds of normal patient 17*

closer to the unit circle for patients with coronary artery disease. Table 4 shows the averaged poles for the normal/abnormal patients. For the normal patients, both the amplitudes of the second and third poles were considerably smaller than their counterparts in the diseased patients.

Before differentiating between abnormal and normal patients, a T-test (to test means) and an F-test (to test variances) (KENDALL and STUART, 1977) were employed to determine if the decision parameters have the same mean and variance and if the differences in the means and variances were statistically significant. Table 5 shows the T-test and F-test results obtained from the decision parameters $p2$, ap, and z (the amplitude of either the second or third pole pairs, whichever is dominant). Although all three parameters showed significance values less than 0·001, the parameter z was the most significant.

Table 5 T,F,K-S test results of normal/abnormal decision parameters

Parameters	T value	Q	F value	P	D	S
p2	3·33	0·0076	283·24	1·00	0·90	0·0006
ap	2·89	0·0090	243·85	1·00	1·00	0·00009
apr	−2·45	0·0236	102·62	0·70	1·00	0·0148
z	5·36	0·0005	7·36	0·99	0·80	0·00332

z is the dominant pole pair among the second and third pole pair
T value shows Student's T-test
Q shows the significance of T-test
F value shows F-test statistic
P shows the significance of F-test
D shows the K-S distance between two group cumulative distributions
S shows the significance of K-S test

The significance of the F-test also showed that abnormal and normal decision parameters have significantly different variances. In addition to the T-test and F-test, the Kolmogorov-Smirnov (K-S) test (KENDALL and STUART, 1977) was applied to the three decision parameters. Table 5 shows the K-S distance D between the cumulative distribution functions of normal/abnormal patient decision parameters and the related significance level S (which should be very small). All parameters were found to be significant in differentiating abnormal patients from normal patients.

Finally, the moments of the decision parameters belonging to the normal and abnormal patient groups were calculated. Table 6 shows the first moment (mean), the standard deviation, the second moment (variance), the third moment (skewness) and the fourth moment (kurtosis). It can be seen from Table 6 that the decision parameters were not normally distributed because the third moments (which show the degree of asymmetry of distribution of $p2$, ap and z) are not equal to zero. Table 6 shows that all the moments of the decision parameters for normal and abnormal patients were considerably different.

The diagnostic capability of the decision parameters was estimated by constructing curves of sensitivity against specificity for these parameters. Fig. 8 shows curves constructed for parameters $p2$ (only the $p2$ is given because the other curves are almost identical). Each point on the curve represents the combination of true positives against false negatives estimated for a given threshold value of the parameter. It can be seen from Fig. 8 that this curve provides a good basis for determining the usefulness of a decision parameter. For example, in Fig. 8, selecting a threshold of 96·3 leads to a sensitivity of 90 per cent and a specificity of 80 per cent. By using this threshold value, 8 of 10 abnormal and 9 of 10 normal subjects were correctly diagnosed.

Table 6 Moments of normal/abnormal patient parameters

Parameters	Condition	Mean	Standard deviation	Variance	Skewness	Kurtosis
p2	CAD	194·38	177·26	31422·39	1·39	0·86
	Normal	13·39	29·26	857·68	2·23	3·43
ap	CAD	3199·28	3510·51	1230000	1·27	0·41
	Normal	528·90	212·50	45153·79	−0·05	−1·87
apr	CAD	1·95	1·29	1·68	0·35	−1·20
	Normal	12·21	13·14	172·92	1·34	1·04
z	CAD	0·95	0·01	0·01	−0·05	−1·05
	Normal	0·83	0·07	0·05	0·22	−1·17

Skewness which characterises the symmetry is the third moment. Kurtosis which measures the relative peakedness or flatness of a distribution is the fourth moment

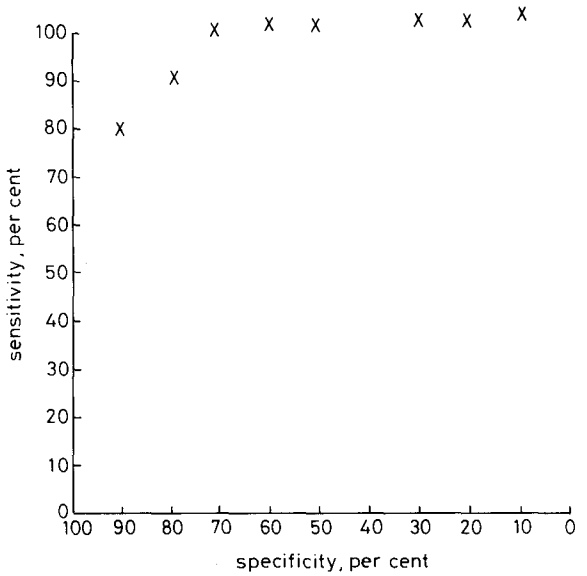


Fig. 8 *Curve of sensitivity against specificity for parameter p2*

All the assessments based on the PSD function parameters and poles of the ARMA method correctly identified 17 of 20 patients.

