Computing and data processing

Automatic detection of sounds and murmurs in patients with Ionescu-Shiley aortic bioprostheses

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Abstract—*The problems encountered in the automatic detection of cardiac sounds and murmurs are numerous. The phonocardiogram (PCG) is a complex signal produced by deterministic events such as the opening and closing of the heart valves, and by random phenomena such as blood-flow turbulence. In addition, background noise and the dependence of the PCG on the recording sites render automatic detection a difficult task. In the paper we present an iterative automatic detection algorithm based on the a priori knowledge of spectral and temporal characteristics of the first and second heart sounds, the valve opening clicks, and the systolic and diastolic murmurs. The algorithm uses estimates of the PCG envelope and noise level to identify iteratively the position and duration of the significant acoustic events contained in the PCG. The results indicate that it is particularly effective in detecting the second heart sound and the aortic component of the second heart sound in patients with Ionescu-Shiley aortic valve bioprostheses. It has also some potential for the detection of the first heart sound, the systolic murmur and the diastolic murmur.*

Keywords—*Bioprosthetic heart valves, Heart sound detection, Parameter extraction, Phonocardiography, Spectral analysis*

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List of symbols

AOC	aortic opening click
A2	aortic component of the second heart sound
BW_{30}	bandwidth at -30 dB
C	threshold parameter
CP	control population
DA2	duration of A2
DM	diastolic murmur
ECG	electrocardiogram
F_c	crossover frequency: frequency of minimum absolute difference found between two spectra
F_1	dominant frequency peak
F_2	second dominant frequency peak
K	Kappa statistic
P_c	chance agreement
PCG	phonocardiogram
P_{ij}	probability for rejecting the hypothesis that the mean values in the parameters estimated by i and by j are equal
P_0	observed agreement
P2	pulmonary component of the second heart sound
QRS	complex wave of the ECG
SM	systolic murmur
S1	first heart sound
S2	second heart sound
T_i	threshold level of the ith iteration
TP	test population

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1 Introduction

Considerable research efforts have been devoted in recent years to find in the phonocardiogram (PCG) diagnostic parameters which could reveal abnormal functioning aspects of implanted prosthetic heart valves. Certain spectral and temporal parameters have been shown to be potentially useful by Stein *et al.* (1980; 1981; 1984), Joo *et al.* (1983), Johnson *et al.* (1983), Beyar *et al.* (1984) and Durand *et al.* (1988). However, these parameters are highly variable, not only because the PCG differs morphologically from patient to patient, but also because the PCG analysis criteria can vary from physician to physician. Reliable automatic detection and identification of cardiac sounds and murmurs would certainly help to provide a more objective analysis and reduce this variability. In addition, automatic analysis by a digital computer could be faster and less costly than the analysis by the physician.

In this paper, we propose an iterative automatic detection algorithm for this purpose. This algorithm uses information on the PCG envelopes and background noise, as well as *a priori* knowledge of spectral and temporal characteristics of the cardiac sounds, clicks and murmurs. Special attention has been given to detecting the aortic component A2 of the second heart sound.

2 Automatic detection of sounds, clicks and murmurs

The phonocardiogram is subdivided into five intervals associated with the following acoustic events: the first heart sound S1, aortic opening click AOC, systolic murmur SM, second heart sound S2 and diastolic murmur DM. These intervals, as described in Table 1, are selected from bibliographic information to reduce the complexity of the problem (ALTMAN and DITTMER, 1971).

The envelope of the PCG for each cardiac cycle is estimated by the following two methods:

(*a*) Hilbert transform (OPPENHEIM and SCHAFER, 1975): the negative frequency terms of the discrete Fourier transform of each digitised PCG cycle are set to zero, and the remaining terms, except the DC value and the highest frequency term, are multiplied by 2. The resulting data is bandpassed from 20 to 500 Hz and the inverse discrete Fourier transform is computed. The magnitude of the resulting function so obtained is used as an estimate of the envelope of the PCG.

