*Physiological measurement*

# Cardiac Doppler blood-flow signal analysis

## Part 2 Time/frequency representation based on autoregressive modelling

Z. Guo[1,2] L.-G. Durand[1] L. Allard[1,3] G. Cloutier[1]
H. C. Lee[2] Y. E. Langlois[3]

[1] Biomedical Engineering Laboratory, Clinical Research Institute of Montreal, 110 West Pine Avenue, Montreal, Quebec H2W 1R7, Canada
[2] Department of Electrical Engineering, McGill University, 3480 University Street, Montreal, Quebec H3A 2A7, Canada
[3] Noninvasive Cardiovascular Research Laboratory, Hotel-Dieu de Montreal Hospital, 3840 St-Urbain, Montreal, Quebec H2W 1T8, Canada

**Abstract**—*Doppler spectrograms obtained by using autoregressive (AR) modelling based on the Yule-Walker equations were investigated. A complex AR model using the in-phase and the quadrature components of the Doppler signal was used to provide blood-flow directions. The effect of model orders on the spectrogram estimation was studied using cardiac Doppler blood flow signals taken from 20 patients. The 'final prediction error' (FPE) and the 'Akaike's information criterion' (AIC) provided almost identical results in model-order selection. An index, the spectral envelope area (SEA), was used to evaluate the effect of window duration and sampling frequency on AR Doppler spectrogram estimation. The statistical analysis revealed that the SEA obtained from AR modelling was not sensitive to window duration and sampling frequency. This result verified the consistency of the AR Doppler spectrogram. The white-noise characteristics of the AR modelling error signal indicated that the Doppler blood-flow signal can be adequately modelled as a complex AR process. With appropriate model orders, AR modelling provided better Doppler spectrogram estimates than the periodogram.*

**Keywords**—*Autoregressive modelling, Doppler spectrogram, Modelling errors, Model order, Window duration*

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## 1 Introduction

THE TIME/FREQUENCY properties of the Doppler blood-flow signal are usually characterised by computing a temporal sequence of power spectra, called a spectrogram. As the signal is due to the moving red blood cells, certain cardiovascular diseases can be assessed by analysing the blood-flow pattern contained in the Doppler signal (PANIDIS *et al.*, 1986; GIDDENS and KITNEY, 1985; CANNON *et al.*, 1982). Because of the random nature of the signal, the diagnostic information is usually extracted from an ensemble averaged spectrogram computed over several cardiac cycles.

The periodogram has been the method most often used to compute the Doppler spectrogram owing to its relatively fast computation (CLOUTIER *et al.*, 1990; RITTGERS, 1987; CANNON *et al.*, 1982). However, the periodogram has limitations, such as frequency resolution, frequency leakage and statistical variance. For instance, frequency resolution is inversely proportional to the duration of the signal segment analysed. In the spectrogram of a time-varying Doppler signal, the frequency components can be smeared in the time domain if a long segment is used, or spread in the frequency domain if the signal segment is too short. Frequency leakage means that the energy of a spectral estimate leaks into sidelobes, distorting other spectral components. To reduce the leakage effect, smoothing windows such as the Hanning window are usually used. However, the use of windows results in an additional reduction of the frequency resolution. Finally, the statistical variance of the estimate depends on the duration of the signal segment and the number of segments averaged. Consequently, noninvasive assessment of the early stage of cardiovascular disease may be difficult owing to these limitations.

Modern parametric methods offer better potential for achieving significant improvements in estimating the power spectral density of Doppler ultrasound signals. Such improvements may enable disturbed flow to be detected in a more sensitive manner and thus improve the diagnosis of cardiovascular pathologies. Recently, some authors proposed autoregressive (AR) modelling to carry out the power spectrum estimation of the Doppler signal

*Correspondence should be addressed to Zhenyu Guo at address 1.*

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(KALUZYNSKI, 1989*a*; *b*; SCHLINDWEIN and EVANS, 1989; VAITKUS and COBBOLD, 1988; VAITKUS *et al.*, 1988; YAMAGUCHI *et al.*, 1987; KITNEY *et al.*, 1986). KITNEY *et al.* (1986) explained that AR modelling improves the resolution of coherent features in a disturbed flow pattern. VAITKUS *et al.* (1988) found that AR modelling yields estimates with variances considerably smaller than that of the periodogram. KALUZYNSKI (1987) reported the better statistical stability of AR spectra in comparison with the periodogram. These studies confirmed the usefulness of AR modelling for Doppler blood-flow signals. VAITKUS *et al.* (1988) have also demonstrated that the AR and autoregressive-moving average (ARMA) are good methods for Doppler signal processing. However, AR modelling is preferred to ARMA modelling because of its reduced computational complexity.