5 Conclusion

In this study, ARMA modelling of diastolic heart sound segments was studied using the MYW ARMA method. Spectra and poles obtained from individual diastolic cycles showed some variation. To obtain representative frequency information, averages were calculated over 10 diastolic periods. The results obtained when comparing groups showed that the spectral energy distribution differed markedly between pre- and post-angioplasty patients and between normal and diseased patients and that the energy over 400 Hz is greater for pre-angioplasty and diseased patients. In all subjects it was found that the second, and usually the third, poles of the ARMA method obtained from normal patients were further from the unit circle than those of diseased patients. A similar finding applied to pre- against post-angioplasty patients. The curve of sensitivity against specificity using the ARMA PSD second peak as a decision criterion shows that this method can be used to noninvasively detect coronary artery disease.

Acknowledgment—The authors wish to thank M. Bauer, A. Smith and V. Padmanabhan for collecting the data used in this study. This work was supported by a grant from Colin Medical Instrument Corporation, Nagoya, Japan.

References

AKAY, M., BAUER, M., SEMMLOW, J. L., WELKOWITZ, W. and KOSTIS, J. (1988*a*) AR modeling of diastolic heart sound. *Proc. IEEE Frontiers in Medicine*, New Orleans, 72–175.

AKAY, M., BAUER, M., SEMMLOW, J. L., WELKOWITZ, W. and KOSTIS, J. (1988*b*) Analysis of diastolic heart sounds before and after angioplasty. *Proc. IEEE Frontiers in Medicine*, New Orleans, 257–260.

AKAY, M., SEMMLOW, J. L., WELKOWITZ, W. and KOSTIS, J. (1989) Parametric analysis of diastolic heart sounds before and after angioplasty. *Proc. IEEE Frontiers in Medicine*, Seattle, 51–53.

AKAY, M., SEMMLOW, J. L., WELKOWITZ, W., BAUER, M. and KOSTIS, J. (1990*a*) Detection of coronary occlusions using AR modelling of diastolic heart sounds. *IEEE Trans. Biomed. Eng.*, **BME-37,** 366–373.

AKAY, M., SEMMLOW, J. L., WELKOWITZ, W., BAUER, M. and KOSTIS, J. (1990*b*) Noninvasive detection of coronary occlusions using eigenvector methods before and after angioplasty. *IEEE Trans. on Biomed. Eng.*, **BME-37,** 1095–1104.

AKAY, M. (1990) Noninvasive detection of coronary artery disease using advanced signal processing methods. Ph.D. Dissertation, Rutgers University, Piscataway, New Jersey.

BOX G. and PIERCE, D. (1970) Distribution of residual autocorrelations in autoregressive-integrated moving average time series models. *J. Am. Statist. Assoc.*, **64,** 122–145.

BRUZZONE, S. P. and KAVEH, M. (1984) Information tradeoffs in using the sample autocorrelation function in ARMA parameter estimation. *IEEE Trans. Acoustics, Speech, Signal Processing*, **ASSP-32,** 701–715.

CHENG, T. O. (1970) Diagnostic murmur caused by coronary artery stenosis. *Ann. Intern. Med.*, **72,** 543–546.

DOCK, W. and ZONERAICH, S. (1967) A diastolic murmur arising in a stenosed coronary artery. *Am. J. of Med.*, **42,** 617.

DUNCAN, G. W., GRUBER, T. O., DEWEY, C. F., MYERS, G. S. and LEES, R. S. (1975) Evaluation of cartoid stenosis by phonoangiography. *New England J. of Med.*, **27,** 1124–1128.

FRIEDLANDER, B. and PORAT, (1984) Modified Yule-Walker of ARMA spectral estimator. *IEEE Trans. Aerospace, Electron, Syst.*, **AES-20,** 158–172.

GIDDENS, D. P., MABON, R. F. and CASSANOVA, R. A. (1976) Measurements of disordered flows distal to subtotal vascular stenoses in the thoracic aortas of dogs. *Circulation Research*, **39**(1), 112–119.

IZRAELEVITZ, D. and LIM J. S. (1983) Spectral characteristics of the overdetermined normal equation method for spectral estimation. Proc. 2nd ASSP Spectral Estimator Workshop, 49–54.

KARTCHNER, M. M., MCRAE, L. P., MORRISON, F. D. (1973) Noninvasive detection and evaluation of carotid occlusive disease. *Arch. Surg.*, **106,** 528–535.

KAVEH, M. (1979) High resolution estimator for noisy signals. *IEEE Trans. Acoustic, Speech, Signal Processing*, **ASSP-27,** 286–297.

