Evaluation of FFT-Based and Modern Parametric Methods for the Spectral Analysis of Bioprosthetic Valve Sounds

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Abstract—**The objective of this paper is to compare the performance of conventional FFT-based (basic periodogram and Welch's method) and modern parametric (all-pole and pole-zero modeling) methods in estimating the spectral distribution of cardiac bioprosthetic valve sounds, and for the extraction of the two most dominant frequency peaks (DFP). These methods were tested for stability by adding random noise and truncating the bioprosthetic valve closing sounds, and for reproducibility by measuring the variance of the spectra obtained from three consecutive recordings of each patient. Results from a group of 11 patients show that the basic periodogram and Steiglitz-McBride's method with maximum entropy (pole-zero modeling) provide the most consistent (minimal variance) estimates of the DFP's of the closing sounds. However, for estimating spectral distributions, the most stable methods appear to be the basic periodogram and Steiglitz-McBride's method with extrapolation to zero. The basic periodogram appears to be the best compromise to estimate both the spectral distribution and the DFP's of the bioprosthetic closing sounds.**

I. Introduction

It is now widely accepted that spectral analysis of the closing sounds produced by bioprosthetic valves can provide useful indication of degenerative changes which can lead to dysfunction of the valve. For instance, recent studies [5], [7], [10]–[12] have clearly demonstrated that the dominant frequency peaks of the closing sounds shift towards the higher frequencies as a result of valve tissue calcification, fibrosis, and stiffening. 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), while others utilize more recent ("modern") 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 a bioprosthetic valve, only a portion of the closing sound is available for analysis. It has thus been suggested [5], [7] that FFT-based methods do not provide sufficient frequency resolution to completely characterize the spectrum of bioprosthetic closing sounds. A high-resolution maximum entropy method (Steiglitz–McBride's method) based on pole-zero modeling has been shown [6] to give superior frequency resolution but its stability has not been evaluated in the case of bioprosthetic closing sounds. In addition, some *a priori* knowledge on the properties of the signal has not been taken into account. For instance, it is known that bioprosthetic closing sounds are composed of quasi-periodic transients of short duration. Data modeling procedures used in modern parametric methods should therefore account for the fast decaying rate of the temporal signal by forcing the impulse response of the model to decrease rapidly towards zero outside the sampled interval.

In this paper, we propose to present a brief summary of conventional FFT-based methods (basic periodogram and Welch's method) and modern parametric methods based on all-pole and pole-zero modeling for this particular problem of spectral estimation. A comparative analysis of the stability and performance of these methods for the data obtained from a group of 11 patients with normally functioning bioprosthetic valves implanted in the aortic position is presented and discussed.

II. Spectral Estimation

Nonparametric methods of spectral analysis utilize various combinations of the FFT, windowing, and autocorrelation functions [3]. For instance, the basic periodogram of a signal $x(n)$ of duration N is defined as

$$P_N(w) = \frac{1}{N}\left|\sum_{n=0}^{N-1} x(n)\, e^{-jwn}\right|^2. \tag{1}$$

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Welch [13] has introduced a modification of the periodogram which is particularly well adapted to the FFT algorithm and reduces both the variance and the bias of the periodogram. The signal $x(t)$ is first sampled and divided into R segments $(x_r(n))$ of duration N and the spectrum is estimated with

$$S_{xx}(w) = \frac{1}{RNU} \sum_{r=1}^{R} |X_r(e^{jw})|^2 \tag{2}$$

where

$$X_r(e^{jw}) = \sum_{n=0}^{N-1} x_r(n)\, w(n)\, e^{-jwn} \tag{3}$$

and U is the power of the windowing function. The exact frequency resolution is determined by the spectral properties of the windowing sequence $w(n)$. For estimating the spectrum of transient signals like bioprosthetic valve sounds,[1] the input signal is subdivided such that each segment comprises only one transient which is assumed to exist for $0 \leq t \leq T$.

