Spectral analysis of closing sounds produced by Ionescu-Shiley bioprosthetic aortic heart valves

Part 3 Performance of FFT-based and parametric methods for extracting diagnostic spectral parameters

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Abstract—*The objective of the paper is to compare the performance of conventional FFT-based and modern parametric methods when extracting, from aortic closing sounds produced by Ionescu-Shiley bioprosthetic heart valves, three features used in diagnosing valve dysfunction. Eight algorithms were tested by adding random noise and truncating 15 simulated aortic closing sounds. The performance of each algorithm was evaluated by computing the absolute error between the parameters obtained from the reference spectra of the simulated sounds and those obtained from the estimated spectra. Results show that the fast Fourier transform with rectangular window (FFTR) can locate the dominant spectral peak of the valve sound with an average accuracy of 10 Hz. Pole-zero modelling using the Steiglitz-McBride method with maximum entropy (SMME) is the best technique for estimating the frequency of the second dominant spectral peak and the bandwidth at −30 dB of the spectrum, with an average accuracy of 50 Hz and 27 Hz, respectively. In addition to this analysis, the accuracy of the frequency distribution of the estimated spectra was evaluated. Results show that the Steiglitz-McBride method with extrapolation to zero and FFTR are the best algorithms to estimate the distribution of the reference spectra in the 20–200 Hz frequency bands. In the 200–500 Hz and 500–1000 Hz frequency bands, SMME gives the best results.*

Keywords—*All-pole modelling, Bioprosthetic heart valves, FFT-based method, Parametric spectral estimation, Phonocardiography, Pole-zero modelling, Simulated sounds, Spectral parameters*

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List of abbreviations

APA	all-pole modelling with autocorrelation method
APC	all-pole modelling with covariance method
A_2	aortic component of the second heart sound
BW_{30}	bandwidth at -30 dB of the spectrum
dB	decibel
FFT	fast Fourier transform
FFTM	fast Fourier transform with Hamming window
FFTN	fast Fourier transform with Hanning window
FFTR	fast Fourier transform with rectangular window
FFTS	fast Fourier transform with sine-cosine window
F_1	frequency of the most dominant spectral peak
F_2	frequency of the second dominant spectral peak
Hz	Hertz
ms	millisecond
S/N	signal-to-noise
SD	standard deviation
SMME	Steiglitz-McBride method with maximum entropy (pole-zero modelling)
SMEZ	Steiglitz-McBride method with extrapolation to zero (pole-zero modelling)
WN	Welch's method with Hanning window

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1 Introduction

It is now widely accepted that spectral analysis of the closing sounds produced by bioprosthetic heart valves can provide useful indications of degenerative changes which can lead to dysfunction of the valve. For instance, recent studies have clearly demonstrated that the two dominant peaks of an aortic closing sound's spectrum shift towards the higher frequencies as a result of valve tissue calcification, fibrosis and stiffening (Stein *et al.*, 1980; 1984 for F_1; Foale *et al.*, 1983; Joo *et al.*, 1983 for F_1 and F_2). As a clinical technique for periodically monitoring patients with prosthetic valves, spectral analysis of valve sounds is particularly attractive since it is noninvasive, atraumatic and potentially very sensitive.

Several methods have been investigated for obtaining the spectral characteristics of bioprosthetic valve sounds.

Some methods are based on the fast Fourier transform (FFT), whereas others use more recent parametric methods of system identification. Both approaches have been applied in clinical studies and have given interesting results. However, because of the occurrence of other cardiac vibrations during the closure of the aortic valve, only a portion of the closing sound is available for analysis (CLOUTIER *et al.*, 1987*b*). It has thus been suggested by FOALE *et al.* (1983) and JOO *et al.* (1983) that FFT-based methods do not provide sufficient frequency resolution to completely characterise the spectrum of bioprosthetic aortic closing sounds. High-resolution maximum entropy methods have been proposed to overcome this difficulty.

In addition to the relatively low resolution of FFT-based methods, due to the short duration of aortic closing sounds, DURAND *et al.* (1986) have shown that changes in background noise and signal duration can also affect the accuracy of spectra. In their study, the performance of various spectral estimation techniques was tested by decreasing the duration of the aortic closing sounds by 5 per cent and adding 5 per cent of random noise. These tests gave interesting results but could not provide a comparison of the spectra obtained with a given technique to a 'gold standard'. In addition, no attempt was made to find an optimal number of poles and zeros for the parametric methods; so the comparison may have been slightly biased.