It has been shown in Part 1 of this study that the Doppler blood-flow signal over a short-time interval approximates a stationary complex Gaussian process. It was also shown that this approximation is more precise when the signal segment is shorter. Because the frequency resolution of AR modelling is higher than that of the FFT method for short signal segments, AR modelling should provide Doppler spectrograms with higher resolution than those obtained with the periodogram. Another advantage of using AR modelling is the reduction of the Doppler 'speckles', the granular structure in the Doppler spectrogram (MO and COBBOLD, 1986). For a stationary signal segment, the power spectrum obtained by using the AR approach is an optimal estimate if the signal can be modelled by a true AR process. So far, however, no study has been carried out to verify that the Doppler signal is a complex AR process for which the model order can be selected by an objective criterion. The objectives of the present work are:

(*a*) to study the consistency of spectrograms obtained by using complex AR modelling
(*b*) to investigate objective criteria to determine model order automatically
(*c*) to verify that the cardiac Doppler signal can be modelled adequately by a complex AR process.

## 2 Materials and methods

The patient database and data-acquisition technique used in this paper were the same as those described in Part 1 of this study (GUO *et al.*, 1993).

### 2.1 *AR model identification and Doppler spectrogram estimation*

The Doppler blood flow signal is a complex-valued signal expressed as

$$x(n) = x_d(n) + jx_q(n) \tag{1}$$

where $x_d(n)$ and $x_q(n)$ are the in-phase and quadrature components. The forward and reverse flow components can be expressed as (VAITKUS and COBBOLD, 1988)

$$x_f(n) = x_d(n) + x_q^H(n) \tag{2}$$

$$x_r(n) = x_d(n) - x_q^H(n) \tag{3}$$

where the superscript $H$ denotes the Hilbert transform. In the past, AR modelling was applied separately on $x_f(n)$ and $x_r(n)$. According to HERMENT *et al.* (1990), it is possible to compute the forward and reverse flow components directly from the AR model of the complex signal $x(n)$. A complex AR process of order $p$, as described below, is required:

$$x(n) = -\sum_{k=1}^{p} a_{pk}\, x(n-k) + e(n) \tag{4}$$

where $x(n)$ is a complex signal composed of the in-phase and the quadrature components of the Doppler signal, $p$ is the model order, $a_{pk}$ are the complex AR parameters, and $e(n)$ is the complex modelling error.

The Yule-Walker equations were used to compute the complex AR parameters $a_{pk}$ and the modelling error variance $\sigma_k^2$. The Yule-Walker equations relate the AR parameters to the complex autocorrelation function of $x(n)$. This method is also known in the literature as the all-pole modelling with autocorrelation method. The Levinson-Durbin algorithm (KAY and MARPLE, 1981) provides an efficient recursive solution for the Yule-Walker equations. This algorithm proceeds recursively to compute the parameter sets $\{a_{11}, \sigma_1^2\}$, $\{a_{21}, a_{22}, \sigma_2^2\}$, ..., $\{a_{p1}, a_{p2}, \ldots, a_{pp}, \sigma_p^2\}$, as follows:

$$a_{11} = -R_{xx}(1)/R_{xx}(0) \tag{5}$$

$$\sigma_1^2 = (1 - |a_{11}|^2)R_{xx}(0) \tag{6}$$

The recursion for $k = 2, 3, \ldots, p$ is given by

$$a_{kk} = -\left[R_{xx}(k) + \sum_{m=1}^{k-1} a_{k-1,m} R_{xx}(k-m)\right] \Big/ \sigma_{k-1}^2 \tag{7}$$

$$a_{ki} = a_{k-1,i} + a_{kk}\, a_{k-1,k-i}^* \quad (i = 1, \ldots, k-1) \tag{8}$$

$$\sigma_k^2 = (1 - |a_{kk}|^2)\sigma_{k-1}^2 \tag{9}$$

where $R_{xx}(k)$ is the complex autocorrelation function of $x(n)$ computed by

$$R_{xx}(k) = \frac{1}{N}\sum_{n=0}^{N-k-1} x(n+k)x^*(n) \tag{10}$$

where $x^*(n)$ denotes the complex conjugate of $x(n)$, and $N$ is the number of data points.

For each recursion, the final prediction error (FPE) or the Akaike's information criterion (AIC) was evaluated and tested. The recursion was initiated with the model order $p = 1$ and terminated when an increase in model order resulted in an increase of FPE or AIC function. The parameter set of the AR model of order $p$ was $\{a_{p1}, a_{p2}, \ldots, a_{pp}, \sigma_p^2\}$. The definitions of FPE and AIC are (KAY and MARPLE, 1981)

$$FPE(p) = \frac{N + p + 1}{N - p - 1}\sigma_p^2 \tag{11}$$

$$AIC(p) = \ln(\sigma_p^2) + 2(p+1)/N \tag{12}$$

where $\sigma_p^2$ is the variance of the modelling error corresponding to the model order $p$.