(*b*) Ideal rectification: The absolute value of each PCG cycle is smoothed by a low-pass filter with the following weighting function (-3 dB frequency about 250 Hz).

$$h(n) = \begin{cases} 1/3 \text{ for } n = 0 \\ 2/9 \text{ for } n = 1, -1 \\ 1/9 \text{ for } n = 2, -2 \\ 0 \text{ otherwise} \end{cases} \qquad (1)$$

Table 1 Location of cardiac sound and murmur intervals (time t = 0 at the R-wave of the ECG)

Interval	Beginning, ms	End, ms
S1	−25	75
AOC	75	125
SM	125	300
S2	300	480
DM	480	25 ms before the next peak of the QRS

For both methods, the envelopes of 14–22 cycles are averaged to produce a characteristic PCG envelope for each patient. Fig. 1 shows an example of such an envelope estimated by using the Hilbert transform method. Note the high correlation of the peaks of the envelope with the acoustic events.

In our algorithm, we associate the significant peaks of the envelope with the acoustic events. Thus, these peaks are the desired signal, and the points outside the yet-to-be-defined boundaries of these peaks are due to noise. As a first step to find the significant peaks, a pre-specified limiting number (four in our experiments) of the highest peaks of the smoothed characteristic envelope are identified initially in each of the intervals described in Table 1. The peaks are then validated iteratively by using the adaptive threshold

$$T_i = X_i + CS_i \qquad (2)$$

where C is a constant and X_i and S_i are, respectively, the mean and the standard deviation of the magnitude of the envelope outside the boundaries of the detected peaks in each interval under consideration in the ith iteration. In the first iteration, the boundaries of a peak are defined by the first minimum on each side of the peak. In all subsequent iterations they are given by the points of the envelope which equal the mean value X_i. In each iteration, all peaks above the threshold are accepted; but when a peak becomes lower than X_i, it will be considered as noise in the computation of a new threshold for the next iteration. The iterative process continues until the variation of the threshold from one iteration to the next becomes negligible (e.g. less than 4 per cent). The remaining peaks in each of the intervals described in Table 1 are assumed to indicate the position of the corresponding acoustic event, and the duration of the event is bounded by the two outermost boundary points of the peaks in the interval.

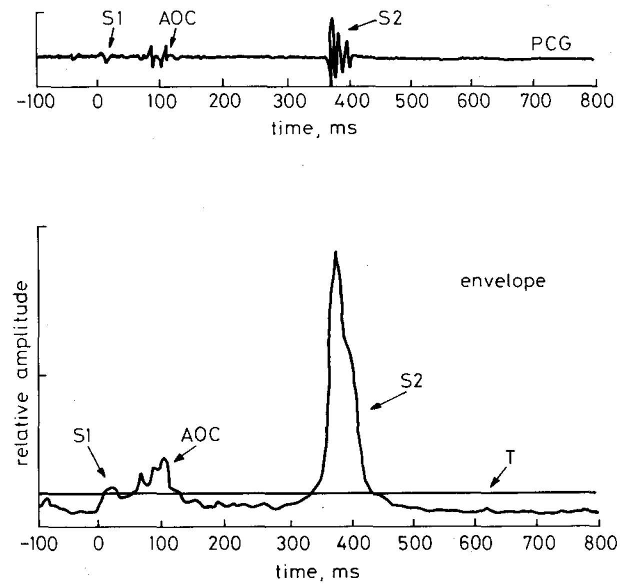

Fig. 1 *Envelope of the PCG of a patient produced by using the Hilbert transform method (T is the threshold value of the final iteration)*

The choice of the value for the parameter C depends on the variance of the noise in the envelope. By the Chebyshev inequality (MAISEL, 1971), the probability of noisy data above the mean X_i is less than $1/C^2$. For our experiments, the value of C was determined empirically by using data from a control population (CP) of 15 patients.