In the present study, the accuracy of different spectral estimation techniques was determined by varying the duration and S/N ratio of simulated bioprosthetic aortic heart valve closure sounds (A_2). Because the spectrum of the synthesised sounds can be accurately determined by analytical means, a reliable 'standard' for comparing the various methods is available. The accuracy of three spectral parameters has been evaluated: the frequency of the most dominant spectral peak F_1, the frequency of the second dominant spectral peak F_2 and the bandwidth BW_{30} at -30 dB of the spectrum. This last parameter was added to estimate the frequency content of the signal. The diagnostic potential of BW_{30} has not been evaluated for bioprosthetic valves but has been used by KAGAWA *et al.* (1980) to detect the state of metallic prosthetic valves. It will be shown that FFTR is the best method to extract F_1 whereas SMME dominates for F_2 and BW_{30}.

2 Methods

The electrocardiogram and phonocardiogram of 15 patients with aortic Ionescu-Shiley pericardial xenografts implanted for less than 5 years were recorded three times over a period of 3 years. For each recording, a coherent detection algorithm was used to extract 20 aortic closing sounds and compute an averaged sound as described by CLOUTIER *et al.* (1987*b*). From the averaged A_2 components obtained from the first recording of each patient, 15 simulated aortic closing sounds were generated (CLOUTIER *et al.*, 1987*b*).

Eight algorithms of spectral estimation based either on the fast Fourier transform or parametric analysis were used to extract the three previously described parameters. With FFT-based techniques, the power spectra of the aortic closing sounds $s(n)$ was evaluated by

$$S_{ss}(e^{jW}) = \left| \sum_{n=0}^{N-1} s(n)\omega(n)e^{-jWn} \right|^2 \qquad (1)$$

where $\omega(n)$ represents the temporal window. Three types of windows: rectangular, Hanning and Hamming, as described by OPPENHEIM and SCHAFER (1975), were tested. A sine-cosine window has also been tried. This window is defined as follows (YOGANATHAN *et al.*, 1976): the first 10 per cent of $\omega(n)$ are described by the sine function sin W for W ranging between 0 and 90° and the last 10 per cent of $\omega(n)$ by the cosine function cos W with W ranging also between 0 and 90°. All other samples of this window are set to 1. Four parametric spectral techniques: APA, APC, SMME and SMEZ, described by MAKHOUL (1975), and STEIGLITZ and MCBRIDE (1965), were finally tested. The number of poles and zeros used in the present study for parametric spectral techniques was based on the results of CLOUTIER *et al.* (1987*a*).

2.1 *Accuracy of the spectral parameters*

The accuracy of each algorithm was obtained by computing the absolute error between the parameters extracted from the reference spectrum of the simulated sounds and those extracted from each estimated spectrum,

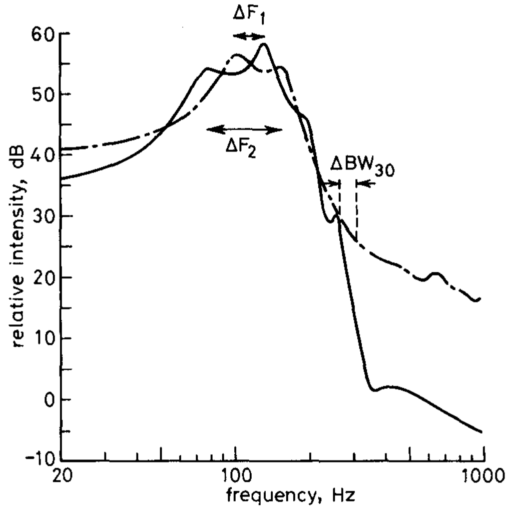

Fig. 1 *Accuracy of F_1, F_2 and BW_{30} obtained by computing the absolute error between the parameter of the reference spectrum (solid line) and those of the estimated spectrum (broken line)*

as shown in Fig. 1. The power spectrum of the simulated sounds $\hat{s}(n)$, which consist of a series of exponentially decaying sinusoids (CLOUTIER *et al.*, 1987*b*), was computed analytically by

$$\hat{S}_{ss}(e^{jW}) = \left| \sum_{i=1}^{R} A(i) \frac{e^{2jW}\sin(\phi(i)) + e^{((-1/T(i))+jW)}\sin(\omega(i)-\phi(i))}{e^{2jW} - 2e^{((-1/T(i))+jW)}\cos(\omega(i)) + e^{-2/T(i)}} \right|^2 \qquad (2)$$

where R = number of decaying sinusoids
$A(i)$ = amplitude of the ith sinusoid
$T(i)$ = decay time constant of the ith sinusoid, s
$\omega(i)$ = frequency of the ith sinusoid, rad s^{-1}
$\phi(i)$ = phase of the ith sinusoid, rad.