Once the AR parameters had been estimated, the power spectral estimate $S_{AR}(f)$ of $x(n)$ was computed by

$$S_{AR}(f) = \frac{\sigma_p^2\,\Delta t}{\left|1 + \sum_{k=1}^{p} a_{pk}\, e^{-j2\pi fk\Delta t}\right|^2} \tag{13}$$

where $\Delta t$ is the sampling interval. The rectangular data window (10 or 5 ms) was applied to the in-phase and quadrature Doppler components, and eqns. 5 to 13 were used to compute a 256-sample power spectrum with zero padding of the AR coefficients. This window was then slid over the entire cardiac cycle, and a power spectrum was computed at each increment of 5 ms to produce an AR spectrogram of the Doppler signal. To reduce the amplitude variability and the beat-by-beat variance, an ensemble average of spectrograms for each patient was computed over five cardiac cycles synchronised by the QRS wave of the ECG.

For $x(n)$ weighted by a temporal window $w(n)$, the power spectral estimate based on the periodogram was computed by

$$S_{FFT}(f) = \frac{1}{U} |X(f)|^2 \tag{14}$$

where $X(f) = \sum_{n=0}^{N-1} x(n)w(n)e^{-j2\pi fn}$, and $U = \sum_{n=0}^{N-1} w^2(n)$

Here $U$ is a correcting factor associated with the change in signal energy due to windowing. The spectrogram based on the periodogram was obtained by using the same window shift procedure as in the computation of the AR spectrogram and zero padding of the windowed signal to 256 samples.

### 2.2 *Effect of window duration on the spectral envelope area*

It was shown in CANNON *et al.* (1982) and CLOUTIER *et al.* (1990) that the spectral envelope area (SEA) can be used to assess aortic stenosis. In the present study, this parameter was computed for window durations of 5 and 10 ms, and it was compared for spectrograms estimated with periodogram and AR modelling. After having computed the mean spectrogram of each patient, minimum and maximum frequency contours were determined by using

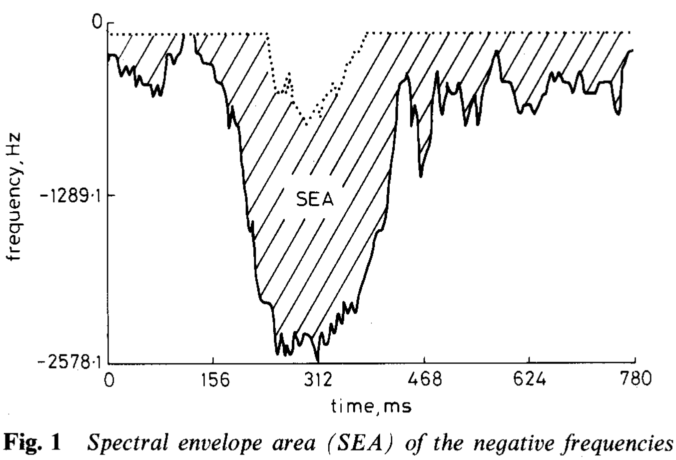


**Fig. 1** *Spectral envelope area (SEA) of the negative frequencies of an averaged spectrogram obtained from a patient with a normal aortic valve*

the modified threshold crossing method described in CLOUTIER *et al.* (1990). By adequately thresholding each mean spectrogram, the blood-flow signal was separated from the background noise, and the frequency envelope of the spectrogram was determined accurately. The SEA value was then computed as the area between minimum and maximum frequency contours of the negative frequency portion of the spectrogram. Fig. 1 shows an example of SEA. A paired $t$-test was then used to evaluate, for the 20 patients, the statistical consistency of SEA for the two window durations and the two spectral estimation techniques tested.

### 2.3 *Can a Doppler signal be considered as an AR process?*

Spectral estimation is a procedure assuming an *a priori* model of the signal (VAITKUS and COBBOLD, 1988). For instance, a sum of sinusoids is assumed for the periodogram. If the signal can be appropriately modelled by a parametric model, then it is possible to obtain a better spectral estimate based on the model by determining its parameters. If the AR model is appropriate for the Doppler blood-flow signal, the modelling errors should have white-noise characteristics (BOX and JENKINS, 1976). The essential check of a good AR model is thus to observe the modelling error signal $e(n)$, where

$$e(n) = x(n) + \sum_{k=1}^{p} a_{pk} x(n-k) = \sum_{k=0}^{n} a_{pk} x(n-k) \qquad 0 \leqslant n \leqslant N-1 \tag{15}$$

with $a_{00} = 1$. If we define the normalised autocorrelation function $c_{xx}(k)$ of the modelling error signal as

$$c_{xx}(k) = r_{xx}(k)/r_{xx}(0) \tag{16}$$

where $r_{xx}(k)$ is the autocorrelation function of the error signal, and compute a $Q$ value

$$Q = N \sum_{k=1}^{K} c_{xx}^2(k) \tag{17}$$

then it has been shown (BOX and JENKINS, 1976) that the $Q$ approximates the chi-square distribution if the model is appropriate ($N$ is the number of samples in the signal segment, and $K$ is the number of time lags of the normalised autocorrelation function). At a certain significance level of $\alpha$, the error signal is a white noise if the value of $Q$ is less than the chi-square value with $K$ degrees of freedom.

