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Processing of Prosthetic Heart Valve Sounds for Classification

J. V. Candy
H. E. Jones
Lawrence Livermore National Laboratory

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J. V. Candy & H. E. Jones
University of California
Lawrence Livermore National Laboratory
P.O. Box 808, L-495
Livermore, CA 94550

Abstract

People with serious heart conditions have had their expected life span extended considerably with the development of the prosthetic heart valve especially with the great strides made in valve design. Even though the designs are extremely reliable, the valves are mechanical and operating continuously over a long period, therefore, structural failures can occur due to fatigue. Measuring heart sounds non-invasively in a noisy environment puts more demands on the signal processing to extract the desired signals from the noise. In this paper we discuss acoustical signal processing techniques developed to process noisy heart valve sounds measured by a sensitive, surface contact microphone and used for the eventual classification of the valve.

1: Introduction

The Bjork-Shiley Convexo-Concave (BSCC) prosthetic heart valve was manufactured from 1979 to 1986 and is currently estimated to have been implanted in approximately 23,000 patients in the United States and Canada [1]. This mechanical valve controls the flow of blood with a disc occluder that rotates between inlet and outlet struts. In an unusually small number of these valves, the outlet strut fractures from fatigue resulting in the mortality of two-thirds of the patients. Current technology suggests that one of the legs of the strut separates from the flange. If this single leg separation (SLS) condition can be detected, then the valve can be replaced before the remaining leg fractures. Although actuarial analysis predicts that the risk of a fracture of the two-legged outlet strut is usually less than the risk associated with open-heart surgery required to replace the BSCC valve with a different type of prosthetic heart valve, Shiley Heart Valve Research Center, (SHVRC) is conducting research in an attempt to identify the SLS valves. This research includes a variety of methods for screening patients with BSCC valves in minimally invasive methods in an attempt to determine if the outlet strut is intact (INT) or SLS.

Sounds are produced by the BSCC valve as it closes and opens with the heart's pumping action which occurs approximately 39 million times per year in the average patient. Analyzing the signal that acoustically propagates is one approach in determining the condition of the outlet strut. Another method is the use of X-ray imaging of the valve in vivo (in the body). Although this second potential method is also non invasive, it does have the potential disadvantage of radiation exposure. The overall objective of this research is aimed at developing techniques for analyzing heart valve sounds enabling the classification of implanted BSCC heart valves as INT or SLS. This acoustic screening methodology may eventually be used as a means of selecting particular valves, which may benefit from further examination by X-ray methods currently being developed by the SHVRC. The current approach to solve the

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Heart Valve SLS Classification Problem is based on the fact that the dynamic action of the valve propagates acoustical signals at various frequencies which can be measured using sensitive, surface contact microphones. Currently, each heart cycle is measured and separated into valve *closing* as well as *opening* cycles or beats [2]. The acoustic energy radiated by a functioning heart valve is contaminated by numerous mechanisms. The human body superimposes biological sounds and distorts the acoustic energy as it travels through tissue. The instrumentation that captures the heart valve sounds influences the data. The microphone, filters, amplifiers, digitizer, and storage media distort the raw acoustic data. Extracting pertinent information from the original heart valve sounds is difficult signal processing problem considering the distortions caused by these biological and electronic sources.

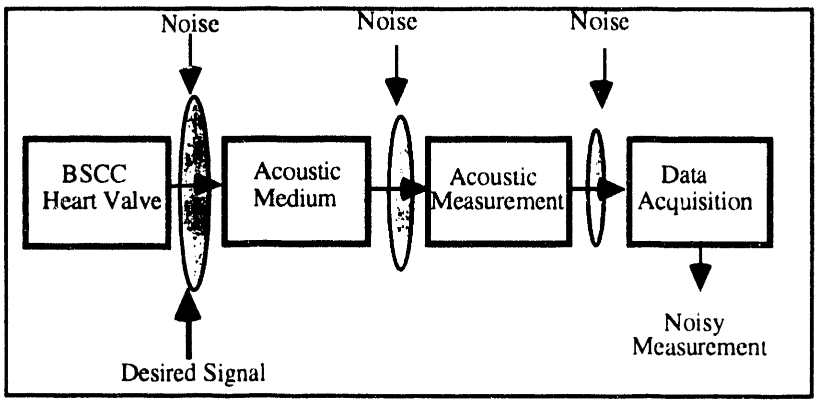

Figure 1. Conceptual Diagram of Prosthetic Heart Valve Acoustic Propagation.

One approach to solve the classification problem is based on *Statistical Pattern Recognition*, [3] which essentially interprets the spectrogram surface as an image, extracts so-called features from it and attempts to define various decision regions within for classification. Another approach is based on applying "adaptive" type classification schemes implemented using *neural networks*. [4]. Here various algorithms modeled after the human brain neuron action are applied to spectrogram data after the important features are extracted. The network is asked to "learn" the various valve classes by repeated application of data. Both techniques offer much promise, but again large quantities of high quality acoustic data must be processed to quantify their performance with acceptable statistical reliability. Of course, improved signal processing of the spectrogram and/or feature vectors can only add to enhanced performance -- this is the main point of this paper in which we discuss techniques to extract, enhance and reject weak opening signals from acoustic measurements of prosthetic heart valve sounds.