For each parameter, the mean absolute error averaged over 15 simulated spectra was used as a measure of the accuracy of a given algorithm. The effect of truncating the simulated sounds by 2 per cent, 8 per cent and 15 per cent of their total energy and adding -50 dB, -40 dB and -30 dB of random noise was investigated in this analysis.

Different constraints were imposed in the search of the spectral parameters. First, spectral peak extraction was limited to frequencies between 20 and 500 Hz. Secondly, a peak detection algorithm was used to differentiate an inflection segment from a true peak. For this purpose, a programmable window was centred over a potential peak which was accepted as such only if two samples (4·9 Hz) before and after it were of lower intensity. Thirdly, to prevent noise from appearing as the second dominant peak F_2, all peaks with an intensity -40 dB lower than that of F_1 were rejected. This -40 dB threshold was chosen because it corresponds to the average S/N ratio of the mean A_2 component of the second heart sound, obtained by coherent detection as estimated by CLOUTIER *et al.* (1987*b*). Finally, estimation of BW_{30} was confined to the frequencies between F_1 and 600 Hz.

2.2 *Sensitivity of the spectral analysis techniques to signal truncation and random noise*

To evaluate the sensitivity of each method of spectral analysis, error spectra were computed by subtracting the spectra obtained from the truncated and noise-contaminated signals from the reference spectra of the simulated sounds. Mean absolute error spectra were then computed and averaged over all patients for each spectral technique.

2.3 *Variability of the spectral parameters*

A last study was performed to assess the variability of F_1, F_2 and BW_{30} extracted from the three recordings that were made for each patient. For each method of spectral analysis, mean and standard deviation (SD) values of the frequency parameters obtained from the three recordings of each patient were computed and averaged for the group of 15 patients. The resulting average SD values were taken as a measure of the variability of the spectral parameters.

3 Results

The durations of the simulated sounds after truncation by 2 per cent, 8 per cent and 15 per cent of their total energy were 28 ± 5 ms, 18 ± 4 ms and 16 ± 4 ms, respectively. As a qualitative result, Fig. 2 shows a comparison of a reference spectrum and the corresponding spectra obtained with the eight algorithms, for 8 per cent truncation and -40 dB of random noise. As shown on the left panel, the FFTR and FFTS algorithms have similar spectral profiles. They are characterised by a large main lobe and many low-amplitude peaks in the high-frequency portion. FFTN and FFTM also display similar spectral profiles with an even smoother main lobe and many high-frequency peaks of lower amplitude.

As shown on the right panel of Fig. 2, APA modelling is not suitable for estimating more than one spectral peak. Generally, this algorithm only models the dominant harmonic content of the signal. The overall spectral profile provided by the APC algorithm is similar to that of