In the present work, the whiteness of the error signal was tested on 10 ms peak-systolic segments taken from 20 patients. The peak-systolic segments were selected at the peak of the maximum frequency contour. For each segment, the whiteness test was carried out on the decimated signal with an effective sampling frequency just above the Nyquist rate. The decimation factor was based on the maximum frequency of the segment, as described in Part 1 of this study (GUO *et al.*, 1993). The value of time lag $K$ was selected to be 20 empirically, and the significance level was 0·05.

## 3 Results

### 3.1 *The AR Doppler spectrogram*

Fig. 2 shows an example of the mean AR spectrogram obtained using the Yule-Walker method. The negative and positive frequency components correspond to the forward and reverse blood flow through the aortic valve. The AIC was used to optimise the model order of each spectrum.

Fig. 3 shows the histograms of the relative occurrence of

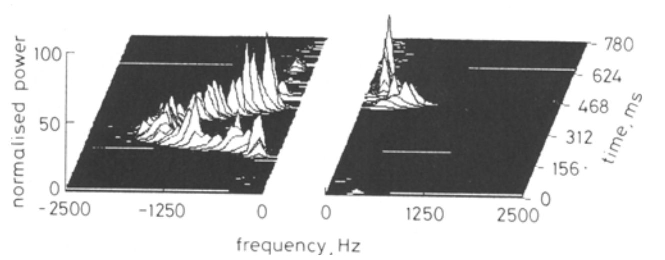


**Fig. 2** *Example of bidirectional AR spectrogram estimated from a normal aortic valve. The model order for each spectral line was optimised by using the AIC*

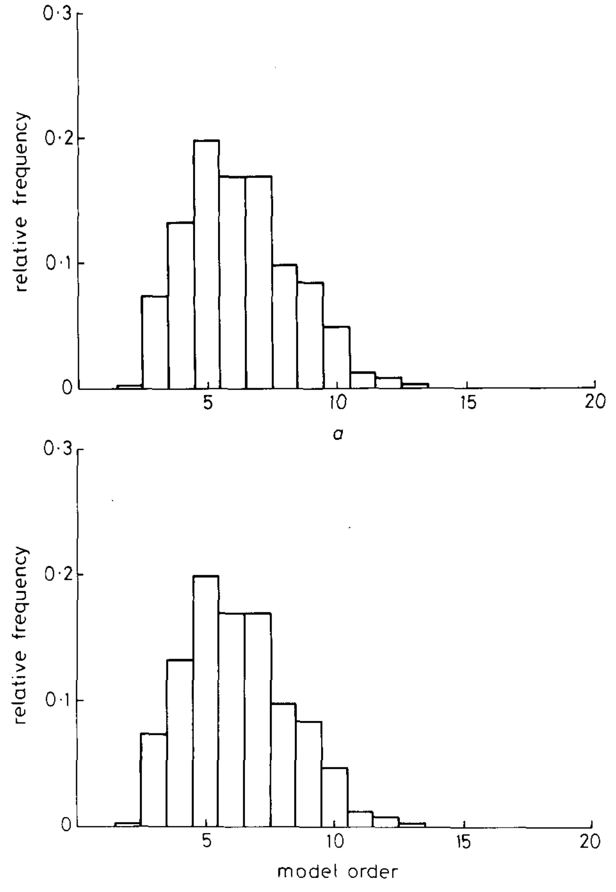


**Fig. 3** *Histograms of the optimal AR orders for the Doppler signals of 20 patients: (a) determined by FPE; (b) determined by AIC*

model orders using the FPE (Fig. 3*a*) and the AIC (Fig. 3*b*). Each panel shows the histogram from 20 patients computed for each spectrum over one cardiac cycle. As can be seen, the two histograms are almost identical, and no order larger than 16 was required to model the cardiac Doppler signal. This indicates that the Doppler spectrograms obtained by using AIC and FPE are essentially identical. This observation is in agreement with the results of SCHLINDWEIN and EVANS (1990).