The iterative process can be shown to converge heuristically. From eqn. 2, we have

$$T_{i+1} - T_i = X_{i+1} - X_i + C(S_{i+1} - S_i) \qquad (3)$$

Convergence will be assured if both $|X_{i+1} - X_i|$ and $|S_{i+1} - S_i|$ approach zero as i increases. In every iteration, if a boundary point of a peak is below X_i, its new position will be closer to the maximum of the peak, thus increasing the number of points outside the boundaries. Therefore, with an appropriate value of C, X_i and S_i will approach their expected values as i increases such that both $|X_{i+1} - X_i|$ and $|S_{i+1} - S_i|$ approach zero. In our experiments the convergence is very rapid, in four or less iterations for all cases.

3 Automatic detection of the aortic component of the second heart sound

As our experimental results will show later, our algorithm consistently provides a good estimate of the position and duration of S2. We take advantage of this to include in the algorithm the automatic detection of the aortic component A2. Because the splitting between A2 and the pulmonary component P2 of S2 varies with respiration (SHAVER *et al.*, 1985) and because the dominant frequencies of A2 and P2 are generally different, these observations are used to determine the precise position and duration of the A2 component. The following assumptions are made:

(*a*) Because the recordings were made in the aortic position, it is very likely that the largest amplitude component of S2 is the aortic closing sound.
(*b*) If the splitting is normal, A2 is the first event of S2.
(*c*) The duration of A2 is at least 16 ms.
(*d*) There is a strong correlation of A2 among the consecutive cardiac cycles of a given patient.
(*e*) The data analysed does not contain PCGs from patients with paradoxical splitting of S2 (i.e. with P2 preceeding A2).

The first step of the algorithm is to compute a coherent ensemble average of the A2 components. Coherence is established by aligning the maxima of the correlation functions between a reference template and a number of successive cycles of PCG. The reference template is a segment of data where the A2 component of a typical cycle is expected to lie, i.e. starting 4 ms before the first peak of the S2 envelope and ending 12 ms after it. The ensemble average is computed for PCG segments of 150 ms duration, each beginning at 75 ms before the maximum of the correlation functions.

To separate A2 from the P2 component, the ensemble average is weighted by the two 40 ms windows shown in Fig. 2: one to the right of the maximum point of correlation (right-side window) and the other to the left (left-side window). The lengths of the windows are chosen to allow for the jitter and the variability in the duration of S2. Each window is an asymmetric sine-cosine window having a 20 ms decay on one side and 2 ms decay on the other side to reduce both the unwanted data outside S2 and the aliasing spectra due to truncation in separating A2 and P2. The crossover point between the two windows is positioned at the maximum point of correlation. The Fourier spectra of the weighted components are then used to determine the dominant frequencies of A2 and P2. The dominant frequency of S2 weighted by the left-side window is associated with A2, while that of the right-side window is associated with P2 (Fig. 3).

In addition, the algorithm incorporates the following criteria: if the energy of A2 is more than 20 times the energy of P2, then P2 is considered negligible. If the difference between the dominant frequencies of A2 and P2 is greater or equal to 30 Hz, P2 is considered detectable. If not, P2 is assumed negligible and S2 consists only of A2. This difference of 30 Hz is within the frequency resolution of the windowed spectra. More importantly, we were able to obtain an estimate of the upper bound for this frequency difference from an analysis performed on a population of 14 patients with Ionescu-Shiley bioprostheses implanted in the aortic position. For each patient, P2 was manually extracted and the mean dominant frequency F_1 of the 14 patients was found to be 62 Hz. Using the same technique with a Hanning window and the same patient database, BRAIS *et al.* (1986) showed that F_1 of A2 is 116 Hz. Thus, an average difference of 54 Hz can be observed between F_1 of A2 and F_1 of P2. Because these are average values, we have concluded that a threshold of 30 Hz would ensure the separability of most of F_1 of A2 from F_1 of P2.

