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

Part 1 Optimal number of poles and zeros for parametric spectral analysis

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Abstract—*The selection of the optimal number of poles (P) and zeros (Q) for parametric spectral analysis of closing sounds produced by Ionescu-Shiley bioprosthetic aortic heart valves was evaluated in 15 patients. These values were obtained by computing the normalised root-mean-square error (NRMSE) function between the aortic closing sounds and the impulse response of the parametric models for different values of P and Q. As expected, the NRMSE function decreased with increasing value of P and Q. The optimal P and Q were selected at the beginning of the plateau of the NRMSE function. For all-pole modelling with autocorrelation and all-pole modelling with covariance, the optimal number of poles is 16. For pole-zero modelling using the Steiglitz-McBride method with maximum entropy and extrapolation to zero, the optimum values are 14 poles and 14 zeros.*

Keywords—*All-pole modelling, Maximum entropy methods, Number of poles and zeros, Parametric spectral analysis, Phonocardiography, Pole-zero modelling*

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List of abbreviations

a_k	parameters describing the poles of the parametric model
APA	all-pole modelling with autocorrelation method
APC	all-pole modelling with covariance method
A_2	aortic component of the second heart sound
b_r	parameters describing the zeros of the parametric model
E	square error
ms	millisecond
NRMSE	normalised root-mean-square error
P	number of poles
Q	number of zeros
SD	standard deviation
SMME	Steiglitz-McBride method with maximum entropy (pole-zero modelling)
SMEZ	Steiglitz-McBride method with extrapolation to zero (pole-zero modelling)
S/N	signal-to-noise

1 Introduction

ONE INTERESTING advantage of biological heart valve substitutes, compared with metallic substitutes, is that they degrade slowly rather than catastrophically. THIENE *et al.* (1982) and GALLUCCI *et al.* (1982) have shown that deposit of calcium constitutes the most important degradation process of bioprosthetic heart valves. Stenosis, stiffness, fibrosis and loss of motility of valve leaflets result from this process and account for 50 per cent of late dysfunctions of bioprosthetic heart valves. They have also shown that calcification is not significant in valves implanted for less than 2 years but contributes to 75 per cent of valve dysfunctions after 8 years of implantation. In a study on the durability of 855 Ionescu-Shiley bioprosthetic heart valves, IONESCU *et al.* (1982) concluded that only a small percentage of valve replacement occurs during the first 4 years following implantation. This percentage increases rapidly after 5 years.

Among the accepted techniques for regularly monitoring patients with valve implants, spectral analysis of the valve closing sounds has been shown to be potentially useful in detecting minute changes in performance (STEIN *et al.*, 1980; 1981; 1984; FOALE *et al.*, 1983; JOO *et al.*, 1983). Several methods have been investigated for obtaining the spectral characteristics of bioprosthetic valve sounds: some were based on the fast Fourier transform, whereas others rely on more recent concepts of parametric system identification.

DURAND *et al.* (1986) have recently shown that the duration of the aortic valve closing sounds (A_2) and the background noise of the phonocardiogram can limit the accuracy of various spectral techniques. However, their study was based on standard methods described in the literature and did not examine the influence of the number of poles and zeros on the performance of parametric spectral methods.

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The choice of the number of poles (P) and zeros (Q) in parametric spectral analysis is very important in the assessment of the spectral characteristics. Indeed, a low-order model will produce a smoothed spectrum with low frequency resolution, whereas a high order model may introduce spurious detail (CHILDERS, 1979; VIJAYA KUMAR and MULLICK, 1979). In addition, STEIGLITZ and MCBRIDE (1965) and JOO (1982) reported that high-order pole-zero algorithms tend to model the noise of the signal. It was also reported by FOUGERE *et al.* (1976) and KAY and MARPLE (1979) that all-pole modelling with autocorrelation behaves poorly even at high signal-to-noise (S/N) ratios, exhibiting frequency shifts of the spectral peaks and 'peak splitting'. LANG and MCCLELLAN (1980) also noted that spurious peaks appear in all-pole modelling with covariance for low S/N ratios.

