The effect of averaging cardiac Doppler spectrograms on the reduction of their amplitude variability

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Abstract—*The effect of averaging cardiac Doppler spectrograms on the reduction of their amplitude variability was investigated in 30 patients. Beat-to-beat variations in the amplitude of Doppler spectrograms were also analysed. The quantification of amplitude variability was based on the computation of the area under the absolute value of the derivative function of each spectrum composing mean spectrograms. Fast Fourier transform using a Hanning window was used to compute Doppler spectra. Results obtained over systolic and diastolic periods showed that the reduction of amplitude variability followed an exponentially decreasing curve characterised by the equation* $f(r) = 100\,e^{-\beta(r-1)}$, *where r is the number of cardiac cycles,* β *the exponentially decreasing rate, and 100 the normalised variability for* $r = 1$. *In systole, the decreasing rate* β *was 0·165, whereas in diastole it was 0·225. Reductions of the variability in systole for a number of cardiac cycles of 5, 10, 15, and 20 were 48, 77, 90 and 96 per cent, respectively. In diastole, reductions of the variability for the same numbers of cardiac cycles were 59, 87, 96 and 99 per cent, respectively. Based on these results, it can be concluded that no significant improvement in the reduction of amplitude variability may be obtained by averaging more than 20 cardiac cycles.*

Keywords—*Amplitude smoothness, Aortic valve, Beat-to-beat amplitude variation, Digital signal processing, Doppler ultrasound spectrum, Left ventricular outflow tract, Statistical variance*

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1 Introduction

PARTICULAR CHARACTERISTICS of cardiac Doppler signals are their randomness and time-varying properties (nonstationarity and quasiperiodicity). Factors contributing to the random properties of cardiac Doppler ultrasonic signals are complex. Interactions between red blood cells (SHUNG *et al.*, 1976; MO and COBBOLD, 1986*a*; ROUTH *et al.*, 1989), random velocity distributions of red cells, propagation mechanisms of ultrasonic waves in human tissues (SEHGAL and GREENLEAF, 1984; MO and COBBOLD, 1986*b*; SLEEFE and LELE, 1988), and ultrasonic transducer characteristics and insonation geometry (MO and COBBOLD, 1986*b*) are some examples. The time-varying properties of Doppler signals within a given cardiac cycle and on a beat-to-beat basis represent the other characteristics of these signals. Variations within a given heartbeat are mainly due to the dynamic of the heart (contraction-relaxation). Variations observed from beat-to-beat are associated with factors such as the electrophysiological stimulation of the heart and interaction with the pulmonary system, which modify the amplitude of Doppler signals and the duration of the cardiac cycle.

Other technical considerations may influence the random property and time-varying particularity of Doppler signals. For example, the background noise of electronic instrumentation adds random components, and tremor of the ultrasonic probe during clinical examinations may contribute to beat-to-beat variations. Because of these particular characteristics of the Doppler signal (a nonstationary quasiperiodic random signal), the estimation of its spectrum is difficult and requires the use of averaging techniques to decrease the variance of the estimate. The use of spectral techniques showing less variance than FFT-based methods could be used to obtain a better estimate (MARPLE, 1987).

2 Reduction of the variability of Doppler spectrograms

Spectrograms (time-frequency representation) are often used to describe properties of time-varying Doppler signals. Theoretically, the statistical inadequacies in the

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estimate of the spectra composing the spectrogram may be reduced by using two different averaging approaches (BENDAT and PIERSOL, 1971, p. 191). The first is to smooth spectra over an ensemble of estimates computed from different recordings (ensemble or time averaging), whereas the second is to smooth adjacent frequency components (frequency averaging). The first technique is known in the literature as Bartlett and Welch periodograms and the second is known as the Daniell periodogram (MARPLE, 1987). In the past, both of these techniques were used to reduce the variability in the amplitude of Doppler spectrograms.

Smoothing of adjacent frequency components was used by RITTGERS *et al.* (1983) to analyse Doppler spectrograms recorded in carotid arteries. In their study, adjacent frequency components were smoothed by using a five-coefficient filter for each spectrum. Usually, most researchers used ensemble averaging of Doppler spectra to reduce amplitude variability. Both averaging over adjacent spectra or spectra taken from different cardiac cycles were performed. Because cardiac Doppler signals are highly nonstationary, averaging over different cardiac cycles is generally preferred. However, averaging adjacent consecutive spectra may be used when studying stationary blood velocities such as those observed in steady flow models. Using *in vitro* steady flow models, MORIN *et al.* (1987; 1988) averaged 130 adjacent power spectra to obtain a consistent estimate of the spectral function, whereas BLACK and HOW (1989) averaged 128 spectra.

In a study of KALMAN *et al.* (1985) on pulsating flow, four consecutive spectra at peak systole were averaged to obtain a spectrum describing maximum blood flow velocities in carotid arteries. The selection of four spectra was performed by assuming that the spectra remain relatively unchanged over the short time interval studied (40 ms). Averaging of spectrograms over several cardiac cycles was accomplished by most investigators interested in cardiac and artery blood flow analyses (GREENE *et al.*, 1982; KNOX *et al.*, 1982; CANNON *et al.*, 1982; SHERRIFF *et al.*, 1982; LANGLOIS *et al.*, 1983; 1984; PHILLIPS *et al.*, 1983; POOTS *et al.*, 1986; HUTCHISON and KARPINSKI, 1988; CLOUTIER *et al.*, 1989; 1990; ALLARD *et al.*, 1991). In the averaging process, signal detection was usually synchronised with the R-wave of the ECG and the spectra of a series of cardiac cycles located at a given time interval from this reference was averaged. This procedure was repeated until each spectrum of the spectrograms was processed.

GREENE *et al.* (1982) were the first to propose a method for reducing the variability of carotid artery spectrograms. In their study, spectra obtained from 20 cardiac cycles were averaged. Only signals obtained from cycles which did not differ by more than 33 per cent of the duration of the preceding cycle were kept for spectral analysis. The selection of 20 cardiac cycles and the 33 per cent criterion were also used by KNOX *et al.* (1982) and LANGLOIS *et al.* (1983; 1984). A more severe criterion was used by HUTCHISON and KARPINSKI (1988), CLOUTIER *et al.* (1989; 1990), and ALLARD *et al.* (1991) to select cardiac cycles to be averaged. Indeed, only those cycles having a duration not differing by more than 10 per cent of the mean R-R interval were used to average 15 (HUTCHISON and KARPINSKI, 1988) or five cardiac cycles (CLOUTIER *et al.*, 1989; 1990; ALLARD *et al.*, 1991). Different numbers of cardiac cycles were used by other groups. In the study of SHERRIFF *et al.* (1982), CANNON *et al.* (1982), POOTS *et al.* (1986) and PHILLIPS *et al.* (1983), the number of cardiac cycles averaged was 2, 3, 15 and 16, respectively.