When the two dominant frequencies associated with A2 and P2 are ascertained, the crossover point F_c in Fig. 3 between the two spectra will be determined. Then, the frequency bond of the ensemble average above F_c is used to compute an estimate of A2. The position and duration of A2 are determined by the portion of the envelope of this estimate above a threshold level. Fig. 4 shows an example of the envelope of A2 and the corresponding coherent average.

4 Materials and methods

4.1 *Patient population and data recording*

A group of 30 patients with normally functioning Ionescu-Shiley bioprostheses implanted in the aortic position for 31 ± 17 months was studied. The mean valve size was 23 ± 2 mm with a range 19–25 mm. For each patient, the ECG and the PCG were recorded simultaneously with an FM multichannel recorder (Racal Store 4). A contact microphone was placed in the second right intercostal space to record the PCG. Each patient was maintained in the supine position in a quiet environment. The microphone used was the HP 21050A, which has a flat frequency

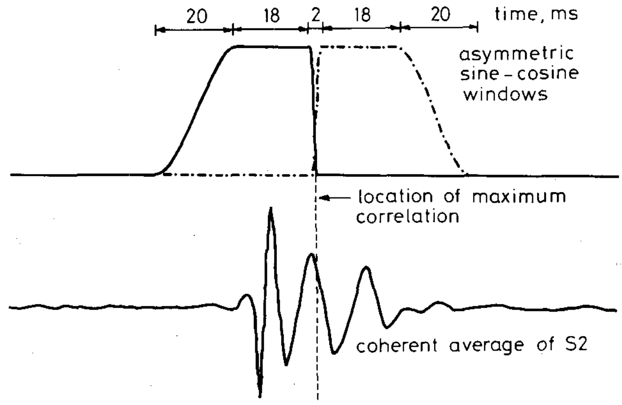

Fig. 2 *Asymmetric sine-cosine weighting windows used in the calculation of the spectrum of A2 (solid line) and that of P2 (dash-dot line). The amplitudes of both windows are unity*

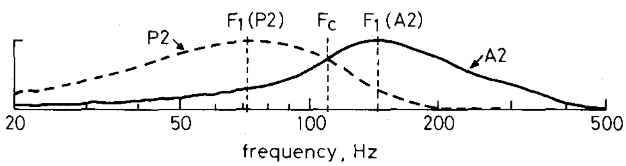

Fig. 3 *Illustrating the frequency of minimum absolute difference (F_C) found between the spectra of A2 and P2*

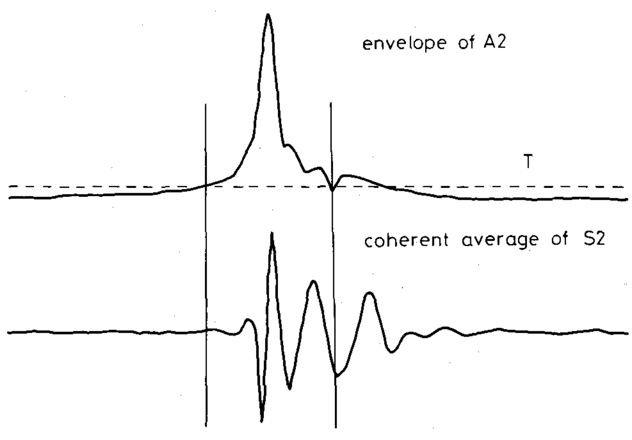

Fig. 4 *Envelope of A2 and coherent average of S2*

response (−3 dB) from 0·2 Hz to 2000 Hz. Before recording, each PCG was filtered by a third-order high-pass filter (18 dB per octave) with a cutoff frequency of 100 Hz to emphasise the spectral content of the high-frequency sounds and murmurs.