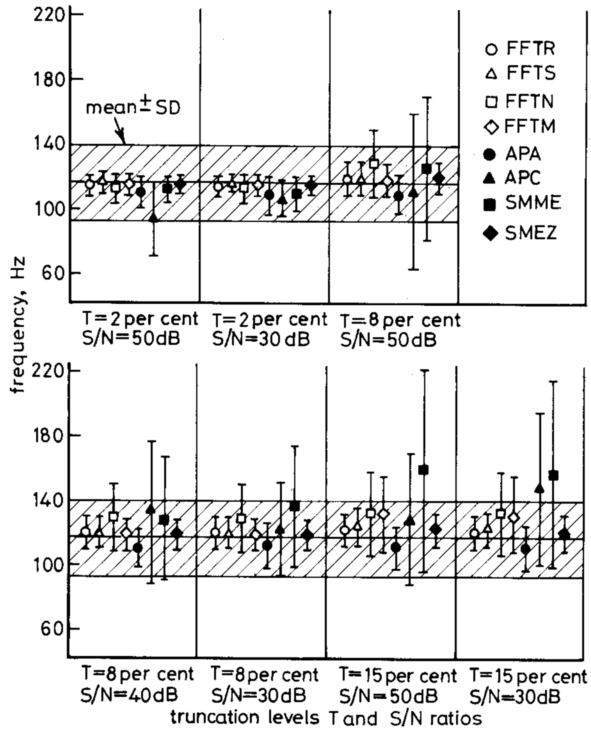

Fig. 3 *Mean values and absolute errors of F_1 in Hz, for eight algorithms of spectral estimation and the reference F_1 (horizontal line), following the truncation of the aortic sounds and addition of random noise. The shaded zone represents the standard deviation of F_1 obtained from 15 reference spectra*

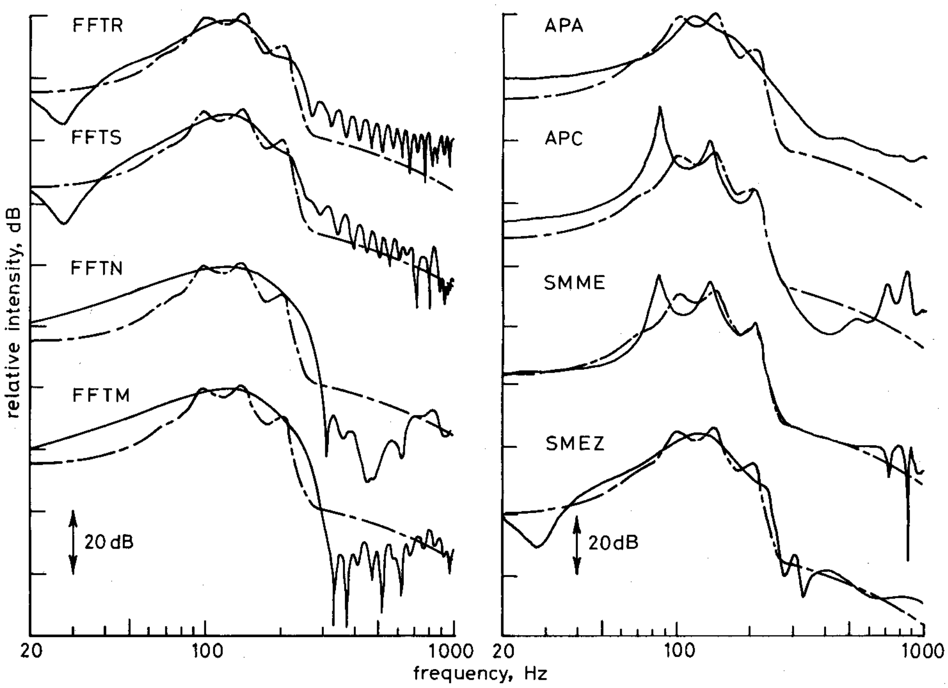

Fig. 2 *Comparison of a reference spectrum (broken lines) with the corresponding eight algorithms of spectral estimation (solid lines) following 8 per cent truncation and addition of -40 dB of random noise to the simulated sound*