In summary, between 2 and 20 cardiac cycles were used in the past to reduce the variability of Doppler spectrogram estimates. The high variation in the number of cycles selected suggested to us to characterise the influence of this parameter on the reduction of amplitude variability of the spectrograms. More precisely, we wanted to know how many cardiac cycles should be averaged to reduce amplitude variability of Doppler spectrograms by a given amount. In addition to this analysis, the evaluation of the amplitude variability from beat-to-beat was another aim of the present study. The information resulting from this second analysis should serve to better characterise the statistical properties of cardiac Doppler spectrograms.

3 Theory

Studies of stationary (ergodic) Gaussian random processes reported theoretical formulation on the statistical variance of the power spectrum (WELCH, 1967; BENDAT and PIERSOL, 1971; 1986; OPPENHEIM and SCHAFER, 1975; MARPLE, 1987). Theoretical considerations concerning this variance are summarised and discussed in this section. The procedure associated with the computation of the spectrogram based on the short-time Fourier transform is also presented.

3.1 *Variance of power spectral estimation*

If a stationary random process $v(t)$, e.g. a voltage, is sampled N times at a frequency f_s over the interval 0 to $(N-1)/f_s$, the sampled waveform can be written as $x(n) = v(n/f_s)$, where $n = 0, \ldots, N-1$. The continuous power spectral density function of $x(n)$ is given by

$$S_{xx}(f) = \lim_{N \to \infty} \frac{1}{N} E[|X(f)|^2] \tag{1}$$

where

$$X(f) = \sum_{n=-\infty}^{\infty} x(n) e^{-j2\pi fn}$$

is the continuous Fourier transform of $x(n)$, and $E[]$ the expectation operation. In practical situations, an estimate of $S_{xx}(f)$ denoted as the discrete power density function $S_{xx}(f_k)$ can be obtained by simply omitting the limiting and expectation operations of eqn. 1. Computing the discrete Fourier transform of the signal over a short number of samples is also often used to minimise the effect of the time-varying properties of the signal. When computing the discrete power spectral density $S_{xx}(f_k)$, a time window $w(n)$ can be used. Considering that $x(n)$ is weighted by such a temporal window, the estimated discrete power spectrum of $x(n)$ (in $V^2\ Hz^{-1}$) is given by

$$S_{xx}(f_k) = \frac{1}{U} |X(f_k)|^2 \tag{2}$$

where

$$X(f_k) = \sum_{n=0}^{N-1} x(n) w(n) e^{-j2\pi nf_k/N}$$

$$U = \sum_{n=0}^{N-1} w^2(n)$$

and f_k is a frequency integer ranging from 0 to $(N-1)$. In the last equation, the spectral energy U is a correcting factor associated with the reduction in signal energy due to the use of the windowing function.

Important limitations of the discrete Fourier transform must be taken into consideration here. The most important shortcomings are limited frequency resolution, spectral dispersion of the frequency components and high

variance of the estimate. The frequency resolution of the spectrum expressed in hertz is inversely proportional to the duration of the short segment analysed. The spectral dispersion is associated with spectral leakage of the temporal window used, whereas variance is related to the statistical properties of the signal and the stability of the spectral estimator. To reduce spectral leakage due to sidelobe effects, special non-rectangular windows may be used (OPPENHEIM and SCHAFER, 1975; MARPLE, 1987). Unfortunately, although windowing of the signal may be useful in specific applications, all non-rectangular windows reduce the frequency resolution of the estimate.

BENDAT and PIERSOL (1971; 1986) have shown, for a stationary Gaussian random process with a zero mean and unit variance, that the ratio of the estimated spectrum $S_{xx}(f_k)$ using a rectangular window to the continuous spectrum $S_{xx}(f)$ follows a sampling distribution given by $X_2^2/2$, where X_2^2 is the chi-square variable with two degrees of freedom ($m = 2$). Because the mean and variance of the standardised chi-square statistical distribution are, respectively, m and $2m$, the normalised standard deviation of $S_{xx}(f_k)$ is thus given by

$$\sigma[S_{xx}(f_k)]/S_{xx}(f) = \sqrt{(2m)}/m = \sqrt{(2/m)} = 1 \qquad (3)$$

for two degrees of freedom. This result is very important because it shows that the standard deviation of the spectral estimate obtained by using the fast Fourier transform with a rectangular window is as great as the quantity being estimated. Furthermore, this normalised standard deviation is constant over frequency. For non-rectangular windows, different values of the normalised standard deviation may be obtained (MARPLE, 1987). From the discussion found in BENDAT and PIERSOL (1986, p. 398), a Hanning window should increase the standard deviation of the spectral estimate by a factor of about $\sqrt{2}$ for data characterised by a uniform spectrum.

To reduce the variability of the estimates, averaging is generally performed. In particular, WELCH (1967) proposed a method based on averaging of modified periodograms computed from stationary random signals. Considering that the mean spectrum is obtained after computing and averaging $S_{xx}(f_k)$ over R nonoverlapping segments (see eqn. 4) of N samples each, it was shown that the normalised standard deviation of the estimate is $1/\sqrt{R}$ (WELCH, 1967; BENDAT and PIERSOL, 1971; 1986; OPPENHEIM and SCHAFER, 1975; MARPLE, 1987). The variance reduction with increasing R is less if the segments used to compute the periodogram are not statistically independent (MARPLE, 1987). Another important property associated with the reduction of the normalised standard deviation is that the reduction factor $\sqrt{R}$ is independent of the temporal window used.

3.2 *Computation of the short-time Fourier transform*

In Doppler signal analysis, averaging over R segments should be addressed with care because cardiac Doppler signals are nonstationary. In addition, the quasiperiodicity of the signals should be taken into account. The following formula (the general form of this equation can be found in PORTNOFF, 1980) corresponds to the approach used to compute the mean spectrogram of time-varying Doppler signals:

$$\langle S_{xx}(t_i, f_k)\rangle = \frac{1}{RU}\sum_{r=1}^{R} |X_r(t_i, f_k)|^2 \qquad (4)$$

In this equation, $\langle\ \rangle$ represents the averaging process, t_i the temporal index of the spectrogram and r the cardiac cycle selected. The ECG R-wave peak corresponds to $i = 1$, i.e. t_1. The maximum value of t_i corresponds to the total number of windowed time segments of the signal over one cardiac cycle. This number considers possible overlapping segments and is defined by dividing the duration of the cardiac cycle by the time interval between each window $w(n)$ of N samples.