For analysis by our proposed algorithm, the ECG and PCG were digitised by a 12-bit A/D convertor at a sampling rate of 500 Hz and 2500 Hz, respectively. Each PCG was low-pass filtered by an eighth-order filter (−48 dB per octave) with a cutoff frequency of 900 Hz to prevent aliasing.

4.2 *Methods for evaluation*

4.2.1 *Sounds, clicks and murmurs:* The performance of the automatic algorithm was evaluated for the detection of sounds, clicks, and murmurs by comparing its result with the decision of a specialist on the presence or absence of S1, AOC, SM, S2 and DM in the phonocardiogram. The specialist had no prior knowledge of the results from the automatic analysis, and his decision was based solely on the visual analysis of five PCG cycles of each patient. No comparison was made with auditory detection (auscultation).

The threshold parameter C of the automatic algorithm was set empirically by using the PCGs of 15 of the patients (control population). Different values of C were used in the algorithm to detect acoustic event in the PCGs of the control population. From these results the 'optimal' value C_0 of the parameter C, which yields the 'best' agreement with the specialist, was then used in the algorithm to analyse the data from the remaining 15 patients (test population).

For a quantitative indication of the degree of agreement between the visual and the automatic methods, we used the Kappa statistic, which was proposed by Cohen as a measure of agreement for categorical data allowing correction for chance agreement (COHEN, 1960; 1968). The Kappa statistic is computed by:

$$\mathrm{K} = (P_0 - P_c)/(1 - P_c) \tag{4}$$

where P_0 is the observed agreement and P_c is the agreement that would occur based on chance alone. The observed agreement is given by the proportion of cases in which the specialist and the algorithm agree. Chance agreement is given as the sum of the product of the marginal agreement and disagreement between the specialist and the algorithm. The quantity $(1 - P_c)$ is a measure of the degree of agreement attainable over and above what would be predicted by chance alone. The degree of agreement attained in excess of chance is $(P_o - P_c)$.

The assumptions underlying eqn. 4 are:

(*a*) The PCGs are independent from one patient to another.
(*b*) The categories of the nominal scale are independent, mutually exclusive and exhaustive.
(*c*) The raters operate independently.

According to eqn. 4, the Kappa statistic K is zero when the observed agreement P_0 equals the chance agreement P_c. A perfect agreement (i.e. when $P_0 = 1$ and $P_c = 0$) gives a maximum value of +1, whereas less than chance agreement leads to negative values. One limitation of the Kappa statistic arises when both raters place all their samples in the same category. In this case P_c and P_0 are both equal to 1, and, according to eqn. 4, the value of K is indeterminate. When this case occurs, we assume that a perfect agreement was obtained even if K cannot be calculated.

4.2.2 *A2 and related parameters:* The performance of the automatic algorithm for detecting the aortic component A2 of the second heart sound S2 was compared with that of two specialists who used a computer-based interactive procedure developed by our group (DURAND *et al.*, 1986; BRAIS *et al.*, 1986; CLOUTIER *et al.*, 1987*a*). The comparison was made by means of a t-test for matched pairs applied to four parameters extracted from the A2 components detected by each specialist and the algorithm. The parameters were the duration of A2 (DA2), the dominant frequency F_1, the second dominant frequency F_2 and the −30 dB bandwidth of the spectrum BW30. The objective was to demonstrate whether the variability between the parameters extracted by the automatic method and by each specialist would be smaller than that observed between the two specialists.

The parameter F_1 was used as a diagnostic tool by STEIN *et al.* (1981; 1984). FOALE *et al.* (1983) and JOO *et al.* (1983) also proposed the utilisation of F_1 and F_2 extracted from the spectra of parametric algorithms. In a recent study, CLOUTIER *et al.* (1987*b*) evaluated the accuracy of F_1, F_2 and BW30 extracted from the spectra computed by using eight different algorithms. The best results were obtained by using the fast Fourier transform with rectangular window to estimate F_1 and the pole-zero Steiglitz-McBride method to evaluate F_2 and BW30. In the present study, these spectral techniques were used to estimate the A2 spectrum and to extract the three spectral diagnostic parameters.