In parametric methods of spectral analysis, a model of an equivalent system is assumed in the formulation of the problem. The objective is then to estimate the parameters of this model from measurements of the signal made over a limited period of time. Maximum entropy methods can be regarded as a special case of linear predictive coding or LPC [8]. The basic idea of LPC is that a signal $s(n)$ can be modeled as the output of an equivalent system excited by a given random stationary signal $x(n)$, such that

$$s(n) = -\sum_{k=1}^{P} a_k s(n-k) + \sum_{k=0}^{Q} b_k x(n-k) \tag{4}$$

and a_k, b_k are the parameters describing the system. These methods do not use windows and their principal objective is to increase spectral resolution and accuracy when only a short-duration sample of the signal is available [2], [4]. In other words, the signal or its autocorrelation function is extrapolated beyond the sampled interval on the basis that the spectral estimate is mostly random and has a maximum entropy behavior. The objective is to preserve the information contained in the signal.

Parameters a_k and b_k are estimated by minimizing the total squared error E between the actual signals $s(n)$ of duration N and the predicted signal such that

$$E = \sum_{n=0}^{N-1} \left[s(n) - \left(-\sum_{k=1}^{P} a_k s(n-k) + \sum_{k=0}^{Q} b_k x(n-k) \right) \right]^2 = 0. \tag{5}$$

The transfer function $H(z)$ of the equivalent system is expressed as

$$H(z) = \sum_{k=0}^{Q} b_k z^{-k} \Big/ 1 + \sum_{k=1}^{P} a_k z^{-k} \tag{6}$$

and the power spectrum of $s(n)$ is estimated by using $z = e^{jw}$ in the transfer function and computing its modulus $|H(e^{jw})|^2$. In the all-pole model, the numerator of (6) is replaced by a constant G representing the gain of the system.

Traditionally, LPC analysis was done by assuming that the input signal to the system was a sample from a given random process. However, for estimating the spectrum of transient signals, the impulse function signal $x(n) = \delta(n)$ is a more appropriate input. Least-squares minimization of (5) has been studied by many groups. The methods proposed by Prony, Shanks, Kalman, and Steiglitz–McBride are well known. A review and comparison of these methods, as they apply to the modeling of heart sounds, was done by Joo *et al.* [6], [7]. Their results indicate that Steiglitz–McBride's method is superior in overall performance. A drawback of this method is that its convergence properties are not known [7], [9]. However, Joo *et al.* have shown that, for $P = Q = 8$, five iterations of the algorithms are usually sufficient to obtain a good estimate of the signal. Increasing the model order did not seem to improve substantially this estimation.

III. Methods

A. Data Acquisition

Patients with normally functioning Ionescu–Shiley bioprosthetic valves implanted in the aortic position were selected for this study. The ECG and PCG were recorded on a multichannel FM recorder with a bandwidth of 0–2500 Hz. At least three recordings were made of each patient over a period of 30 months. The phonocardiograms were recorded in the supine position with a contact microphone placed at the second right intercostal space (aortic area). The microphone (Hewlett Packard No. 21050A) has a flat frequency response (± 3 dB) from 0.2 to 2000 Hz. Prior to recording, the ECG was low-pass filtered (-12 dB/octave) at 100 Hz and the PCG was processed by a third-order high-pass filter (18 dB/octave) with a cutoff frequency of 100 Hz to emphasize the high frequency components of the prosthetic closing sounds.

At playback, the PCG was low-pass filtered (-48 dB/octave) at 900 Hz with an eight-order filter to prevent aliasing. The ECG and PCG were digitized with a 12-bit analog-to-digital converter at sampling rates of 250 and 2500 Hz, respectively. An example of the digitized signals is shown in Fig. 1. Visual examination of the PCG shows that it is composed of quasi-periodic transients of short duration with a fast decay rate and background noise. The first ($S1$) and second ($S2$) heart sounds are the two major features of the PCG. $S1$ is produced during ventricular contraction and may consist of two high frequency components ($M1$ and $T1$) associated to the closure of the mitral and tricuspid valves, respectively. The entire

[1]It should be recalled that for spectral estimation of random transient signals, the "energy" spectrum $\Psi_{xx}(w)$ is more appropriate than the "power" spectrum $S_{xx}(w)$. However, this formalism is generally not enforced because the two spectra are related by $\Psi_{xx}(w) = TS_{xx}(w)$.