4 Methods

4.1 *Patient selection and Doppler data acquisition*

Variability and beat-to-beat variations in the amplitude of cardiac Doppler spectrograms were characterised in a group of 30 patients. Fifteen patients had a normal aortic valve and 15 had a severe aortic valve stenosis and possible concomitant aortic valve regurgitation. The status of the aortic valves was assessed by clinical invasive haemodynamic examinations performed at the Hôtel-Dieu de Montréal Hospital. The patient population having a normal aortic valve was composed of patients referred for pure aortic regurgitation or coronary artery disease.

For each patient, a Doppler investigation was performed generally within one day of the catheterisation examination. Doppler studies were performed with an Ultramark 8 Duplex scanner (Advanced Technological Laboratory) modified to allow the recording of the two quadrature Doppler signals on a four-channel audiotape recorder. Doppler signals and the electrocardiogram (ECG) were recorded on magnetic tapes for a period of approximately 30 s. The TASCAM 22-4 tape recorder used had a dynamic range of 40 dB and was modified to include frequency-modulated channels. Both direct and quadrature Doppler signals were recorded in direct mode while the ECG was recorded in frequency modulation mode. At a speed of 7·5 in per second (19·05 cm s^{-1}), the frequency response of the direct channels was uniform (−3 dB) between 50 and 20 000 Hz, and for the frequency-modulated channels it was uniform between 0 and 2500 Hz.

A 3 MHz pulsed-wave (PW) probe combined with a B-mode mechanical scanner was used to record the Doppler blood flow signals at the midpoint of the left ventricular outflow tract, approximately 1 cm below the aortic valve. The apical long axis echocardiographic view was used to obtain those signals. For each recording, the high-pass 'wall filter' was set at 200 or 400 Hz. The dimension of the sample volume on the axial axis was set at 1·5 mm for all analyses.

4.2 *Spectral analysis*

During tape playback, Doppler signals were low-pass filtered at 9 kHz with two eighth-order filters (−48 dB per octave). The ECG and PW Doppler signals were then digitised for 25 s with 12-bit resolution at sampling rates of 0·2 and 20 kHz, respectively. Data acquisition of at least 20 cardiac cycles was needed to carry out the present study. A Data Translation acquisition card (DT-2828) installed in a compatible 16 MHz IBM-PC/386 computer was used to digitise the signals.

A QRS detection algorithm based on a correlation technique was used to synchronise the analysis of each cardiac cycle. The mean R-R interval of each patient was then computed over the digitised period of 25 s. When visualising signals of each cardiac cycle on the video monitor of the computer, only those having a duration within ±10 per cent of the mean R-R interval were kept. This procedure served to eliminate irregular beats from the spectral

analysis. A total of 20 cycles were then saved on hard disk for each patient. In practice, the 10 per cent criterion was used only in a few patients because the variability in heart rate was generally within this threshold.

A Hanning window of 10 ms was applied to the Doppler signals and a complex fast Fourier transform (FFT) used to compute a 256-sample power spectrum. The Hanning window was slid over the entire cardiac cycle and an FFT computed at each increment of 5 ms to produce a power spectrogram of the Doppler signals (PORTNOFF, 1980). Ensemble averages of the spectrograms computed from 1 up to 20 cardiac cycles were then performed. The temporal reference of the QRS complex of the ECG served to align the spectrograms from beat-to-beat. The averaging process was limited to the interval corresponding to the duration of the shortest heart cycle of the patient found among the 20 cardiac cycles saved on hard disk. Figs. 1 and 2 show typical power spectrograms selected from the same patient. The spectrogram of Fig. 1 was computed using one cardiac cycle; the spectrogram of Fig. 2 was averaged over 20 cycles.

Two kinds of averaging were performed to take into account beat-to-beat variations in the amplitude of Doppler spectrograms. In the first approach, averaging N cycles among 20 was performed by selecting sequentially cycle 1 to N. With the second approach, the N cycles selected were chosen randomly within the 20 cycles available. In the random selection, a given cycle could not be selected twice. The reason for using random averaging was to account for possible movements of the probe during clinical examinations. If such artefacts are present, the last cardiac cycles of the Doppler data-acquisition sequences of each patient might have an increased-amplitude variability. By comparing sequential and random averaging, the presence of this possible artefact will be verified.

After having computed all mean spectrograms of a given patient, minimum and maximum frequency contours of the spectrogram averaged sequentially over 10 cardiac cycles were determined by using the Modified Threshold Crossing method (CLOUTIER *et al.*, 1990). By adequately thresholding the spectrogram, blood flow signals can be separated from the background noise and the frequency envelope of the spectrogram accurately determined. In the present study, a threshold level equivalent to 9·5 times the