5 Results

Table 2 summarises the results obtained for the automatic detection of sounds, clicks and murmurs by using envelopes determined with the Hilbert transform (*a*) and with the ideal rectification method (*b*). For each acoustic event, the observed agreement P_0 between the algorithm and a specialist, and the corresponding Kappa statistic K are listed for different values of the threshold parameter C.

The Kappa statistic K is positive in all cases for S1, implying an agreement greater than chance. The best agreement was obtained when $C = 1·0$ using envelopes estimated by the ideal rectification method (i.e. $P_0 = 0·867$ and $\mathrm{K} = 0·668$ for the control population and $P_0 = 0·733$ and $\mathrm{K} = 0·499$ for the test population).

The automatic algorithm yielded an inferior agreement for the detection of AOC ($\mathrm{K} \leqslant 0·411$). The results show substantial variations in K for the control population when C was varied between 1·0 and 4·0. In any case, the best results were obtained by using envelopes from the Hilbert transform method with $C = 2·0$ (i.e. $P_0 = 0·773$ and $K = 0·411$ for the control population and $P_0 = 0·733$ and $K = 0·00$ for the test population).

For the detection of SM, the algorithm generally produced better results by using envelopes from the ideal rectification method. Although the best value of K is low for the control population (i.e. $C = 3·0$, $\mathrm{K} = 0·286$, $P_0 = 0·600$), it is greater than chance. The good agreement found for the test population with $C = 3·0$ (i.e. $\mathrm{K} = 0·594$ and $P_0 = 0·800$) emphasises the strength of the method for this particular component.

For the automatic detection of S2, the agreement between the visual method and the algorithm was perfect when C was varied from 1·0 to 4·0. As noted in the previous section, because all samples were placed in the same category, P_c and P_0 were equal to 1 and K was indeterminate.

For the detection of DM, the algorithm yielded the best results by using envelopes obtained from the Hilbert trans-

Table 2 Agreement between the algorithm and a specialist for the detection of S1, AOC, SM, S2, and DM

(a) Envelopes estimated by using the Hilbert transform

	S1		AOC		SM		S2		DM		
C	P_0	K	P_0	K	P_0	K	P_0	K	P_0	K	Data
1·0	**0·867**	**0·584**	0·733	0·375	**0·667**	**0·075**	1·00	*	0·733	−0·113	
2·0	0·733	0·444	**0·733**	**0·411**	0·600	0·00	**1·00**	*	**0·867**	**0·446**	
2·5	0·733	0·444	0·733	0·411	0·600	0·00	1·00	*	0·867	−0·073	CP
3·0	0·733	0·444	0·667	0·287	0·600	0·00	1·00	*	0·933	0·00	
4·0	0·600	0·286	0·533	0·053	0·467	0·048	1·00	*	0·933	0·00	
C_0	0·667	0·391	0·733	0·00	0·733	0·375	1·00	*	0·933	0·00	TP

(b) Envelopes estimated by using ideal rectification

C	P_0	K	P_0	K	P_0	K	P_0	K	P_0	K	Data
1·0	**0·867**	**0·668**	0·667	0·194	0·667	0·075	1·00	*	0·800	−0·099	
2·0	0·600	0·286	**0·733**	**0·411**	0·600	0·167	1·00	*	0·876	−0·073	
2·5	0·600	0·286	0·667	0·325	0·600	0·167	1·00	*	0·933	0·00	CP
3.0	0·600	0·286	0·600	0·211	**0·600**	**0·286**	**1·00**	*	**0·933**	**0·00**	
4·0	0·467	0·167	0·667	0·391	0·333	0·074	1·00	*	0·933	0·00	
C_0	0·733	0·499	0·636	−0·106	0·800	0·594	1·00	*	1·00	*	TP