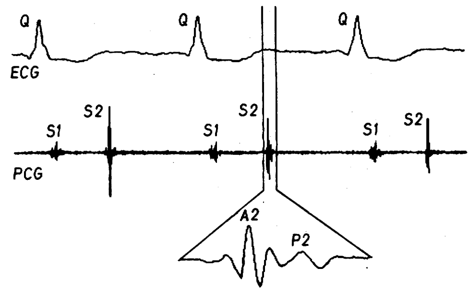

Fig. 1. Example of the ECG and PCG recorded in a patient with an Ionescu–Shiley pericardial xenograft valve implanted in the aortic position.

duration of $S1$ is approximately 100 ms. Similarly, $S2$, which is produced during ventricular relaxation, has two components ($A2$ and $P2$) associated to the closure of the aortic and pulmonary valves. Each component usually lasts less than 50 ms. During inspiration, the two components are often separated from each other by 30–60 ms; during expiration they come close together. Since $A2$ and $P2$ are not temporally correlated during normal breathing and $P2$ is generally smaller than $A2$ when recorded in the aortic area, coherent detection of $A2$ and averaging over several cardiac cycles is used to minimize contributions from $P2$. Coherent detection and averaging increase the signal-to-noise ratio of the $A2$ component.

A *QRS* detection algorithm was developed to locate automatically the beginning of each cardiac cycle. For each patient, a typical aortic closing sound recorded during maximal separation of $A2$ from $P2$ was selected as a reference closing sound. The interval between the detected *QRS* of the corresponding cardiac cycle and the beginning of the reference closing sound was used to locate and select interactively a series of closing sounds. Time alignment with the reference sound was done by a correlation technique and 20 closing sounds having a correlation level greater than 60 percent were chosen for further processing. An ensemble average of the 20 signals was also computed to represent the "mean" closing sound. When processing subsequent recordings of the same patient, the reference template of the first recording was used to maximize the probability of finding similar closing sounds. The reproducibility of the closing sounds from one recording to the other was assessed independently for each patient by computing the correlation levels between the three ensemble averages obtained for each patient. Data from 11 patients with highly reproducible closing sounds ($r \geq 0.80$) were then chosen to compare the performance of the FFT-based and parametric methods described in the previous section.

B. Spectral Analyses

The following abbreviations are used to represent five different algorithms of spectral analysis which were applied to the selected closing sounds.

- *P:* Basic periodogram (FFT) of the mean closing sound,
- *W:* Welch's method with a hanning window,
- AP: All-pole modeling with the autocorrelation method (16 poles),
- SMME: Steiglitz–McBride's method with maximum entropy (8 poles and 8 zeroes),
- SMEZ: Steiglitz–McBride's method with extrapolation to zero values (8 poles and 8 zeroes).

With algorithm W, the 20 closing sounds obtained at each recording were processed with Welch's method. All other algorithms were applied to the mean sound obtained by coherent detection. The spectra were all scaled in decibels (dB) to facilitate the comparisons.

As previously mentioned, prosthetic closing sounds consist of acoustic transients with fast decaying rates. They are low-entropy signals. This *a priori* information is taken into account by algorithm SMEZ, which is identical to algorithm SMME except that the input signal is extended with zero values for a total of 256 samples (102 ms) before the analysis. This simple procedure produces a low-entropy signal by forcing the Steiglitz–McBride algorithm to extrapolate the signal to zero values outside the sampled interval. Eight poles and eight zeroes were used in the Steiglitz–McBride algorithm. This may not be the optimal choice but it allows a direct comparison of our results with those of Joo *et al.* In addition, 16 poles were used for all-pole modeling so as to retain the same number of coefficients for comparison.

C. Comparison Procedures

To evaluate the stability of FFT-based and parametric methods of spectral analysis, two tests were performed on the first recording from each of the 11 patients. The first test consisted in reducing the duration of the closing sounds by 5 percent and repeating the spectral analyses. This test was intended to simulate the difficulty of determining the exact duration of the $A2$ component. The second test consisted in adding random noise equivalent to 5 percent of the total energy of the digitized closing sounds (before the coherent detection) and repeating the spectral analyses for a third time. This second test was used to measure the influence of variations in signal-to-noise ratio (SNR) between successive PCG recordings obtained from the same patient. For each method of spectral analysis, two error spectra were computed by substracting from the original spectrum, the spectra resulting from the truncated or noise-contaminated signals. Mean absolute error spectra were then computed and averaged over all patients.