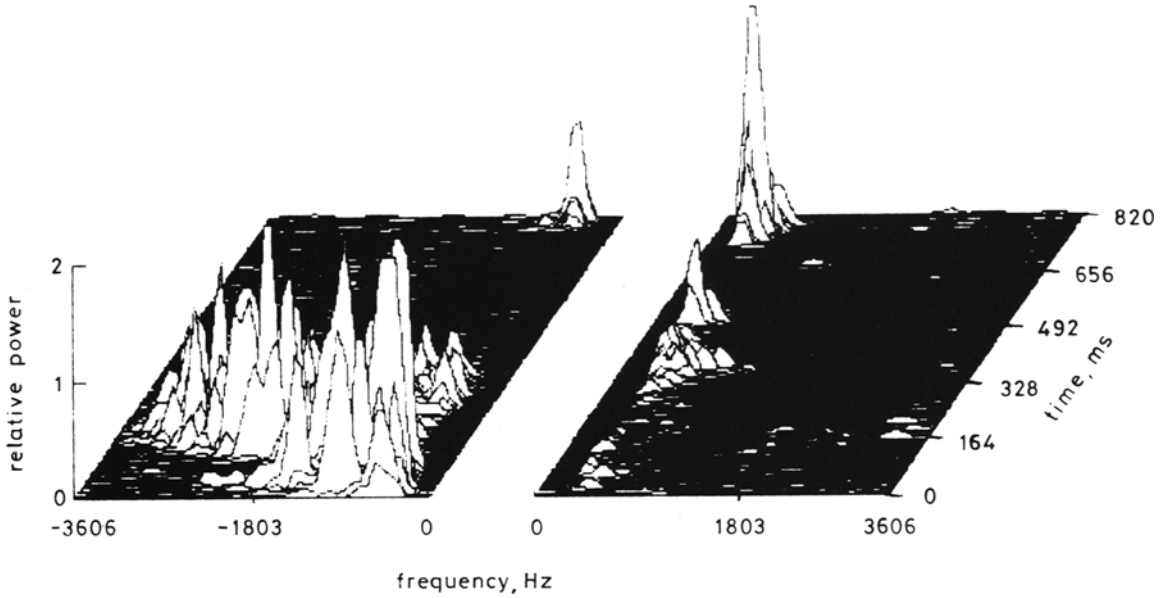

Fig. 1 *Example of a power Doppler spectrogram computed over one cardiac cycle. The pulsed-wave Doppler signals were recorded in the left ventricular outflow tract, approximately 1 cm below the aortic valve. The negative frequencies of the spectrogram represent blood flow moving toward the aorta while positive frequencies correspond to blood flow moving backward to the left ventricle*

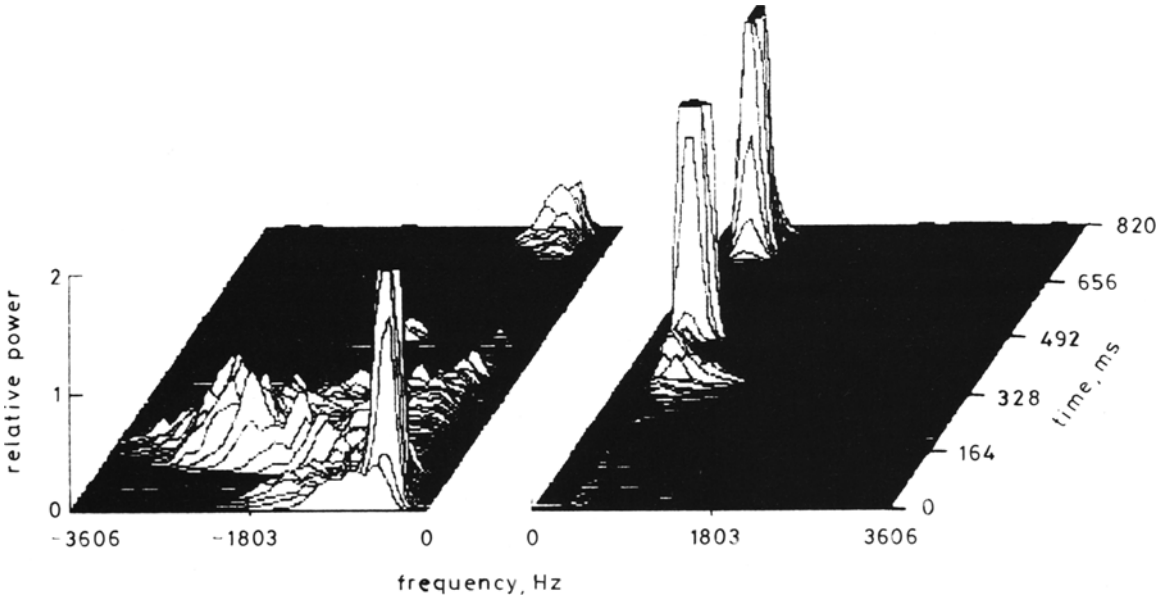

Fig. 2 *Mean power Doppler spectrogram averaged over 20 cardiac cycles. The patient selected for this example is the same as in Fig. 1*

estimated mean amplitude of the background noise was chosen. The amplitude of the background noise was computed from samples localised at $\pm PRF/2$ and $\pm[(PRF/2)-1$ sample] where PRF is the pulse repetition frequency.

The frequency contours of the spectrogram of each

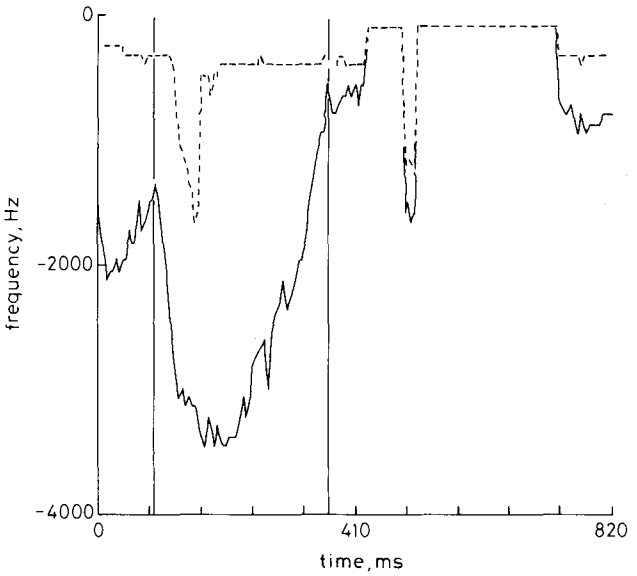

Fig. 3 *Estimated minimum (broken line) and maximum (full line) frequency contours of the negative portion of the spectrogram of the patient used in Fig. 1 and 2. The vertical lines represent the cursors moved to define the beginning and the end of the systolic period*

patient were used to determine visually the beginning and the end of the systolic and diastolic periods. As seen in Fig. 3, the systolic period was easily located from the maximum frequency contours of the negative frequencies of the spectrogram by moving two cursors on the video monitor. Signals located outside both cursors were used to define the diastolic period. The same temporal references were used for all mean spectrograms of a given patient and used to determine the amplitude variability and beat-to-beat variations of Doppler spectrograms in systole or in diastole.

4.3 *Evaluation of the amplitude variability of Doppler spectrograms*

To evaluate the amplitude variability of each mean power spectrogram computed over 1 to 20 cardiac cycles, the area under the absolute value of the derivative function of each spectrum composing the mean spectrogram was computed. These absolute areas were then cumulated for each spectrum in the systolic and diastolic periods. The following equation was used to quantify the amplitude variability of each mean spectrogram:

$$IVAR = \frac{1}{N} \sum_{t_i=1}^{N} \sum_{f_k=500}^{PRF/2} |S_{xx}(t_i, f_k + 1) - S_{xx}(t_i, f_k)| \quad (5)$$

In this equation, $IVAR$ represents the index of variability in V^2, $S_{xx}(t_i, f_k)$ the estimated power spectrum at discrete time t_i and discrete frequency f_k in V^2 Hz^{-1}, and N the number of spectra in the systolic or diastolic period. The index of variability proposed here may be interpreted as a measurement of the smoothness of the spectrograms. A low value of this index corresponds to a smooth spectrogram whereas a high value corresponds to a highly random spectrogram. In the computation of $IVAR$, only Doppler frequency samples corresponding to blood flow moving towards the aorta were used in systole (negative frequencies of the spectrograms). In diastole, only frequency samples corresponding to blood flow moving backward to the left ventricle were considered (positive frequencies of the spectrograms).