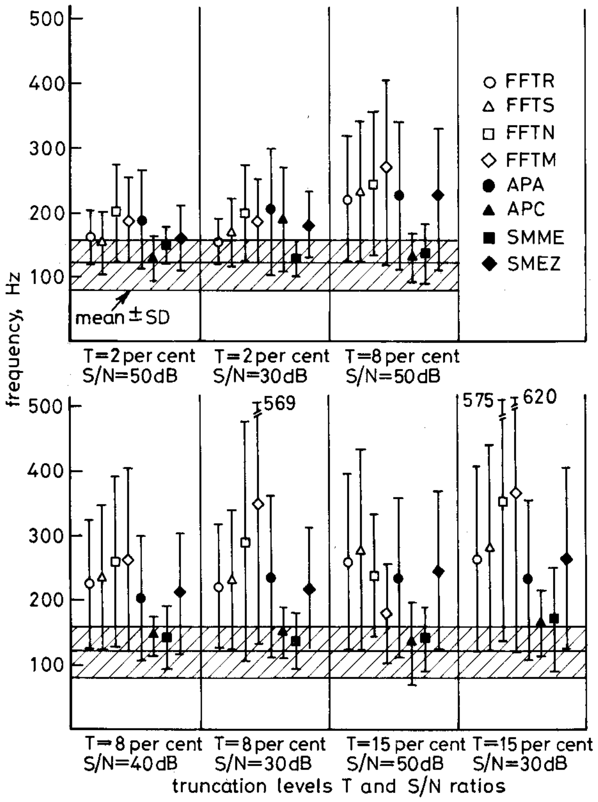

Fig. 4 *Mean values and absolute errors of F_2 in Hz, for eight algorithms of spectral estimation and the reference F_2 (horizontal line), following the truncation of the aortic sounds and addition of random noise. The shaded zone represents the standard deviation of F_2 obtained from 15 reference spectra*

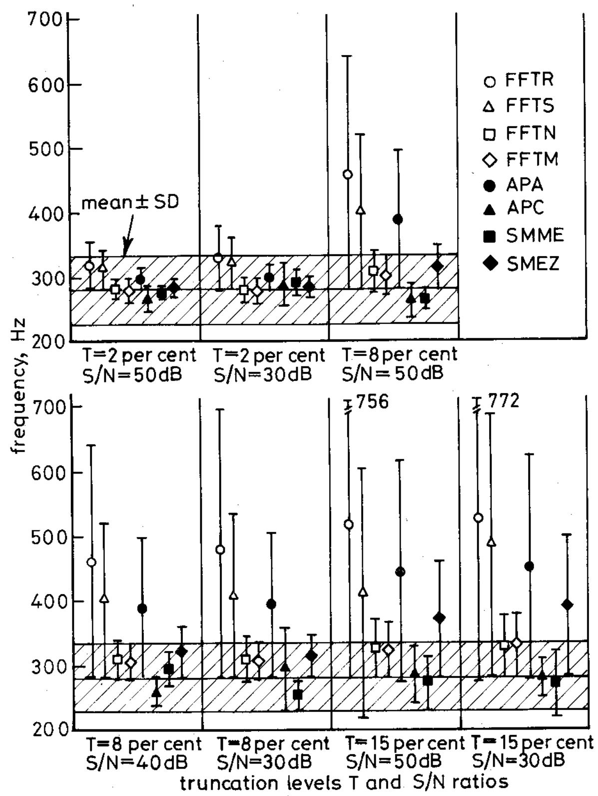

Fig. 5 *Mean values and absolute errors of BW_{30} in Hz, for eight algorithms of spectral estimation and the reference BW_{30} (horizontal line), following the truncation of the aortic sounds and addition of random noise. The shaded zone represents the standard deviation of BW_{30} obtained from 15 reference spectra*

SMME. Both algorithms are maximum entropy techniques and produce suspicious spectral peaks and peaks with unstable amplitude, as reported by DURAND *et al.* (1986) for the SMME algorithm. On the other hand, SMME gives good results when estimating the morphology of the reference spectrum above 200 Hz. Finally, SMEZ gives a large main lobe and a few low-amplitude peaks in the high-frequency range.

Figs. 3, 4 and 5 summarise the results of this study. Each figure reports the values of one parameter (F_1, F_2 or BW_{30}) averaged over the 15 patients for all spectral estimation algorithms, under different conditions of signal truncation and noise contamination. The averaged 'gold standard' value of the parameter is represented by the horizontal line and the absolute differences between that parameter and the 'gold standard', by the deviation measurement. In addition, the SD value of the reference parameter (shaded zone) was added as a complementary information. Generally, the accuracy of the parameters decreases as the truncation level increases. On the other hand, the addition of random noise does not seem to have a drastic effect on the accuracy of F_1, F_2 and BW_{30}. Figs. 3, 4 and 5 show that F_1 is generally overestimated for a truncation level of 8 per cent and 15 per cent and underestimated for a truncation level of 2 per cent. However, APA modelling underestimates F_1 for all truncation levels and S/N ratios. All algorithms overestimate F_2 for all truncation levels and S/N ratios. Finally, both over- and underestimation of BW_{30} is observed for different perturbation conditions.

FFTR and FFTS algorithms are good at estimating F_1 and poor at estimating F_2. Moreover, because of the erratic behaviour of the spectrum in the high frequency range, especially at high truncation levels, they are not suitable for estimating BW_{30}. Generally, FFTN and FFTM spectra give lower accuracies for F_1 and F_2 because of the poor resolution that results from using the Hanning and Hamming windows. On the other hand, they are good at estimating BW_{30}.