A method to select the optimal number of poles for all-pole modelling has been proposed by CHILDERS (1979). It consists in calculating the mean-square error between the modelled signal and its impulse response as P is increased. When the error suddenly decreases by a significant step, then this value may be selected as the optimal P. A different criterion was proposed by JOO (1982) to select P and Q for pole-zero modelling. Essentially, it consists in comparing the signal to the impulse response of the model as P and Q are varied and selecting the combination that provides the minimum error. Other criteria are available and are based on the statistical properties and the autocorrelation function of the modelled signal; among these, the Akaike criteria are widely used (AKAIKE, 1970; 1974).

In the present paper, we propose to evaluate the optimal number of poles and zeros for modelling bioprosthetic aortic closing sounds by computing the normalised root-mean-square error (NRMSE)* function between the aortic valve closing sounds and the impulse response of the parametric models for different values of P and Q. Unlike the criteria of Childers and Joo, we propose to select P and Q at the beginning of the minimum plateau of the NRMSE decreasing curve. The criteria of Akaike, based on the statistical properties of the modelled zero mean random signal, have not been used in this analysis because of the transient nature of acoustic closing sounds.

2 Parametric spectral estimation

The basic idea behind parametric spectral analysis is that a signal $s(n)$ can be modelled as the output of an equivalent linear system excited by an input signal $x(n)$, such that

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

where a_k and b_r are the parameters describing the system and P and Q the number of poles and zeros of the model. The objective of this technique is to estimate the parameters of the model from measurements of the signal made over a limited period of time. Maximum entropy is often used as a criterion in the estimation of a_k and b_r. These 'maximum entropy methods' model the equivalent system by assuming that the spectral estimate of the output signal $s(n)$ is generated by a random process with a maximum entropy behaviour.

The transfer function $H(Z)$ of the equivalent parametric model is expressed by

$$H(Z) = S(Z)/X(Z) = \sum_{r=0}^{Q} b_r Z^{-r} \Bigg/ \left(1 + \sum_{k=1}^{P} a_k Z^{-k}\right) \tag{2}$$

Eqn. 2 describes the transfer function of the pole-zero model. In the all-pole model, the numerator of eqn. 2 is replaced by a constant G representing the gain of the system. Finally, an all-zero model is obtained by removing the denominator of eqn. 2.

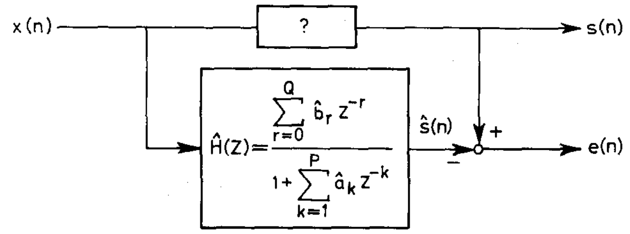

Fig. 1 *Pole-zero model used to estimate the transfer function of the equivalent system*

The methodology used to estimate a_k and b_r has been very well described by MAKHOUL in 1975. Briefly, it involves the minimisation of the total squared error E between the actual signal $s(n)$ of duration N and the predicted signal $\hat{s}(n)$ of the equivalent system (Fig. 1). Mathematically, this error E is given by:

$$E = \sum_n (s(n) - \hat{s}(n))^2$$

$$= \sum_n \left(s(n) + \sum_{k=1}^{P} \hat{a}_k s(n-k) - \sum_{r=0}^{Q} \hat{b}_r x(n-r)\right)^2 \tag{3}$$

where $\hat{a}_k$, $\hat{b}_r$ are the estimated parameters describing the system.

2.1 *Practical aspects of parametric spectral estimation*

Two forms of excitation are generally used to estimate $s(n)$ (MAKHOUL, 1975; RABINER and SCHAFER, 1978). In speech processing, a white noise signal is used to estimate the spectrum of unvoiced sounds such as the fricatives (f, th, s, sh). On the other hand, for estimating the spectrum of voiced sounds such as vowels and nasals, a unit impulse $\delta(n)$ is preferred because of the transient nature of the signal. For this reason, a unit impulse $\delta(n)$ was chosen to estimate the spectrum of acoustic closing sounds. Then, by using $Z = e^{j\omega}$ in the transfer function and computing its squared modulus $|H(e^{j\omega})|^2$, the estimated spectrum of $s(n)$ is obtained.