The derivative functions computed by eqn. 5, were evaluated over frequencies ranging between 500 Hz and $PRF/2$. The lower frequency limit of 500 Hz was selected to reduce the influence of high amplitude low-frequency vibrations. The end limit of $PRF/2$ was chosen because Doppler signals were filtered by the Ultramark 8 Duplex scanner beyond this frequency. The selection of PRF was made during the Doppler examination and was determined by the length of the propagation path of the ultrasonic beam for each patient.

4.4 *Normalisation of the indexes of variability*

Two factors influencing the magnitude of $IVAR$ had to be addressed. The first factor is the gain setting of Doppler signals, which varies from one patient to another because each patient has their own echogenicity. The gain modifies the magnitude of $IVAR$ by influencing the difference between the amplitude of each successive frequency sample. The second factor is the number of frequency samples included between 500 Hz and $PRF/2$ because PRF differs from one patient to another.

To minimise the influence of these factors, normalisation of the magnitude of the indexes of variability was performed using the following procedure. For each patient, the maximum value of $IVAR$ of all mean spectrograms computed between 1 and 20 cardiac cycles was extracted and used as the 100 per cent reference. The magnitudes of the indexes of the other mean spectrograms of the same patient were normalised by multiplying their values by 100 and dividing them by the maximum $IVAR$. This normalisation procedure was performed separately for both systolic and diastolic periods. Usually the maximum value of the index of variability was found for Doppler spectrograms computed on one cardiac cycle.

For comparison of $IVAR$ values between sequential and random averaging, the normalisation was performed by searching the maximum $IVAR$ (100 per cent reference) of each patient from the 40 mean spectrograms computed, i.e. the 20 spectrograms evaluated sequentially and the 20 evaluated randomly. Other values of $IVAR$ of a given patient were then normalised by multiplying by 100 and dividing by this maximum.

4.5 *Correction of the indexes of variability*

In our experiment, as the number of segments averaged increased, the magnitude of the normalised indexes of variability converged to a plateau corresponding to the area under the absolute derivative functions of the continuous spectra $S_{xx}(t_i, f)$ of Doppler signals defined in eqn. 1 for an unspecified value of t_i. In specific cases where $S_{xx}(t_i, f)$ might have a flat profile within the bandwidth analysed, the normalised index of variability converges to zero. In all other practical situations, $IVAR$ converges to a non-zero value. Based on this observation, the mean normalised indexes of variability computed over the patient population were first evaluated as a function of the number of cardiac cycles. The mean normalised indexes were then corrected to obtain values ranging between 0 and 100 per cent. The basic motivation was to have an index of variability with a maximum value of 100 per cent when using only one cardiac cycle and a minimum value of 0 per cent when averaging over a large number of spectrograms.

Two exponentially decreasing models were fitted to the data obtained in systole and in diastole to obtain the cor-

rected indexes. The first model was

$$f(r) = A + Br^{-\alpha} \tag{6}$$

and the second model was

$$f(r) = A + Be^{-\beta(r-1)} \tag{7}$$

In both equations, A corresponds to the amplitude of the plateau, B to the gain of the function, α and β to the exponentially decreasing rate, and r to the number of cardiac cycles ($r \geqslant 1$). An incremental step of 0·05 per cent was used in the curve-fitting analysis for variables A and B, and a step of 0·005 was used for variables α and β. The fitting accuracy of both models was assessed by computing the normalised root-mean-square error (NRMSE) in percent between $f(r)$ and the experimental values of the mean normalised indexes of variability NIVAR(r) by using,

$$\text{NRMSE} = 100 \times \frac{[\sum_{r=1}^{20} (\text{NIVAR}(r) - f(r))^2]^{1/2}}{[\sum_{r=1}^{20} \text{NIVAR}(r)^2]^{1/2}} \tag{8}$$

The cross-correlation coefficient corresponding to the best fit was also evaluated. After having estimated the parameters of eqns. 6 and 7, A was set to zero and B was adjusted to obtain a maximum amplitude of 100 for $r = 1$.

4.6 *Evaluation of the beat-to-beat variations in the amplitude of Doppler spectrograms*

Beat-to-beat variations in the amplitude of Doppler spectrograms were evaluated for each patient by using the statistical coefficient of variation CV. The time-frequency distribution of CV was estimated by computing the following equation:

$$\text{CV}[S_{xx}(t_i, f_k)] = 100 \times \sigma[S_{xx}(t_i, f_k)]/\mu[S_{xx}(t_i, f_k)] \tag{9}$$

where σ represents the standard deviation and μ the mean spectrograms of 20 cardiac cycles. When comparing eqn. 9 with eqn. 3, it can be seen that the coefficient of variation represents an approximation of the normalised standard deviation of the estimate. Fig. 4 shows the time-frequency distribution of the coefficients of variation CV$[S_{xx}(t_i, f_k)]$ of the spectrogram depicted in Fig. 2.

Average values of this function were computed in systole and in diastole over frequencies f_k ranging between 500 Hz and $PRF/2$. Only the negative frequencies of the spectrograms were used in systole and only the positive frequencies in diastole. To take into account possible effects of frequency on values of averaged time-frequency distribution of the coefficients of variation, the spectrograms were subdivided in two portions, one between 500 Hz and $PRF/4$, and another between $PRF/4$ and $PRF/2$. This evaluation was performed to verify if the normalised standard deviation was constant over frequency as predicted by eqn. 3.

4.7 *Statistical analyses*

Results concerning amplitude variability of Doppler spectrograms were analysed with a four-way analysis of variance (ANOVA) with repeated measurement on two factors. The four variables were the presence or absence of aortic valve stenosis, the severity of possible aortic valve regurgitation on a three-degree scale (no regurgitation, minimal-to-mild, and moderate-to-severe), the selection of sequential or random averaging, and the number of cardiac cycles averaged (1 to 20). The repeated measurements were performed on the type of averaging scheme used (sequential or random) and the number of cardiac cycles.

A three-way ANOVA with repeated measurement on one factor (frequency range considered, i.e. between 500 Hz and PRF/4 or between $PRF/4$ and $PRF/2$) was used to characterise beat-to-beat variations in the amplitude of Doppler spectrograms. The two independent variables considered in this specific analysis were the presence or absence of aortic valve stenosis, and the severity of possible aortic regurgitation on a three-degree scale.