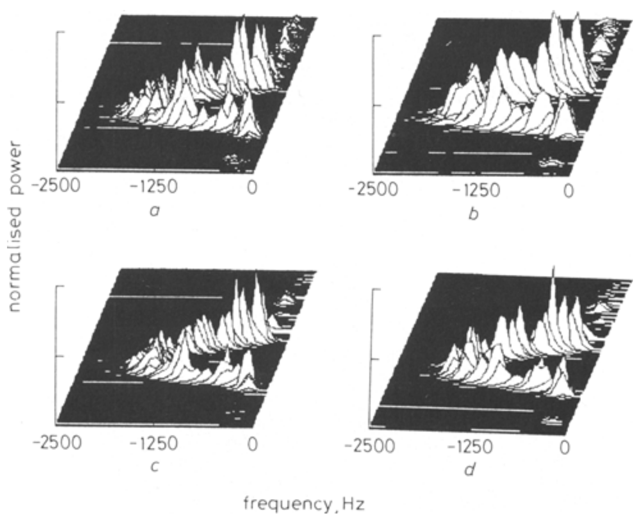


**Fig. 4** *Example of the influence of window duration on the negative frequency portion of the spectrogram of the signal used in Fig. 2: (a) and (b) were obtained by using the periodogram; (c) and (d) were obtained by using AR modelling. The window duration was 10 ms for (a) and (c) and 5 ms for (b) and (d). The AIC was used to determine the optimal order of each spectral line of the AR spectrogram*

### 3.2 *Effect of window duration and spectral techniques on SEA*

Fig. 4 shows an example of the influence of window duration on the negative frequency portion of the mean spectrogram using the same data as in Fig. 2. Figs. 4*a* and *b* were obtained by using the periodogram with window durations of 10 and 5 ms, respectively, and Figs. 4*c* and *d* were obtained by using AR modelling with AIC to select

*Table 1 SEA values, expressed in kHz, computed from the spectrograms of 20 patients with the periodogram (FFT) and AR modelling for window durations of 10 and 5 ms. The last ten patients had aortic valve stenosis, which corresponds generally to larger SEA values. The p-values were obtained by using a paired t-test*

| | SEA (FFT) | | SEA (AR) | |
|---|---|---|---|---|
| Patient | 10 ms | 5 ms | 10 ms | 5 ms |
| 1 | 189 | 193 | 173 | 171 |
| 2 | 147 | 167 | 112 | 110 |
| 3 | 161 | 194 | 153 | 171 |
| 4 | 217 | 255 | 203 | 209 |
| 5 | 127 | 126 | 93 | 90 |
| 6 | 44 | 48 | 36 | 35 |
| 7 | 158 | 171 | 123 | 118 |
| 8 | 79 | 73 | 43 | 40 |
| 9 | 200 | 234 | 181 | 187 |
| 10 | 162 | 166 | 116 | 107 |
| 11 | 408 | 410 | 300 | 299 |
| 12 | 210 | 227 | 177 | 175 |
| 13 | 227 | 201 | 159 | 149 |
| 14 | 237 | 246 | 200 | 198 |
| 15 | 310 | 329 | 303 | 307 |
| 16 | 273 | 274 | 217 | 208 |
| 17 | 369 | 370 | 318 | 300 |
| 18 | 249 | 268 | 233 | 235 |
| 19 | 179 | 184 | 148 | 143 |
| 20 | 214 | 244 | 187 | 199 |
| | $p = 0{\cdot}0052$ | | $p = 0{\cdot}93$ | |

the model orders and the window durations of 10 and 5 ms, respectively. As can be seen from this figure, the shorter window duration widened the frequency components and thus decreased the frequency resolution of the spectrogram based on the periodogram. It resulted in an increased value of SEA. However, the change of window duration had less effect on the Doppler AR spectrogram. Consequently, SEA should be less sensitive to window duration if AR modelling is used.

Table 1 shows the results of the paired *t*-test of SEAs from 20 mean spectrograms obtained by using AR modelling and the periodogram with window duration of 10 and 5 ms. When the window duration was reduced from 10 to

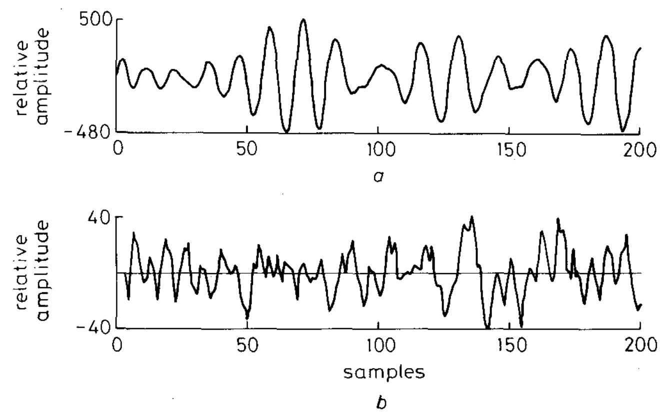


**Fig. 5** *(a) In-phase component of a Doppler signal segment, and (b) corresponding real component of AR modelling error signal. The sampling frequency was 20 kHz*

5 ms, the values of SEA increased significantly for the periodogram ($p = 0.0052$) and were not significantly different ($p = 0.93$) for the AR modelling. The statistical test thus confirmed that SEA is less sensitive to window duration when AR modelling is used.