Two different approaches can be used to generate $s(n)$ with all-pole modelling: the autocorrelation (APA) and covariance (APC) techniques. The main difference between these techniques is the assumption made on the nature of the signal $s(n)$ outside the sampled interval. In APA modelling, $s(n)$ is considered to be zero outside the interval, while with APC no assumption is made outside the N samples of $s(n)$. This minor difference produces significant differences in the resulting impulse response of $s(n)$. With APC, the estimated signal $\hat{s}(n)$ can take any value outside the N samples of $s(n)$, which may produce an unstable solution. With APA modelling, the solution is always stable.

In this analysis, the iterative Steiglitz-McBride algorithm has been used to estimate the spectrum of $s(n)$ with pole-zero modelling (STEIGLITZ and MCBRIDE, 1965). This technique assumes that, at the ith iteration, a previous estimate of the poles of the transfer function is available. At the first iteration, the poles estimated by a simple all-pole algorithm could be used as a first estimate. The basis of this

* $NRMSE = \sum_{n=0}^{N-1} [(s(n) - \hat{s}(n))^2/s(n)^2]^{1/2}$

method is to filter the signal $s(n)$ and $x(n)$ by the poles of the previous iteration and submit the resulting signals to the pole-zero Kalman algorithm as presented by Joo (1982). The poles obtained at this new iteration are used to filter the input signals $s(n)$ and $x(n)$ for the next iteration. The procedure is repeated until the error of the ith iteration reaches a specified level, or a given number of iterations are completed.

A drawback of the SMME algorithm is that its convergence properties are not known for physical signals (STEIGLITZ, 1977; STOICA and SODERSTROM, 1981). However, STEIGLITZ (1977) has shown that 5–10 iterations are sufficient to ensure convergence when all-pole prefiltering is used as a first estimate of the a_k coefficients. JOO *et al.* (1983) have used the SMME algorithm for the estimation of acoustic closing sound spectra. They have shown that five iterations are usually sufficient to obtain a good estimate of the signal for $P = Q = 8$. However, as mentioned by STEIGLITZ (1977), care should be exercised when using this algorithm with large values of P and Q as it may present convergence problems in the iterative procedure and then produce unstable solutions.

Steiglitz-McBride's method models the signal on the assumption that the spectral estimate is mostly random and has a maximum entropy behaviour. Because bioprosthetic closing sounds consist of acoustic transients with fast decaying rates, they are low-entropy signals. As proposed by DURAND *et al.* (1986), this *a priori* information can be taken into account in SMEZ by extending the input signal with zero values before modelling with Steiglitz-McBride's method.

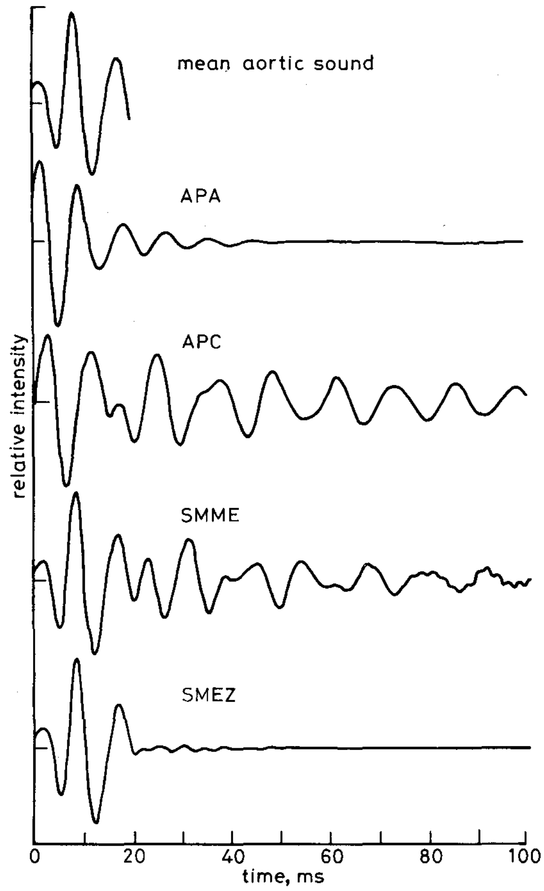

Fig. 2 *Example of an aortic closing sound with the corresponding impulse responses of APA, APC, SMME and SMEZ methods*