5 Results

According to the haemodynamic investigations of the 15 patients with a stenotic aortic valve, the averaged maximum and mean pressure gradients were 107 ± 22 mm Hg (mean ± standard deviation, range 76–150 mm Hg) and 78 ± 18 mm Hg (range 59–120 mm Hg), respectively. Concomitant aortic regurgitation was found in 13 patients. Six had minimal, one mild, four moderate and two severe aortic insufficiency. The mean age of patients with a normal aortic valve was 55 ± 12 years (range 32–76 years) whereas that of patients with a stenotic valve was 64 ± 13 years (range 35–81 years).

5.1 *Amplitude variability of Doppler spectrograms*

Fig. 5 shows an example of two Doppler spectra located at peak systole and computed for 1 and 20 cardiac cycles.

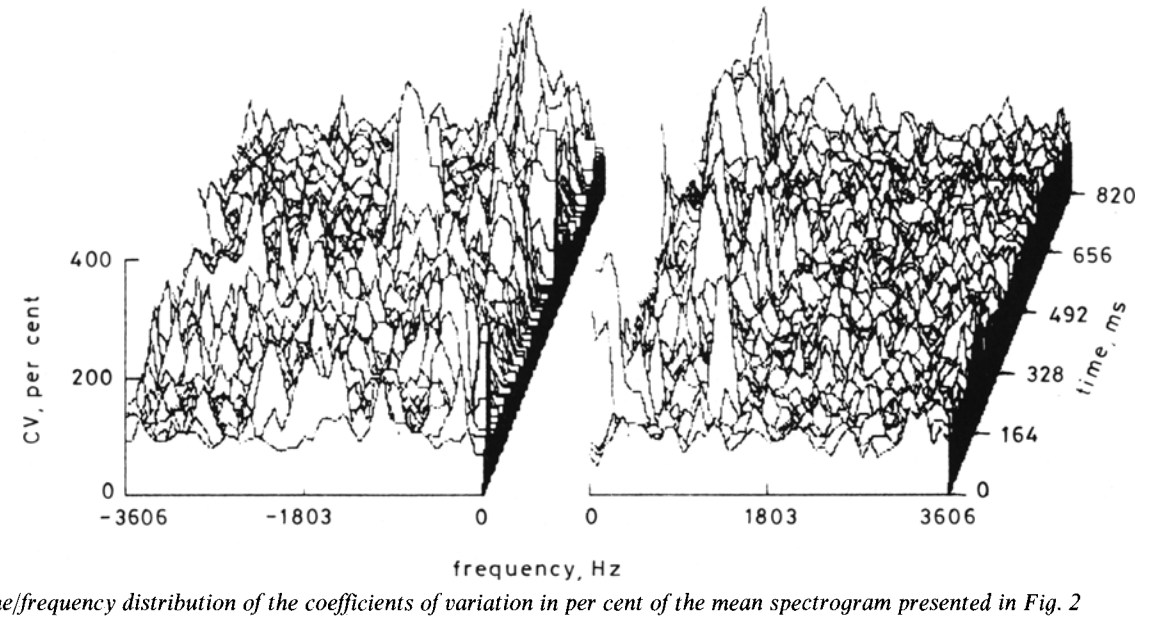

Fig. 4 *Time/frequency distribution of the coefficients of variation in per cent of the mean spectrogram presented in Fig. 2*

As seen, the variability is reduced significantly after averaging. A similar observation can be done by comparing Figs. 1 and 2.

Analyses of variance used to determine the influence of four variables on the value of the normalised indexes of variability provided the following results in systole: all

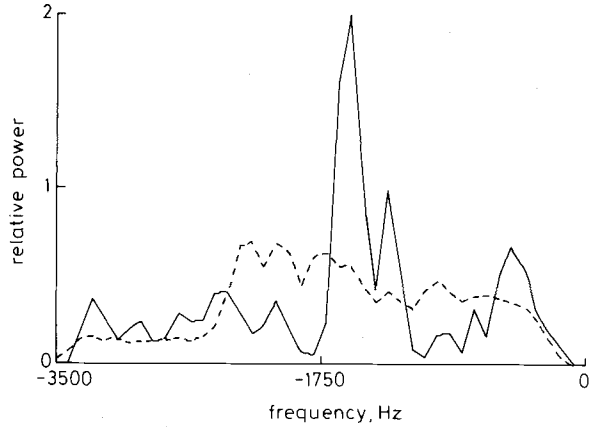

Fig. 5 *Example of Doppler spectra located at peak systole. The full line corresponds to the spectrum of the first cardiac cycle and the broken line corresponds to the mean spectrum averaged over 20 cardiac cycles*

multiple interactions between the presence of aortic valve stenosis, aortic valve regurgitation, sequential or random averaging and the number of cardiac cycles were not significant. In diastole, a significant effect was measured between sequential and random selections of the cycles, the presence of aortic valve stenosis and the number of cardiac cycles averaged ($p = 0{\cdot}02$). No other multiple effect was found.

Based on these statistical analyses, normalised indexes of variability obtained during systole were pooled for the 30 patients and the mean curve presented only for sequential averaging. The results are shown in the top panel of Fig. 6. As seen on this figure, the mean normalised indexes of

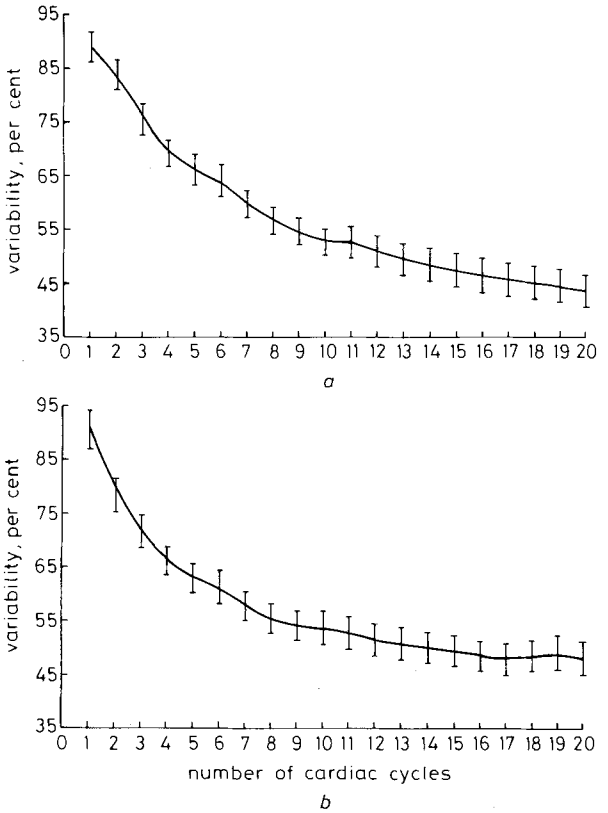

Fig. 6 *Normalised mean indexes of variability (in per cent) of mean Doppler spectrograms in (a) systole and (b) diastole. The error associated with the measurement is the standard error of the mean*

variability decrease exponentially as the number of cardiac cycles increases. Although an interaction was measured in diastole, data were also pooled for the 30 patients and presented only for sequential averaging. The results depicted in the bottom panel of Fig. 6 show an exponentially decreasing curve similar to that obtained for the systolic period.