### 3.3 *Modelling the Doppler signal as an AR process*

Fig. 5 shows a 10 ms segment of the in-phase cardiac Doppler signal at peak systole and its corresponding real component of the complex error signal of AR modelling. Table 2 shows the maximum frequencies of the 20 peak-systolic segments of the 20 patients, which were used to determine the decimation factors, and the $Q$ values corresponding to the error signals. As all the $Q$ values were less than the chi-square value (31·4) with 20 degrees of freedom at a significance level of 0·05, the whiteness of the error signals for all segments was accepted. We can thus conclude that the cardiac Doppler signal can be modelled adequately by a complex AR process.

*Table 2 The maximum frequencies of peak-systolic segments of 20 patients and the corresponding Q values. All Q values are less than the reference chi-square value of 31·4*

| Patient | Maximum frequency, kHz | $Q$ value | Patient | Maximum frequency, kHz | $Q$ value |
|---|---|---|---|---|---|
| 1 | 3·1 | 25·1 | 11 | 2·5 | 14·6 |
| 2 | 3·2 | 16·0 | 12 | 2·6 | 14·8 |
| 3 | 2·4 | 14·9 | 13 | 2·0 | 27·7 |
| 4 | 3·4 | 15·4 | 14 | 3·0 | 30·3 |
| 5 | 3·0 | 19·8 | 15 | 5·0 | 30·9 |
| 6 | 2·0 | 25·9 | 16 | 3·0 | 14·8 |
| 7 | 2·6 | 18·4 | 17 | 2·7 | 16·2 |
| 8 | 2·5 | 21·2 | 18 | 3·7 | 19·7 |
| 9 | 3·0 | 14·2 | 19 | 2·5 | 12·9 |
| 10 | 3·3 | 20·4 | 20 | 2·5 | 14·4 |

## 4 Discussion and conclusion

### 4.1 *AR modelling of Doppler blood-flow signal*

One concern with model identification is to obtain a reasonable estimate of the specific value of the model order $p$ that best describes the finite duration of the signal, and to estimate these parameters from the signal. In the present work, two well known criteria were studied to select $p$. When the window duration was 10 ms, FPE and AIC had almost identical behaviours, as shown in Fig. 3. This indicates that either the FPE or AIC can be used for AR modelling of the Doppler signal. Schlindwein and Evans (1990) showed that overestimating the order of the AR model introduces less error in the spectral estimation than underestimating it. Thus, a relatively high fixed-order implementation for cardiac Doppler spectrogram estimation would also be an acceptable approach. However, it has been noted that too high a model order can introduce spurious peaks in the spectrogram. Based on the results of Fig. 3 obtained from the 20 patients, the order most often used was five, and no order greater than 16 was required. Thus, a model order between five and 16 should be used when a fixed order is selected to estimate each spectrum.

In practice, the Doppler spectrogram has a deterministic structure related to the mean blood-flow field on which random fluctuations of scatters are superimposed. To reduce the amplitude variance of the spectrogram and enhance the flow field components, an ensemble average is usually used. Averaging between two and 20 cardiac cycles was used in the past to reduce these fluctuations on the spectrogram (Cloutier *et al.*, 1992). The advantage of using an AR spectral estimator is to smooth these fluctuations, as a $p$th-order AR model is constrained to have fewer than $p$ spectral peaks. As stated previously, the AR model order most often used for cardiac Doppler signals was around five in the present study. For this small value of $p$, a smoothed spectrogram is consequently obtained. Thus to achieve the same reduction of amplitude variability, fewer spectrograms are required in the ensemble average if the AR method is used.

When the periodogram is used, both the stationarity of the signal and the frequency resolution of the spectra are factors to determine window duration. A shorter window used to ensure signal-segment stationarity introduces a spread in the frequency domain and therefore reduces the spectral resolution. Thus, a compromise between frequency resolution and signal stationarity is required. However, when AR modelling is used, the choice of window duration only depends on the stationarity of the signal. Thus, a shorter sliding window can better reflect the nonstationarity of the Doppler signal and describes the variation of blood velocity with time more accurately.

### 4.2 *The appropriateness of the AR model for Doppler signals*

In the present study, the modelling error signals were used to evaluate the appropriateness of the AR process as a model of the Doppler blood-flow signal. It should be noted that, for power spectral estimation of a signal with unknown properties, the modelling error is not necessarily a white-noise process. However, it has the characteristics of white noise only when the model order $p$ is very large or if the signal is a true AR process for a low order. The results listed in Table 2 confirmed that the Doppler blood-flow signal can be modelled as a true complex AR process.