3 Methods

The optimal number of poles and zeros for parametric methods were evaluated by computing the normalised root-mean-square error function between the aortic valve closing sound and the impulse response of the models (APA, APC, SMME, SMEZ) for different values of P and Q. The NRMSE was computed on the interval corresponding to the duration of the closing sounds and the optimal P and Q were chosen at the beginning of the plateau of the NRMSE function.

Fig. 2 shows an original sound $s(n)$ and the impulse responses $\hat{s}(n)$ obtained with APA, APC, SMME and SMEZ. As may be seen, the correspondence between $s(n)$ and $\hat{s}(n)$ is not very good for all-pole modelling. A better match is obtained by adding a lagging period to the impulse responses of the model. This is done by adding zeros before the beginning of $\hat{s}(n)$. The NRMSE was computed for P varying between 6 and 22. No lagging period is required for maximal matching of $s(n)$ and the impulse

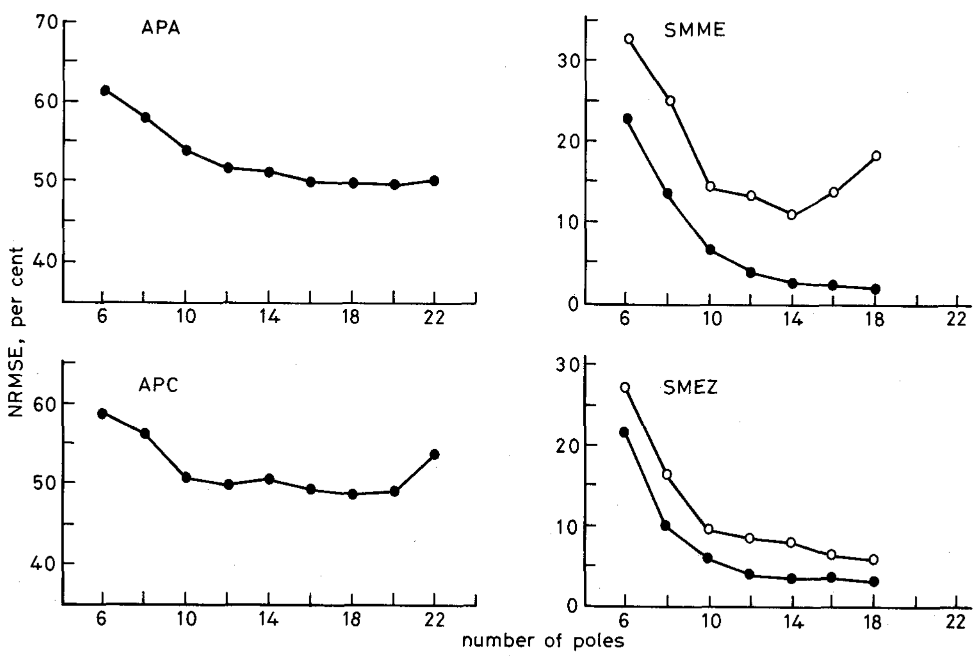

Fig. 3 *Normalised root-mean-square error between the aortic closing sounds and the impulse responses of four parametric models: APA, APC, SMME and SMEZ. The curves represent the averaged NRMSE as a function of the number of poles P (black circles correspond to Q = P and white circles to Q = P/2)*

responses of pole-zero modelling. The NRMSE between A_2 and the impulse response of the model has been computed for $Q = P$ and $Q = P/2$, with P varying between 6 and 18.