Two frequency parameters, the dominant frequency peaks (DFP), were also extracted from each spectrum. The DFP's (F_1 and F_2) were chosen such that the intensity of F_1 was higher than that of F_2. When F_1 and F_2 had almost the same intensity (± 1 dB), F_1 was chosen as the lowest frequency and F_2 as the highest frequency. Mean absolute errors between the frequency parameters of the original spectra and those measured after truncation and noise addition were computed for each method.

In order to evaluate the practical usefulness of each method for the follow-up of patients with cardiac bioprosthetic valve, another study was done on the three recordings obtained from each patient. This study was based on the assumption that bioprosthetic valve degeneration is not significant during the first five years following valve implantation [5]. For this specific study, each spectrum was normalized to its peak spectral value (0 dB) in order to minimize the influence of microphone coupling and variability in heart sound intensity observed between the various recordings of the same patient. 18 frequency parameters were then obtained from each spectrum and submitted to a statistical analysis of variance. Parameters $P1$ and $P2$ were the DFP's, while parameters $P3$ to $P18$ were 16 intensity levels (in decibels) of frequency bands selected as follows:

- eight 25 Hz frequency bands centered at 25, 50, · · ·, 200 Hz
- six 50 Hz frequency bands centered at 250, 300, · · ·, 500 Hz
- two 100 Hz frequency bands centered at 650 and 850 Hz

For each method of spectral analysis, mean values and variances of the frequency parameters obtained from the three recordings of each patient were computed and averaged individually for the group of 11 patients. The resulting mean values were then compared to find which methods showed minimum variance.

IV. Results

A. Stability of the Methods

An example of the influence of small variations (5 percent) in SNR and closing sound duration on the spectrum estimation of the five algorithms is shown in Fig. 2. All methods except SMME appear to be quite stable to both types of perturbation. The basic periodogram, all-pole modeling and SMEZ seem to be more sensitive to truncation than to noise addition in the high frequency portion of the closing sound spectrum (above 400 Hz).

A comparison of a typical mean closing sound (panel A) with the impulse response of the model obtained by Steiglitz-McBride's method with extrapolation to zero values (panel B) and maximum entropy (panel C) is shown in Fig. 3. The impulse responses from both methods match relatively well the mean closing sound inside the sampled interval (0–24 ms). However, under the maximum entropy criterion, the addition of 5 percent of noise or reduction of sound duration by 5 percent produced a completely different impulse response outside the sampled interval. For extrapolation to zero values, no significant changes were observed in that region. These results show clearly that maximum entropy methods are not suitable for modeling transient signals of short duration.

Inspection of the mean absolute error spectra obtained from the 11 patients revealed that the error due to truncation and noise addition was generally higher above 300 Hz. The mean value of these spectra were thus computed from 20 to 300 Hz and from 300 to 1000 Hz in order to better characterize the frequency dependence of these disturbances. Results are given in Table I. In the low-frequency range (20–300 Hz), all methods except SMME show very small errors (≤ 1.3 dB) for both truncation and noise addition. Above 300 Hz, the error due to truncation is small for Welch's method (1.8 dB). The error increases gradually with SMME (3.0 dB), SMEZ (3.6 dB), and all-pole modeling (4.2 dB). As expected, the highest error is obtained with the basic periodogram (5.7 dB). For noise addition, the error above 300 Hz is small for all-pole modeling (1.4 dB) and the basic periodogram (2.2 dB). Welch's method and SMEZ give similar errors (3.1 and 3.3 dB) while the error increases significantly with SMME (5.9 dB).