All-pole modelling with autocorrelation method (16 poles) is of limited use because this algorithm only estimates the main harmonic component of the signal. It is a good method for estimating F_1 but it fails for F_2 and BW_{30}. APC (16 poles) and SMME (14 poles and 14 zeros) give similar results. Compared with other techniques, they are not suitable for estimating F_1 and good in estimating F_2 and BW_{30}. The best accuracy for estimating F_1 is obtained with the SMEZ method (14 poles and 14 zeros), but it gives bad results for F_2. It is better than FFTR, FFTS and APA, and worse than the other methods, in estimating BW_{30}.

3.1 *Best spectral techniques for estimating F_1, F_2 and BW_{30}*

Because of the computation time required by the SMEZ algorithm, FFTR is to be preferred in estimating F_1. For the normal truncation level and S/N ratio of the aortic mean closing sounds (8 per cent and 40 dB), as estimated by CLOUTIER *et al.* (1987*b*), the FFTR algorithm slightly overestimates F_1 (120 Hz compared with the real value of 116 Hz of the reference spectra). The accuracy of this algorithm, as may be seen from Fig. 3, is about 10 Hz.

Two methods could be used to extract F_2: APC and SMME. All-pole modelling with covariance method is faster than SMME because the latter involves an iterative procedure. However, SMME produces more consistent results. As shown in Fig. 4, a mean absolute error of 81 Hz has been obtained with APC for a truncation level of 2 per cent and an S/N ratio of 30 dB. The SMME method is to be preferred for estimating F_2 but APC could be used if computation time is important. For a truncation level of 8 per cent and an S/N ratio of 40 dB, SMME overestimates F_2 (143 Hz compared with 121 Hz) and has an accuracy of about 50 Hz.

FFTN, FFTM, APC and SMME are adequate for estimating BW_{30}. FFTN and FFTM give consistent results and the accuracy decreases with increasing truncation level and S/N ratio. APC also gives interesting results especially for a truncation level of 15 per cent and S/N ratios of 50 dB or 30 dB. For a truncation level greater than 2 per cent, the SMME algorithm provides the best results. SMME has been chosen to extract BW_{30} except for a truncation level of 2 per cent where FFTM is preferred. SMME is characterised by an overestimation of 13 Hz and by an accuracy of 27 Hz for a truncation level of 8 per cent and an S/N ratio of 40 dB.

3.2 *Best spectral techniques for estimating the frequency distribution*

Inspection of the mean absolute errors for the 15 patients suggests subdividing the spectra into three frequency ranges. Mean spectra were thus computed for bandwidths of 20–200 Hz, 200–500 Hz and 500–1000 Hz, to better characterise the effect of truncation and random noise on the lower, middle and higher frequencies.

Table 1 Mean absolute error in dB evaluated in three frequency ranges ((a) 20–200 Hz, (b) 200–500 Hz and (c) 500–1000 Hz) following a truncation level of 8 per cent and S/N ratios of 40 and 30 dB

	Mean absolute error in dB					
	S/N = 40 dB			S/N = 30 dB		
Algorithm	*a*	*b*	*c*	*a*	*b*	*c*
FFTR	2·6	11·7	20·4	2·6	11·8	21·0
FFTS	3·1	10·9	13·2	3·1	10·8	15·9
FFTN	5·6	10·2	9·0	5·6	9·4	13·8
FFTM	5·2	9·3	9·6	5·3	9·6	14·1
APA	3·3	12·0	20·7	3·3	12·0	21·7
APC	6·5	8·2	11·3	6·1	8·4	16·1
SMME	5·5	3·5	5·8	4·4	4·2	10·5
SMEZ	2·5	6·4	8·2	2·5	6·3	11·0