4 Results

The averaged NRMSE functions for 15 patients are shown in Fig. 3. The optimal number of poles is 16 for modelling normal aortic closing sounds with APA and APC. Two plateaus are observed for all-pole modelling with covariance method, one for $10 \leqslant P \leqslant 14$ poles and another for $16 \leqslant P \leqslant 20$ poles. The optimal value of P has been selected at the beginning of the plateau which has the minimal value of the NRMSE. For SMME and SMEZ, the optimal numbers of poles and zeros are $P = Q = 14$*.

As we mentioned previously, zero values were added to the aortic closing sounds in the SMEZ algorithm. The selection of the number of samples added to the aortic sounds was done by computing the NRMSE between the aortic sound and the corresponding impulse response of the SMEZ model. This value was computed on the first N points (60 ± 22 samples (mean $\pm$ SD)) after completing the aortic sounds to 128, 256 and 512 samples. The corresponding averaged NRMSE were $3{\cdot}8 \pm 2{\cdot}0$ per cent, $3{\cdot}6 \pm 2{\cdot}0$ per cent and $3{\cdot}6 \pm 1{\cdot}7$ per cent. An array of 512 samples was chosen to force the impulse response of the SMEZ algorithm to decrease to zero and maintain this value for a period of time relatively longer than the duration of the aortic closing sounds.

5 Discussion and conclusion

The selection of the optimal number of poles and zeros for parametric spectral analysis of closing sounds produced by Ionescu-Shiley bioprosthetic aortic heart valves has been presented here. Sixteen poles were selected for all-pole modelling with autocorrelation or covariance method and 14 poles and 14 zeros were chosen for pole-zero modelling with SMME and SMEZ.

A method to select the optimal number of poles has been proposed by Childers (1979). Their approach was to calculate the mean-square error between the modelled signal and its impulse response as P is increased, and to select P when the error suddenly decreases by a significant step. Joo (1982) has proposed a similar approach for pole-zero modelling but with P and Q selected at the minimum value of the error between the signal and the impulse response of the model. In this analysis, we chose to select the optimal value of P and Q at the beginning of the plateau of the NRMSE function. This criterion is justified by the fact that aortic closing sounds are deterministic transient signals perturbed by a small amount of random noise. Then, larger values of P and Q than those allowed by Childers' criterion can be chosen because the algorithm is less perturbed by background noise. Furthermore, the criterion proposed by Joo cannot always be used because the NRMSE function does not necessarily reach a local minimum.

A lagging period was required for optimal matching of the impulse responses of the all-pole models with the valve closing sound. This was also observed by Joo (1982) and could be associated to a lack in flexibility of the algorithms, owing to the use of a fixed numerator G in the transfer function of the system.

In the present analysis, the NRMSE function was computed for $Q = P$ and $Q = P/2$. Other combinations of P and Q were not tested because this procedure is time consuming. However, the NRMSE was also computed for $P = 14$ and $Q = 28$. Results were slightly better than those with $P = Q = 14$. For instance, the NRMSE was $1{\cdot}8$ per cent lower for SMME and $1{\cdot}3$ per cent for SMEZ. However, this combination ($Q = 2P$) did not appear to be interesting because it increased significantly the execution time of the algorithms.

It is interesting to note that the criterion proposed by Joo (1982) to select the optimal number of poles and zeros has not been used by its author. The reason is probably because of the excessive computing time required. Foale *et al.* (1983) used 3–4 poles in modelling aortic closing sounds with APC and Joo used 8 poles and 8 zeros for SMME. Based on the results presented in this analysis, lower modelling errors are obtained with 16 poles for APC and 14 poles and 14 zeros for SMME. Better diagnostic potential in the assessment of normal and abnormal heart valves should be obtained with these parameter values.

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* *In this analysis, ten iterations were used to model A_2 with SMME and SMEZ. However, when the modelling error between $s(n)$ and $\hat{s}(n)$ dropped under 0·1 per cent, the iteration process was stopped.*

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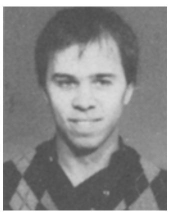
Authors' biographies



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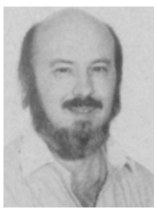

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