KAVEH, M. and BRUZZONE, S. P. (1981) A comparative overview of ARMA spectral estimators. Proc. 1st. ASSP Spectral Estimation Workshop, 2.4.1–2.4.8.

KAY, S. M. and MARPLE, S. L. (1981) Spectral analysis: a modern perspective. *Proc. IEEE*, **69,** 1380–1419.

KENDALL, M. and STUART, A. (1977) *The advanced theory of statistics.* 4th edition, Griffin and Co., London.

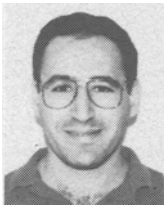
KHALIFA, A. M. A. and GIDDENS, D. P. (1981) Characterization of poststenotic flow disturbances. *J. Biomechanics*, **14,** 275–296.

KURTZ, K. J. (1984) Dynamic vascular auscultation. *Am. J. Med.*, **76,** 1066–1074.

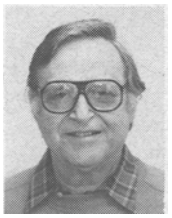
LEES, R. S. and DEWEY, Jr. C. F. (1970) Phonoangiography: A new noninvasive diagnostic method for studying arterial disease. *Proc. Natl. Acad. Sci.*, **67,** 935–942.

LEES, R. S. and MYERS, G. S. (1982) Noninvasive diagnosis of arterial disease. *Adv. Intern.*, **23,** 475–509.
PADMANABHAN, V., FISHER, R., SEMMLOW, J. L., WELKOWITZ, W. and KOSTIS, J. (1989) High sensitivity PCG transducer for extended frequency applications. *Proc. IEEE Frontiers in Medicine*, Seattle, 57–59.
SANGSTER, J. F. and OAKLEY, C. M. (1973) Diastolic murmur of coronary artery stenosis. *Br. Heart J.*, **35,** 840–844.
SEMMLOW, J. L., WELKOWITZ, W., KOSTIS, J., MACKENZIE, J. W. (1983) Coronary artery disease-correlates between diastolic auditory characteristic and coronary artery stenoses. *IEEE Trans. Biomed. Eng.*, **BME-30,** 136–139.
SEMMLOW, J. L., AKAY, M. and WELKOWITZ, W. (1990) Noninvasive detection of CAD using parametric analysis methods. *IEEE, EMBS Magazine*, **9,** 33–37.

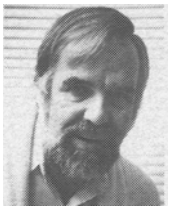
Authors' biographies



Metin Akay was born in Sivas, Turkey. He received his BS and MS degrees in Electrical Engineering from the Bogazici University, Istanbul, Turkey, in 1981 and 1984, respectively. From 1984 to 1986 he continued the Ph.D. programme at the same University. In 1986, he joined the Biomedical Engineering Department at Rutgers University, where he is now a Research Associate. He received his Ph.D. in Biomedical Engineering from Rutgers University, New Jersey, in 1990. His areas of interest are adaptive signal processing, stochastic modelling of signals, detections and estimation biomedical signals.



Walter Welkowitz was born in Brooklyn, New York, in 1926. He received the BS degree in Electrical Engineering from Cooper Union, New York, in 1948 and the MS and Ph.D. degrees from the University of Illinois, Urbana, in 1949 and 1954, respectively. He was a Research Associate at Columbia University, for a year until joining Gulton Industries, working in medical instrumentation until 1964. He then joined Rutgers University, New Brunswick, where he is currently Professor and Chairman of the Department of Biomedical Engineering and Adjunct Professor in the Department of Surgery (Bioengineering) Robert Wood Johnson Medical School (UMDNJ).



John Semmlow was born in Chicago, in 1942, and attended the University of Illinois, receiving the BSEE degree in 1964. He was then employed as design engineer for the Communications Division of Motorola. In 1970 he received a Ph.D. in Physiology (Bioengineering) from the University of Illinois Medical Center in Chicago. His thesis involved the quantitative analysis of iris motor behaviour. He currently holds a joint position as Associate Professor of Surgery, UMDNJ—Robert Wood Johnson Medical School, and Associate Professor of Biomedical Engineering at Rutgers University. His active research areas include physiological motor control and medical instrumentation particularly in cardiology.

Dr John Kostis, a native of Greece, graduated from the Medical School of the University of Salonica, Greece, in 1960. In 1964 he came to the United States and after completing two fellowships in cardiology returned to Greece to become an instructor at the School of Aviation Medicine in Athens. Since 1976, Dr Kostis has served as professor of medicine at the UMDNJ-Robert Wood Johnson Medical School. In 1982, he was appointed chief of the Division of Cardiovascular Diseases and Hypertension this school. In November 1988, Dr Kostis was elected president of the American Heart Association, New Jersey Affiliate.