Results are given in Table 1 for 8 per cent of truncation and addition of −30 dB and −40 dB of random noise. These perturbation values correspond to the S/N ratios of the mean aortic closing sounds before and after coherent detection of A_2 with the technique described in part 2 of this series of papers (Cloutier *et al.*, 1987*b*). In the low-frequency range, SMEZ and FFTR show the best results with a mean absolute error of 2·5 dB and 2·6 dB for both S/N ratios. FFTS and APA give similar results with a mean absolute error of 3·1 and 3·3 dB, followed by FFTM, SMME, FFTN and APC. Except for maximum entropy algorithms (APC and SMME), the other techniques do not seem to be affected by the noise addition in the low-frequency range. Between 200 and 500 Hz and above 500 Hz, the error due to truncation and addition of −40 dB of random noise is small for SMME, with a mean error of 3·5 dB and 5·8 dB. With the addition of −30 dB of random noise, this algorithm also gives the best results, with a mean error of 4·2 and 10·5 dB. Observation of the results for −40 and −30 dB of random noise shows clearly that noise addition has almost no effect in the middle-frequency range except for FFTN and SMME, which present a variation of 0·8 and 0·7 dB, respectively. However, noise perturbation is evident for all algorithms in the high-frequency range.

3.3 *Variability of F_1, F_2 and BW_{30}*

The variability of the spectral parameters has been computed with FFTR for F_1 and SMME for F_2 and BW_{30}. Results show a variability of 13 Hz for F_1 with a mean value, averaged over the 15 patients, of 116 Hz. Finally, the variabilities of F_2 and BW_{30} have been estimated to 42 Hz (146 ± 42 Hz) and 62 Hz (286 ± 62 Hz).

4 Discussion

The results of this study indicate that two spectral techniques should be used for optimal extraction of parameters F_1, F_2 and BW_{30}: the fast Fourier transform with rectangular window for F_1 and the Steiglitz-McBride method with maximum entropy for F_2 and BW_{30}. The accuracy of the FFTR algorithm in estimating F_1 is approximately 10 Hz and SMME extracts F_2 and BW_{30} to within 50 and 27 Hz, respectively. An accuracy of 50 Hz for F_2 can be considered to be rather poor but this may be explained by the fact that SMME gives spectral peaks with unstable amplitude (Durand *et al.*, 1986). Indeed, it was observed that the amplitude of F_2 was overemphasised for some patients and the algorithm substituted F_2 for the real value of the dominant spectral peak. Then, although this algorithm estimates the location of the spectral peaks well, its accuracy is reduced because of the interchanging of F_1 and F_2.

These results on the accuracy of the spectral parameters can be compared with those of Durand *et al.* (1986), who studied the influence of signal truncation and background noise on the spectra of aortic bioprosthetic valve sounds. However, the results on the accuracy of BW_{30} could not be compared to any reported study. In the analysis of Durand *et al.*, the aortic closing sounds were perturbed by a relative change in the sound duration and noise addition, and their influence on F_1 and F_2 were observed. Following truncation of the signal, SMEZ and FFTR presented the best stability for F_1 and SMME for F_2, which is in accordance with our results. Following addition of random noise, no variation was observed for F_1 estimated with FFTR. As shown in this analysis, F_1 estimated with FFTR is also little affected by random noise. However, a variation of 20 Hz was obtained by Durand *et al.* for F_2 estimated with SMME, which is different from our result. As seen in Fig. 4, addition of random noise had little effect on the accuracy of F_2, except at a truncation level of 15 per cent.

This difference can be explained by the methodology used to extract the frequency peaks. Durand *et al.* searched for spectral peaks between 20 and 1000 Hz. In this analysis, the detection of the spectral peaks has been limited between 20 and 500 Hz to minimise the rebound effects seen in the high-frequency range with the FFTR and FFTS algorithms, and to limit the contribution of false spectral peaks when using maximum entropy algorithms. Indeed, as presented by Lang and McClellan (1980), spurious peaks are generated by parametric methods of spectral analysis for low S/N ratios. By evaluating the spectral peaks between 20 and 500 Hz, fewer false peaks of higher amplitude have been substituted for the real value of F_2 obtained with SMME. Thus, the accuracy of F_2 has been less affected by the noise addition.

Limiting the peak detection to frequencies below 500 Hz is justified by three analyses. First, Brais *et al.* (1986) found no significant information beyond 500 Hz when using Welch's method of spectral estimation (Welch, 1967) in patients with normal aortic Ionescu-Shiley bioprosthetic heart valves. Secondly, FOALE *et al.* (1983) and Joo *et al.* (1983) found no dominant spectral peaks (F_1 or F_2) above 342 Hz in patients with normal and abnormal aortic bioprosthetic heart valves.