A complementary study was done to evaluate the effect

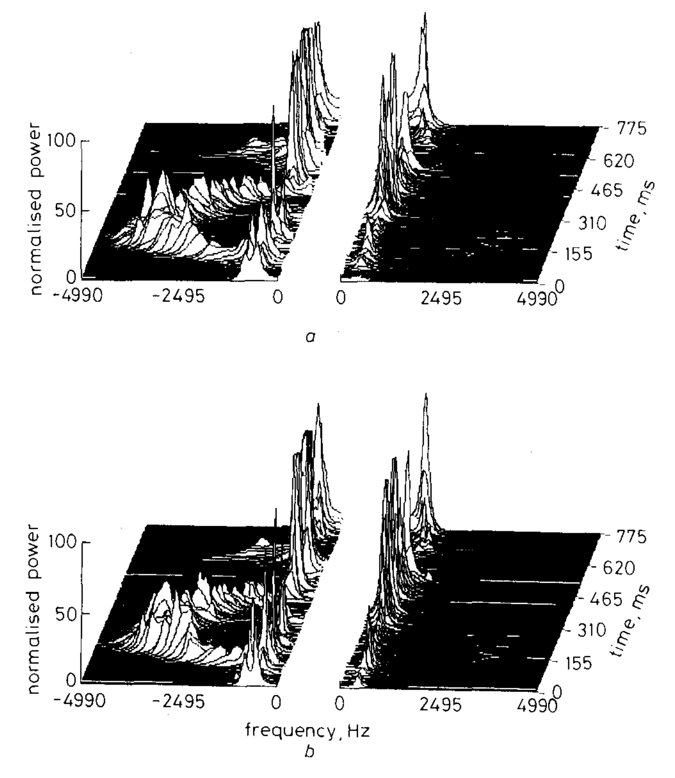


**Fig. 6** *Two AR Doppler spectrograms of a patient with a stenotic aortic valve. The sampling frequency was (a) 20 kHz and (b) 10 kHz. The model order of each spectral line was estimated by AIC*

of sampling frequency on the Doppler spectrogram estimation. Fig. 6 shows an example. The sampling rate of Fig. 6*a* was kept at 20 kHz, and that in Fig. 6*b* was reduced to 10 kHz. No important difference was observed from these two spectrograms. Figs. 7*a* and *b* show the histograms of the model orders used for computing Figs. 6*a* and *b*, respectively. Lower orders were more often selected for Fig. 6*b*, which indicates that the model order also depends on the sampling frequency. A paired *t*-test was carried out on the two groups of SEAs obtained from the AR spectrograms of the 20 patients with sampling frequencies of 20 and 10 kHz, respectively. At a significance level of 0·05, no statistical difference was found between these two groups of SEAs. This implies that SEA is not sensitive to sampling rate when AR modelling is used. A proper low sampling

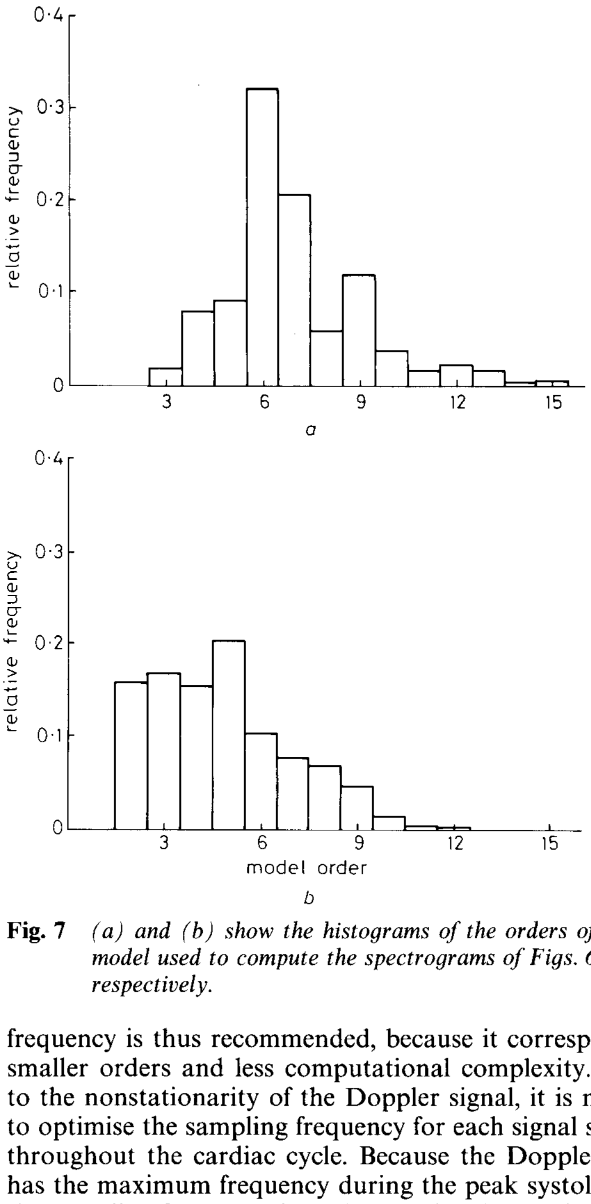


**Fig. 7** *(a) and (b) show the histograms of the orders of the AR model used to compute the spectrograms of Figs. 6a and b, respectively.*

frequency is thus recommended, because it corresponds to smaller orders and less computational complexity. Owing to the nonstationarity of the Doppler signal, it is not easy to optimise the sampling frequency for each signal segment throughout the cardiac cycle. Because the Doppler signal has the maximum frequency during the peak systole, using the sampling frequency just above twice the maximum significant frequency of the peak-systolic signal is recommended when carrying out the AR Doppler spectrogram estimation.