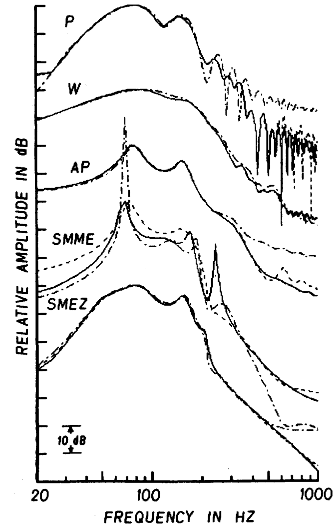

Fig. 2. Example of the influence of small variations in SNR and closing sound duration on the spectrum estimation of five algorithms: P = basic periodogram, W = Welch's method, AP = all-pole modeling, SMME = Steiglitz-McBride's method with maximum entropy and SMEZ = Steiglitz-McBride's method with extrapolation to zero values. Full lines represent spectra obtained by processing a closing sound from a typical recording, dot-dashed lines represent spectra obtained following reduction of sound duration by 5 percent and dashed lines represent spectra obtained after adding 5 percent of random noise to the total energy of the original closing sounds.

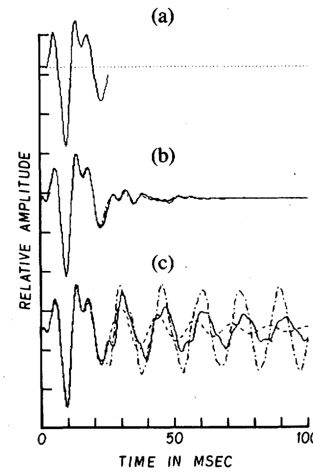

Fig. 3. Comparison of the original mean closing sound (a) with the impluse response of Steiglitz-McBride's method with extrapolation to zero values (b) and with maximum entropy (c).

Mean absolute errors (MAE) (measured in Hertz) of F_1 and F_2 after truncation and noise addition are given in Table II. Estimation of F_1 appears to be relatively insen-

TABLE I
MEAN ABSOLUTE ERRORS IN DECIBELS OBTAINED FROM 11 PATIENTS FOLLOWING TRUNCATION OF SIGNAL DURATION BY 5 PERCENT AND ADDITION OF 5 PERCENT OF RANDOM NOISE

	TRUNCATION		NOISE	
ALG	20-300 Hz	300-1000 Hz	20-300 Hz	300-1000 Hz
	dB	dB	dB	dB
P	1.2	5.7	0.1	2.2
W	1.3	1.8	0.05	3.1
AP	0.7	4.2	0.1	1.4
SMME	3.6	3.0	2.3	5.9
SMEZ	0.7	3.6	0.6	3.3

TABLE II
MEAN ABSOLUTE ERRORS IN HERTZ OF THE TWO MOST DOMINANT FREQUENCY PEAKS (F_1 AND F_2) FOLLOWING TRUNCATION BY 5 PERCENT OF THE CLOSING SOUND DURATION OR ADDITION OF 5 PERCENT OF NOISE TO THESE CLOSING SOUNDS

	TRUNCATION		NOISE	
ALG	F1 (Hz)	F2 (Hz)	F1 (Hz)	F2 (Hz)
P	0.4	37.7	0.0	8.0
W	3.1	50.6	0.0	21.8
AP	1.3	131.7	0.5	55.9
SMME	35.1	33.2	20.9	19.5
SMEZ	0.0	75.4	2.2	62.9

sitive to truncation and noise addition for all algorithms (MAE $\leq$ 3.1 Hz) except for SMME which produced MAE of 35.1 and 20.9 Hz, respectively. Estimation of F_2 is very sensitive to both truncation and noise for all algorithms. Best results are obtained with the basic periodogram, SMME and Welch's method (8.0 $\leq$ MAE $\leq$ 50.6 Hz). SMEZ produced errors of 75.4 and 62.9 Hz for truncation and noise addition while all-pole modeling produced the largest errors, 131.7 and 55.9 Hz, respectively. In summary, all algorithms are better than SMME for estimating F_1 while the basic periodogram and SMME are the most consistent methods for estimating F_2.