In a previous analysis reported by CLOUTIER *et al.* (1987*b*), it was shown that the coherent detection algorithm used to select the mean aortic closing sounds increased the S/N ratio of the signals by approximately 10 dB. The mean S/N ratios of A_2, before and after coherent detection, were 30 and 40 dB, respectively. In this analysis, the accuracy of F_1, F_2 and BW_{30} computed for -40 dB and -30 dB of random noise and a truncation level of 8 per cent were both 10 Hz for F_1 estimated with FFTR, 50 and 45 Hz for F_2 and 27 and 23 Hz for BW_{30} estimated with SMME. We can therefore conclude that the coherent detection algorithm of A_2 did not increase the accuracy of the spectral parameters. However, as seen in Table 1, coherent detection of A_2 reduced the error in the high-frequency range (500–1000 Hz) of the estimated spectra significantly.

In the last analysis, the variability of the spectral parameters computed from three recordings of the 15 patients was estimated. This variability can be explained by the limited accuracy of the spectral estimation technique, the changing physiological conditions of the patient, changes in the coupling between the microphone and the thorax as well as its location, and many other factors. However, the accuracy of the spectral technique should be considered independent of the other factors. The accuracy and variability of F_1 were estimated to be 10 and 13 Hz, respectively. Almost no difference is observed between them. Thus, F_1 extracted from different recordings of the same normal patient presents a good reproducibility. The variability of the normal acoustic signature of F_2 was 42 Hz and the accuracy of the SMME algorithm was 50 Hz. Then, we can only conclude that the reproducibility of F_2 is less than 50 Hz and could not be estimated because of the lack of accuracy of the SMME algorithm. Finally, the accuracy and variability of the normal acoustic signature of BW_{30} were estimated at 27 and 62 Hz, respectively. This difference between the two measurements shows clearly the variability of this parameter from one recording to the other. These results should give some insight when studying F_1, F_2 and BW_{30} from normal or abnormal patients.

As reported in part 2 of this series of papers (CLOUTIER *et al.*, 1987*b*), the mean aortic closing sounds were characterised by a duration of 24 ± 9 ms and a truncation level of 8 per cent. The duration of the simulated sounds for a truncation level of 8 per cent is 18 ± 4 ms. This difference between the duration of the aortic closing sounds and the corresponding simulated sounds could be explained as follows. For some patients, a period of low sound activity was included before the onset of A_2. By averaging the aortic closing sounds in the coherent detection algorithm, this low sound activity was often reduced to the background noise of A_2. Then, in the simulation approach, this period of inactivity was excluded and the synthesised sounds began with the onset of A_2.

5 Conclusion

The results on the accuracy of F_1 and F_2 provide an opportunity to discuss the clinical results of STEIN *et al.* (1980; 1984), BRAIS *et al.* (1986), FOALE *et al.* (1983) and Joo *et al.* (1983).

An important finding of our studies is that the FFT with a rectangular window is one of the best techniques for estimating F_1 of aortic closing sound spectra. This result confirms the validity of the clinical studies performed by Stein *et al.* Welch's method with Hanning window (WN) was used by Brais *et al.* to characterise the spectral distribution of normal patients with an Ionescu-Shiley bioprosthetic heart valve. Because WN and FFTN used the same temporal window, we can expect better results with FFTR and SMME because FFTR has a mean error in the spectral distribution of 3·0 dB lower than FFTN between 20 and 200 Hz and because SMME has a mean error of 6·7 dB lower than FFTN between 200 and 500 Hz. In addition to this analysis, Brais *et al.* estimated F_1 of normal patients also with the WN algorithm. Better results should be expected with FFTR.

Foale *et al.* and Joo *et al.* used parametric spectral techniques in their clinical analyses. Their choices were based on the fact that the FFT-based methods did not provide sufficient frequency resolution. However, as reported in this analysis, the FFT-based method gives good results for extracting F_1. Then, in the study of Foale *et al.* and Joo *et al.*, based on the extraction of F_1 and F_2, better results could have been obtained by using the FFTR algorithm for extracting F_1.

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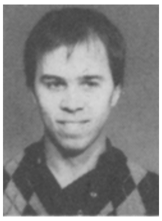
Authors' biographies



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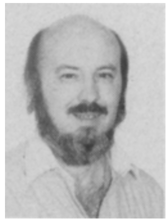

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