5.2 *Corrected values of the indexes of variability*

Both theoretical models described in eqns. 6 and 7 were fitted to the experimental data of the systolic and diastolic periods. The best results were obtained with the model of eqn. 7. In systole, the minimum NRMSE was 1·33 per cent (cross-correlation = 99·3 per cent) and was associated to the following optimal parameters: $A = 42{\cdot}55$ per cent, $B = 46{\cdot}70$ per cent and $\beta = 0{\cdot}165$. In diastole, the minimum NRMSE was 1·56 per cent (cross-correlation = 99·4 per cent) and was obtained by using $A = 48{\cdot}60$ per cent, $B = 40{\cdot}35$ per cent and $\beta = 0{\cdot}255$.

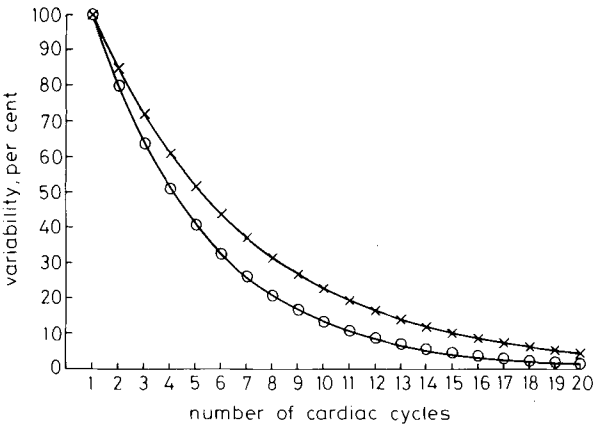

Fig. 7 *Corrected mean normalised indexes of variability (in per cent) in systole (×) and in diastole (○)*

Corrected values of the mean normalised indexes of variability were obtained by using the following equation:

$$f(r) = 100e^{-\beta(r-1)} \text{ for } r \geqslant 1 \quad (10)$$

The results are shown in Fig. 7. As seen, the decrease in variability of Doppler spectrograms converges rapidly to zero for both systolic and diastolic periods. Values of the corrected mean normalised indexes of variability are lower in systole compared with diastole for all numbers of cardiac cycles averaged. Reductions in amplitude variability for a number of cardiac cycles equal to 5, 10, 15 and 20 were, respectively, 48, 77, 90 and 96 per cent in systole. In diastole, reductions of amplitude variability were 59, 87, 96 and 99 per cent for a number of cardiac cycles of 5, 10, 15 and 20, respectively.

5.3 *Beat-to-beat variations in the amplitude of Doppler spectrograms*

Results of the analysis of variance showed that the presence of aortic valve stenosis and regurgitation had no significant effect on the coefficient of variation in systole. However, the coefficients of variation computed between 500 Hz and $PRF/4$, and between $PRF/4$ and $PRF/2$, showed significant differences ($p = 0{\cdot}0001$). Pooled results from the 30 patients are presented in Table 1. In diastole, the presence of aortic regurgitation ($p = 0{\cdot}037$) and the selection of the frequency band ($p < 0{\cdot}0001$) influenced values of the coefficient of variation. Results are presented in Table 2.

As seen in Tables 1 and 2, the mean values of the coefficient of variation are higher in the frequency band ranging

Table 1 Coefficients of variation in systole. SD represents the standard deviation and N the number of patients

Frequencies	Mean, per cent	SD, per cent	N
500 Hz–*PRF*/4	137·7	22·7	30
PRF/4–*PRF*/2	122·0	26·4	30

Table 2 Coefficients of variation in diastole. SD represents the standard deviation and N the number of patients

Frequencies	Mean, per cent	SD, per cent	N
No regurgitation			
500 Hz–*PRF*/4	114·0	15·4	17
PRF/4–*PRF*/2	98·9	3·2	17
Minimal-to-mild regurgitation			
500 Hz–*PRF*/4	123·0	11·4	7
PRF/4–*PRF*/2	105·9	14·5	7
Moderate-to-severe regurgitation			
500 Hz–*PRF*/4	126·6	16·0	6
PRF/4–*PRF*/2	109·3	11·2	6

between 500 Hz and *PRF*/4. In diastole, the magnitude of the averaged CV increases for both frequency bands with the severity of aortic regurgitation. The higher mean value (137·7 per cent) was found in systole in the frequency range 500 Hz–*PRF*/4. The lower mean value (98·9 per cent) was found in diastole for frequencies ranging between *PRF*/4 and *PRF*/2 for patients with no aortic regurgitation.

6 Discussion

Although most investigators used spectrogram averaging to reduce the variability of the time-frequency representation of the Doppler signal, this technique is not optimal. Problems with this approach are possible timing artefacts and variability in the duration of the cardiac cycle from beat-to-beat. By using an efficient QRS detection algorithm, timing artefacts can be reduced significantly. However, variability in the duration of the cardiac cycles represents a more complicated problem. This variability can distort the time-frequency representation of mean spectrograms because averaging is usually realised over a duration corresponding to the shortest of a series of preselected cardiac cycles. Because variations in the duration of cardiac cycles are mostly observed in end diastole, possible distortion of the mean spectrogram is more important over this interval. Although this problem may encourage some investigators to consider other smoothing methods, the technique consisting in rejecting cardiac cycles having a duration differing by more than 10 per cent of the mean R-R interval is interesting and must be considered. For instance, we think that the information lost in end-diastole is minimal and can be neglected.