B. Application to the Follow-Up of Patients with Prosthetic Valves

Results from the multiple analysis of variance are shown in Table III for parameters $P1$ and $P2$ and in Fig. 4 for parameters $P3$–$P18$. The variance of the two DFP's (F_1 and F_2) were normalized with their mean values to compensate for their tendency to increase proportionally with frequency [5]. According to Table III, estimation of F_1 is quite uniform for all algorithms. Corresponding normalized variances (nv) are relatively small except for SMME. Estimation of the second DFP (F_2) varies significantly from one algorithm to another. In this case, the methods can be separated in two groups: the basic periodogram, SMME and SMEZ produced estimates around 200 Hz while Welch's method and all-pole modeling produced

TABLE III
MEAN VALUE ($\bar{m}$) AND NORMALIZED VARIANCE (nv) OF THE TWO MOST DOMINANT FREQUENCY PEAKS (F_1 AND F_2) OF PROSTHETIC CLOSING SOUNDS OBTAINED FROM THREE CONSECUTIVE RECORDINGS OF 11 PATIENTS. VARIANCES WERE NORMALIZED WITH THE MEAN VALUES OF THE DOMINANT FREQUENCY PEAKS IN ORDER TO COMPENSATE THEIR DEPENDENCE ON FREQUENCY

	F_1 (Hz)		F_2 (Hz)	
ALG	$\bar{m}$	nv	$\bar{m}$	nv
P	114	1.7	205	35.2
W	116	2.5	375	56.9
AP	104	1.3	344	191.1
SMME	117	8.8	154	15.9
SMEZ	112	2.2	227	91.6

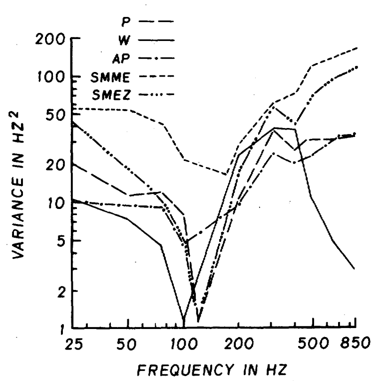

Fig. 4. Plot of the variance of the spectral intensity levels of the five algorithms obtained from three successive recordings of 11 patients. The same abbreviations of Fig. 2 are used.

estimates around 360 Hz. SMME and the basic periodogram seem to give the most stable estimates on the basis of lowest normalized variance. It is also interesting to note that all-pole modeling is a very unstable estimator of F_2.

Information on the variance of the spectral intensity levels of these closing sound spectra is provided by Fig. 4. As shown in this figure, the variance is generally minimum around F_1 (115 Hz) and increases rapidly above and below this dominant frequency peak. The basic periodogram, Welch's method and SMEZ give minimal variances of about 1 Hz^2 while all-pole modeling and SMME show minimal variances of 5 and 20 Hz^2, respectively. The limitations of SMME for estimating spectral intensity levels are clearly demonstrated here. A similar, but less important, effect can be observed for all-pole modeling.

The small variance of the spectral intensity levels obtained with Welch's method compared to the other algorithms for frequencies above 400 Hz requires some explanations. Even if the significant frequency content of bioprosthetic closing sounds decreases rapidly above 400 Hz, coherent detection and averaging of 20 closing sounds increase their SNR but do not modify the truncation effect on the signal. As shown in Table I, the effect of truncation was always significant ($\geq$3 dB) above 300 Hz except for Welch's method. Indeed, Welch's method reduced considerably the effect of truncation in the high frequency band because it used a hanning window which tapers the signal to zero values at its beginning and end. However, this window also reduces the frequency resolution of the method.

V. Discussion and Conclusion

Present methods of "signature" analysis of prosthetic valve sounds are mostly based on a few parameters extracted from the spectra of the valve closing sounds. For instance, an FFT-based method has been used by Stein *et al.* [10]–[12] for relating changes in F_1 to the degeneration of porcine xenograft valves. Joo *et al.* [7] were the first investigators to use Steiglitz–McBride's methods with maximum entropy for the spectral analysis of porcine valve sounds. They have shown that a heuristic vector $X(F_1, F_2)$ can be used to develop a Gaussian classifier capable of separating normal from abnormal valve sounds. A similar method used by Foale *et al.* [5] showed that, following valve dysfunction due to degeneration of the leaflets and infection, F_1(89 $\pm$ 15 Hz) and F_2(154 $\pm$ 25 Hz) of normal porcine valves increased up to 139 $\pm$ 54 Hz and 195 $\pm$ 75 Hz, respectively.