In comparison with the periodogram, AR modelling is better for Doppler spectrogram estimation, owing to the higher frequency resolution, higher statistical consistency and lower sensitivity to Doppler speckles, window duration and sampling frequency. The Doppler blood-flow signal can be adequately modelled as a complex AR process when the order *p* is determined by either FPE or AIC.

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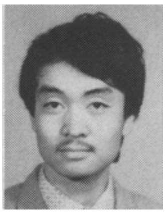
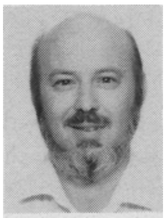
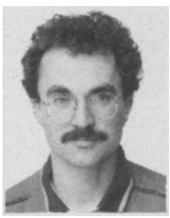
## Authors' biographies



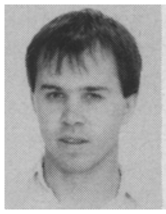
Zhenyu Guo was born in Kunming, China, in 1963. He received the B.Sc. and M.Sc. degrees in Electronics from Yunnan University, Kunming, China, in 1983 and 1986, respectively. From 1986 to 1988, he was with the Department of Radio Electronics, Yunnan University. He is currently working toward the Ph.D. degree at the Department of Electrical Engineering, McGill University, and the Laboratory of Biomedical Engineering, Clinical Research Institute of Montreal, Montreal, Canada. His research interests are digital signal processing and pattern recognition applied to echo-Doppler and phonocardiographic signals.



Louis-Gilles Durand was born in St-Jean de Matha, Québec, Canada, in 1949. He received the B.Sc., M.Sc. and Ph.D. degrees in Electrical Engineering from the Ecole Polytechnique, University of Montreal in 1975, 1979 and 1983, respectively. He is presently Director of the Biomedical Engineering Laboratory at the Clinical Research Institute of Montreal, Research Associate Professor in the Department of Medicine at the University of Montreal and Adjunct Professor at the Institute of Biomedical Engineering of the Ecole Polytechnique, Montreal, Canada. His current interests are digital signal processing of the phonocardiogram and echo-Doppler signal, modelling of the heart/thorax acoustic system and medical instrumentation.

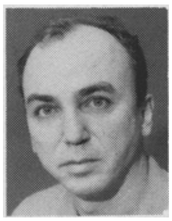


Louis Allard was born in Québec City, Québec, Canada, in 1961. He received the B.Sc.A. degree in Engineering Physics from Laval University, Québec, in 1985, and a M.Sc.A. degree in Biomedical Engineering from the Ecole Polytechnique, University of Montreal, in 1988. He is presently a Research Associate at the Biomedical Engineering Laboratory of the Clinical Research Laboratory of the Hôtel-Dieu de Montréal Hospital. His major interests are digital signal processing, image processing and pattern recognition applied to echo-Doppler signals.



Guy Cloutier was born in Trois-Rivières, Québec, Canada, in 1961. He received a B.Eng. degree in Electrical Engineering from the Université du Québec à Trois-Rivières in 1984, and M.Sc. and Ph.D. degrees in Biomedical Engineering from the Ecole Polytechnique, Université de Montréal in 1986 and 1990, respectively. Currently, he is a Postdoctoral Research Fellow of the Natural Sciences & Engineering Research Council of Canada at the Laboratory of Medical Ultrasonics, Bioengineering Program, the Pennsylvania State University. His principal research interests are blood-flow characterisation, ultrasonic tissue characterisation and digital signal processing and pattern recognition of Doppler echocardiographic signals.

Howard C. Lee received the B.Sc. degree in Engineering Physics from the University of Manitoba in 1959, and M.Eng. and Ph.D. degrees in Electrical Engineering from McGill University, Canada, in 1964 and 1969, respectively. He has been active in biomedical engineering for over 20 years, with past research interests in neural signals and systems and computed tomography, and current interests in biomedical signal processing and sensory aids for the deaf and the blind. He is an Associate Professor in the Department of Electrical Engineering at McGill University.



Yves Langlois was born in Montreal, Canada, in 1950. He received his MD in 1975 from the University of Montreal. He is presently Associate Professor of Surgery at the University of Montreal and active Cardiovascular Surgeon at Hôtel Dieu de Montréal Hospital. He is also Director of the Cardiovascular Research Laboratory at the Hôtel Dieu and Senior Researcher at the Biomedical Engineering Laboratory of the Clinical Research Institute of Montreal. His major interests are cardiovascular physiology and the use of complex biological signals in their clinical application for the detection and quantification of arterial and cardiac diseases.