As reported previously, RITTGERS *et al.* (1983) smoothed carotid artery Doppler spectrograms by using a five-coefficient frequency filter. The filter was applied to each spectrum and no beat-to-beat averaging was performed. Although this technique eliminates timing artefact and artefacts associated with the variability of the end-diastolic period, it limits the performance of the estimator because this approach does not take into account the beat-to-beat varying properties of Doppler spectrograms. A combined technique discussed in BENDAT and PIERSOL (1971, p. 329) may be used to take advantage of both time and frequency averaging. With this technique, spectrograms may be averaged over some cardiac cycles to reduce amplitude variability and to consider beat-to-beat variations of the signal. Residual variance of the estimate may be reduced further by using a frequency filter. Because fewer cardiac cycles may be used with this combined technique, the selection of cardiac cycles may be made by minimising R-R interval variations. For stationary ergodic Gaussian random signals, it was shown (BENDAT and PIERSOL, 1971) that the standard deviation of the estimate is reduced by $\sqrt{(RL)}$ with this combined approach, where R is the number of cardiac cycles and L is the number of samples used in the frequency filter. Other techniques based on digital image processing may also be used to reduce amplitude variability of Doppler spectrograms (HOSKINS *et al.*, 1990).

6.1 *Amplitude variability of Doppler spectrograms*

It was found in the present study that the reduction of the amplitude variability of Doppler signals followed an exponentially decreasing curve characterised by the equation $f(r) = 100\ e^{-\beta(r-1)}$, where $\beta = 0{\cdot}165$ in systole and 0·255 in diastole. This finding is interesting because it signifies that, above 20 cardiac cycles, the variability of the spectrogram computed with the FFT and a Hanning window of 10 ms may not be reduced by more than 4 per cent in systole and by more than 1 per cent in diastole. This rapidly decreasing rate of the amplitude variability could be attributed to the fact that cardiac Doppler signals might not be pure random signals. A significant deterministic component might certainly be present from beat-to-beat. The deterministic component could be related to the fact that the global distribution of red blood cell velocity is somewhat regular and predictable from one beat to the next.

From the results presented in Fig. 7, it can be seen that fewer cardiac cycles are needed in diastole to reduce amplitude variability to a given amount. The reason for this could be associated with the fact that beat-to-beat variations in the amplitude of Doppler spectrograms were lower in diastole compared with systole as shown in Tables 1 and 2.

There was some variability in the consistency of the tracking of Doppler signals by the physician because the normalised indexes of variability shown in Fig. 6 for one cardiac cycle were not 100 per cent for all patients. However, this variability was probably negligible because the analysis of variance showed that sequential or random selection of the cardiac cycles had no significant effect on the values of the indexes of variability. This result then suggests that tracking of Doppler signals was relatively constant throughout the duration of the clinical examination. In other words, this means that possible tremor and artefactual movements of the probe during clinical examinations were not significant.

6.2 *Practical considerations concerning the selection of the index of variability*

Because the statistical property of the normalised standard deviation presented in eqn. 3 is well known for Gaussian random signals, the characterisation of the amplitude variability of Doppler spectrograms with this index would have been preferable. However, this approach may be difficult to evaluate in practical situations. Indeed, to have a precise estimate of the normalised standard deviations for various numbers of cardiac cycles, a huge amount of data may be needed. An alternative to the computation of the normalised standard deviation has then been proposed in the present study. The main advantage associated with the computation of this index is that it can be evaluated accurately from each mean spectrogram.

6.3 *Beat-to-beat variations in the amplitude of Doppler spectrograms*

Theoretically, as discussed in BENDAT and PIERSOL (1986, p. 398), the coefficient of variation of spectra of stationary ergodic Gaussian random signals windowed by a Hanning function should be near 141 per cent ($\sqrt{2}$) for uniform spectra. In our experiment, this value should be addressed with care because Doppler signals had non-uniform spectra. In practice, different factors may influence the value of the coefficient of variation (e.g. the random nature of the signal, the temporal window used, the lag between each window, the kind of spectral estimator). As a guideline for interpreting the significance of the coefficient of variation, a small value indicates a smooth spectral estimate whereas a much greater value indicates a very noisy spectrogram with large fluctuations (MARPLE, 1987).

In our experiment, mean coefficients of variation ranged between 98·9 and 137·7 per cent (see Tables 1 and 2). Higher values were found in the frequency range of 500 Hz–$PRF/4$ for both systolic and diastolic periods. In diastole, coefficients of variation increased in the presence of aortic valve regurgitation. Based on previous discussions, these differences should be attributed to an increase in the random property of Doppler signals because the same spectral algorithm was used for all measurements (Welch method using a Hanning window and a time overlap of 5 ms). The observation of a frequency dependence of the coefficient of variation may be surprising considering eqn. 3. However, this could be explained by the fact that frequency components located in the higher portion of the spectrograms (see Figs. 1 and 2) were mainly associated with the background noise of the duplex echo-Doppler system in which statistical characteristics were different from those of Doppler blood flow signals.

7 Summary and conclusions

Variability and beat-to-beat variation in the amplitude of Doppler spectrograms were characterised in a group of 30 patients. It was shown, for both systolic and diastolic portions of the spectrograms, that reduction of the amplitude variability followed an exponentially decreasing curve characterised by the equation $f(r) = 100\ e^{-\beta(r-1)}$, where r is the number of cardiac cycles and β the exponentially decreasing rate. The value of β in systole was 0·165 and in diastole 0·225. Results on beat-to-beat variations of Doppler spectrograms showed higher variability in systole compared with diastole. Moreover, higher variability was measured in the frequency range 500 Hz–$PRF/4$.

The reduction of the amplitude variability of Doppler spectrograms is very important in clinical applications. As seen in Figs. 1 and 5, large random amplitude variations are present on the Doppler spectra when no averaging is performed. These amplitude fluctuations may greatly affect the reliability of diagnostic features extracted from the spectrum. Consequently, when using those parameters to discriminate patients having different categories of disease, lower diagnostic performance may be expected if no averaging is performed. An important question associated with this observation is to find the number of cardiac cycles to be averaged to eliminate these random amplitude variations. Based on the results showed previously, it can be concluded that no significant improvement in the reduction of amplitude variability is obtained by averaging more than 20 cardiac cycles.

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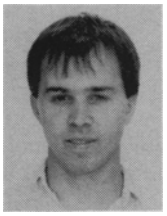
Authors' biographies



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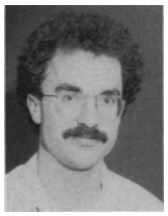

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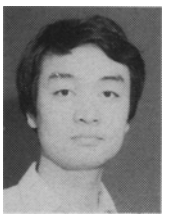

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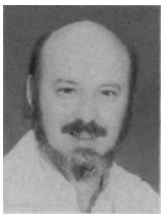

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