C is a threshold parameter; P_0 is the observed agreement between the algorithm and the specialist; and K is the corresponding Kappa statistic. (*) denotes an indeterminate value of K due to a perfect agreement between the algorithm and the specialist. C_0 is the value of C tested, which yields the highest value (in bold type) of K for the control population (CP) of 15 patients. TP is the test population (15 patients).

form method with $C = 2{\cdot}0$ for the control population. However, it produced a perfect agreement with $C = 3{\cdot}0$ for the test population when the envelopes were estimated with the ideal rectification method. It should be pointed out that P_c was high in the control population such that in spite of the high P_0 (0·933), K was low (0·00).

It is interesting to note that lower values of C tend to produce better results for detecting events that generally present low intensity in recordings at the aortic position (S1, AOC and DM). However, for events presenting higher intensity, such as SM and S2, higher values of C seem better.

Table 3 shows the results of comparing the estimates of the spectral and temporal parameters of the aortic component A2 obtained by the algorithm and two specialists. For each parameter the value of C shown in the table is the best of four values (1·0, 1·5, 2·0 and 2·5) used in our study. P_{a1} denotes the probability for rejecting the hypothesis that the mean values of the parameter estimated by the algorithm and by specialist 1 are equal. P_{a2} and P_{12} are similarly defined, where the subscript a refers to the algorithm and subscripts 1 and 2 refer to the specialists. The probabilities are calculated with the Student t-statistics with a 95 per cent confidence interval and 14 degrees of freedom. The results show that in all cases except one (F_1 in the control population) the agreement between the algorithm and each specialist is higher than the agreement between the two specialists.

Table 3 Probabilities relating the estimates of A2 parameters

Parameter	C	P_{a1}	P_{a2}	P_{12}	Data
F_1	1·5	0·419	0·692	0·422	
F_2	1·5	0·727	0·293	0·775	
BW30	2·0	0·161	0·466	0·704	CP
DA2	2·0	0·195	0·062	0·308	
F_1	1·5	0·174	0·805	0·920	
F_2	1·5	0·907	0·081	0·932	
BW30	2·0	0·419	0·144	0·474	TP
DA2	2·0	0·301	0·757	0·949	

P_{a1} denotes the probability for rejecting the hypothesis that the mean values of the parameter estimated by the algorithm and by specialist 1 are equal. P_{a2} and P_{12} are similarly defined, where the subscript a refers to the algorithm and subscripts 1 and 2 refer to the specialists. F_1, F_2, BW30 and DA2 represent, respectively, the dominant frequency, the second dominant frequency, the −30 dB bandwidth and the duration of A2. CP is the control population (15 patients), TP is the test population (15 patients).

6 Discussion and conclusions

Our algorithm is one among many for automatic detection of events in the PCG. Its basic features are as follows:

(*a*) It emulates a visual analysis method.
(*b*) The threshold is iteratively adjusted according to the level of noise and 'insignificant' data in the PCG.
(*c*) It can provide automatically an estimate of the duration of cardiac events and murmurs.
(*d*) It uses only the QRS position of the ECG as reference for timing the PCG cycles.
(*e*) It is flexible enough so that spectral information may be added for specific applications such as the detection of A2 and the estimation of related parameters.

The results of evaluation show that the algorithm using the ideal rectification method to compute the envelopes performs very well for the automatic detection of S2 and can be acceptable for the detection of S1, SM and DM. In addition, the automatic detection and identification of A2 was excellent. Indeed, the agreement between most parameters extracted automatically from A2 and those extracted after the manual selection of A2 by the specialists was better than the agreement obtained between the two specialists.