Our results on the stability (Table II) and reproducibility (Table III) of the two DFP's show that all algorithms, except SMME, produced estimates of F_1 which are highly stable. All-pole modeling introduces a small bias which consists in underestimating the value of F_1 by 10 Hz. Poor performance of SMME results from the fact that this algorithm models the signal as the output of an underdamped system for which the relative intensity of F_1 and F_2 are very sensitive to both truncation and noise. For closing sound spectra with two DFP's of about the same intensity, F_1 may be interchanged with F_2 from recording to recording. For most algorithms, estimation of F_2 is much more sensitive to truncation and noise than estimation of F_1. All-pole modeling is unable to estimate F_2 because, most often, close DFP's of different intensity are merged in one peak as F_1 and a third frequency peak of lower intensity is found as F_2. Similarly, the windowing function used in Welch's method produced smoothed spectra where the true F_2 is merged with F_1 and a smaller peak of higher frequency is found as F_2. Finally, the three other algorithms seem to provide consistent estimates of F_2 (around 200 Hz). Best methods are SMME and the basic periodogram, while SMEZ gives acceptable results. Indeed, SMEZ produced results very similar to those of the basic periodogram except for a higher variance in the estimation of F_2. This discrepancy results from the limitation of Steiglitz–McBride's method to match a signal over a long period of time with a small number of poles and zeros. Extrapolation to zero values was obtained by matching the impulse response of the system with a signal extended with zero values up to 100 ms while under maximum entropy, the impulse response was always matched with a signal of duration less than 40 ms. A better match for SMEZ would require a greater number of poles and zeros according to the Akaike criterion [1]. In this way, second DFP's of small intensity would not be missed by the least-squares minimization procedure. The basic periodogram and SMME are thus the best methods to estimate both F_1 and F_2, the true advantage of SMME being in the evaluation of F_2 only.

Stability and reproducibility of each method for the estimation of spectral distribution of prosthetic valve sounds were also evaluated. While underestimating the real problems of closing sound selection (truncation) and SNR variations, the two studies on the stability of the five algorithms gave interesting results. As expected, the effect of truncation and noise addition produced large errors in the high frequency range (300–1000 Hz) of the spectral estimates. In addition, Steiglitz–McBride's method with maximum entropy also produced significant errors in the low frequency range (20–300 Hz). As emphasized in Fig. 3, Steiglitz–McBride's method with maximum entropy seems to produce spectral estimates with DFP's whose damping factor is very sensitive to noise and truncation. In other words, signal truncation and noise addition have a negligible effect on the central frequency of the DFP's but a strong effect on their relative intensity. For estimation of spectral distributions, Steiglitz–McBride's method is stable only when modeling is done by extrapolating the signal to zero values outside the sampled interval. Thus, the model underlying SMEZ reflects much better the transient nature of the valve sounds than the model underlying SMME, which is more appropriate for modeling signals of indefinite duration. Results on the reproducibility of the spectral distribution of bioprosthetic valve sounds are in good agreement with those obtained from the stability analyses. For instance, all three studies show that SMME is not a stable estimator of the spectral distribution of bioprosthetic valve sounds. Welch's method seems very stable but suffers from a lack of frequency resolution. Best methods are the basic periodogram and SMEZ, while all-pole modeling can give good results.

It can thus be concluded that the basic periodogram is the best compromise for estimating both the spectral distribution and the dominant frequency peaks of bioprosthetic valve sounds. This suggests that, because of the fast decaying rate of bioprosthetic closing sounds, truncation error is generally not very important and probably represents only a small portion of the total energy of these sounds. This is confirmed by SMEZ which extrapolates the signal to zero values outside the sampled interval and produces results very similar to the basic periodogram.

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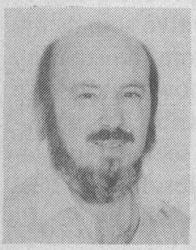

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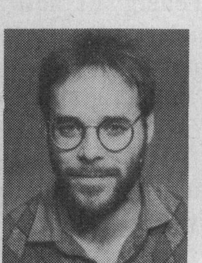

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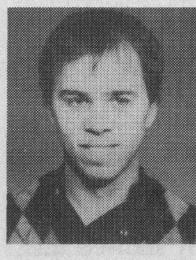

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