We have also tested the influence of the method used to estimate the envelope of the PCG (ideal rectification and Hilbert transform methods) on the performance of the algorithm. Although in some cases (AOC, S2 and DM) comparable results were obtained with either method, the algorithm using envelopes estimated by the ideal rectification method seemed to be superior in all other cases. Furthermore, envelope estimation with the ideal rectification method is much faster than with the Hilbert transform method.

In previous works, automatic detection of cardiac sounds and murmurs were compared with that made by a specialist using only the observed agreement parameter P_0. In this paper, we used a more constraining statistic which takes into account the proportion of agreement due to chance.

Although often used (LANGLOIS *et al.*, 1984; KORAN, 1975; FLEISS, 1971; LIGHT, 1971), the Kappa statistic can be a very severe measurement of agreement. This severity arises if P_c is calculated when the frequency distribution of the ratings is very skewed. For instance, if both raters accepted 90 per cent of S2 in a population, P_c would be equal to 0·82. If the observed agreement were equal to 90 per cent, then K would be 0·444. However, if the observed agreement is increased to 95 per cent, then K would increase to 0·722. The important point to note is that positive values of K imply agreement in excess of what can be obtained by chance.

According to COHEN (1960), the statistical significance of the Kappa statistic is a function of the standard error, which can be approximated by:

$$\sigma_K = [P_0(1 - P_0)/N(1 - P_c)^2]^{0\cdot5} \qquad (5)$$

For a normal distribution, COHEN (1960) suggests that the 95 per cent confidence limits L can be set by

$$L = K \pm 1{\cdot}96\,\sigma_K \qquad (6)$$

If we can assume a normal approximation to the sampling distribution of K, we may obtain an insight into the statistical significance of the results. As an example, we consider the cases where the best value of K was obtained for the detection of S1 and AOC with envelopes determined by the ideal rectification method. For S1, the confidence intervals for K are (0·239, 1·00) for the control population with $\sigma_K = 0{\cdot}219$ and (0·080, 0·918) for the test population with $\sigma_K = 0{\cdot}214$ when $C = 1{\cdot}0$. This indicates that the detection of S1 was made in excess of chance with a greater than 95 per cent confidence limit. For AOC, the confidence intervals for K are (−0·083, 0·905) for the control population when $\sigma_K = 0{\cdot}252$ and (−0·847, 0·635) for the test population with $\sigma_K = 0{\cdot}378$ when $C = 2{\cdot}0$. Thus, negative Kappa statistics may be generated and no clear conclusion can be drawn in this case.

In conclusion, we believe that our algorithm is particularly effective for the detection and identification of the second heart sound S2 and the aortic component A2 of S2 in patients with Ionescu-Shiley aortic valve bioprosthesis. The algorithm could be easily modified to detect paradoxical splitting of S2 by using the following criterion when comparing the dominant frequencies of the two asymmetric sine-cosine windows: if the dominant frequency of the right-side window is higher than that of the left-side window, paradoxical splitting of S2 is present; if not, normal splitting is assumed. When paradoxical splitting is present, the left-side window is associated with P2 and the right-side window with A2. When normal splitting is present, the left-side window is associated with A2 and the right-side window with P2.

The algorithm can also be useful for the detection of the first heart sound, the systolic murmur SM and the diastolic murmur DM. To improve the performance of the algorithm, especially for the detection of the opening click AOC, SM, and DM, further clinical and physiological data will be needed. Information on the nature, morphology, timing and frequency content of these three components will be required, so that a detector based on a threshold could be enhanced, as done here for A2. These three latter components are of great interest for the detection of sounds and murmurs from patients with Ionescu-Shiley bioprostheses implanted in the aortic position. However, information contained in S1 is generally ignored when recorded at the aortic area, except for timing purposes or for computing intensity ratios between S1 and S2.

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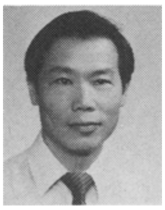

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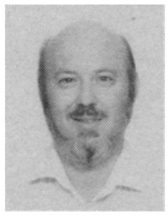

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