In section 2, we develop a parametric approach to extract and process raw heart valve sounds from noisy acoustic data. Here we motivate the selected algorithms and indicate their performance on typical clinical data. We develop a monitor to screen and select "good" beats for further processing and classification in section 3. We summarize our results in section 4.

2.: Signal Processing of Heart Valve Acoustics

In this section we discuss the development of various signal processing techniques to detect and extract the low-level heart sound signals from the noisy acoustic measurements and then enhance them for use in classification schemes. We have concentrated our efforts on the heart valve opening sounds. The opening sound yields direct information about outlet strut fracture with minimal amount of disturbance caused by disc radiation; hence, the opening sound is a very desirable acoustic signal to extract. Unfortunately, the opening sounds have much lower signal levels and therefore, noise plays a more significant role than during the closing event. Prior to spectral estimation and classification the opening valve sounds or beats must be extracted.

An automated beat extraction process has been designed which relieves human operators of the tedious task of manually extracting these beats from the digitized audio data [5]. This process attempts to provide a general solution for extracting both opening and closing sounds from a wide array of clinical acoustic data, including data from patients with irregular, paced, or atrial fibrillation heartbeat patterns. Once the opening sounds from each valve session have been extracted and imported into the data base, they are available for processing and classification. We have developed a *parametric approach* to estimate the power spectrum emanating from the prosthetic heart valve opening sounds during each beat cycle. This approach is based on estimating a parametric model of the beat transient signal characterized by an *autoregressive* (AR) or all-pole model which is used primarily to extract damped sinusoidal signals in noise -- a reasonable representation of the acoustical signal. The AR model is defined by the difference equation

$$y(n) = -\sum_{i=1}^{N} a_i y(n-i) + \sigma\varepsilon(n), \tag{1}$$

where $y(n)$ is the output or response (valve sound), $\varepsilon(n)$ is the input or excitation (impulse or prediction error), $[\{a_i\}, \sigma]$ is the set of AR model parameters. Applying Z-transforms to Eqn. 1, then we obtain the *transfer function* given by

$$H(z) = \frac{Y(z)}{E(z)} = \frac{\sigma}{A(z)}, \tag{2}$$

where $A(z) = 1 + a_1 z^{-1} + \cdots + a_N z^{-N}$ is the characteristic polynomial of the AR model whose roots $\{p_i\}$ are the *poles* of the system. Since the data are noisy, the excitation $\varepsilon(n)$ of the $AR(N)$ is modeled as a zero-mean, unit variance, completely random (white) noise process whose discrete Fourier spectrum $H_{AR}(\Omega)$ must be replaced by the corresponding power spectral density [6] defined by

$$S_{AR}(\Omega) = H_{AR}(\Omega)H^*_{AR}(\Omega) = \frac{\sigma^2}{|A(\Omega)|^2}, \tag{3}$$

in order to "average out" the effect of the noise, that is, $S_{AR}(\Omega) = E\{Y(\Omega)Y^*(\Omega)\}$. Thus, the "parametric approach" to represent the heart valve sounds essentially becomes that of estimating the parametric set defined by $\Theta_{AR} := [\{\hat{a}_i\}, \hat{\sigma}]$ from the noisy acoustic measurement data $\{y(n)\}$. Once these parameters are estimated, then the corresponding $AR(N)$ model and spectrum $\hat{S}_{AR}(\Omega)$ are constructed for <u>each</u> individual heart valve sound, creating the corresponding heart valve acoustic spectrogram (beat power versus frequency). It should also be noted that the order N of the $AR(N)$ model must be estimated. Order estimation is accomplished using the *Akaike Information Criterion* (AIC) statistic defined by

$$AIC(N) = -2\ln\sigma_{\varepsilon}^2 + 2N, \tag{4}$$

where σ_{ε}^{2} is the prediction error variance, N is the model order. The optimal order is the selected as the

$$N = \min AIC(N), \tag{5}$$

There are a variety of parameter estimation algorithms available for this application, we choose to use the lattice algorithms [6] which essentially is obtained by performing an LD-decomposition of a Toeplitz correlation matrix [7]. Using the lattice algorithm, we estimate the required parameter set $\hat{\Theta}_k$ and the corresponding power spectrum $\hat{S}_k(\Omega)$ for the k^{th} heart valve sound and stack them to create the spectrogram. A typical clinical spectrogram is shown in Figure 2.

Note the repeatability of each spectrum along with the average spectrum. The corresponding spectrogram is shown in the figure as beat power versus beat number versus frequency along with the corresponding resonant peak histogram. Once the spectral estimator is designed, the resonant frequencies are also estimated from the power spectrum. Here our approach is to estimate the peaks of the spectrum above a pre-set threshold. From this spectrum of peaks, we estimate the corresponding resonant frequencies present in the data from its location. Clearly, if the heart valve sounds were stationary, then only a single spectral line would appear at each frequency during each beat, but due to reasons discussed previously the acoustic data is non-stationary and therefore, we expect frequencies to "cluster" about a mean frequency. Here the approach is to estimate the probability of occurrence of a set of resonant frequencies and look for clustering about various mean frequencies. We estimate this multivariate probability mass function using a histogram estimator with bin size corresponding to the frequency resolution of the processed data. This approach leads to a new set of features which are used in the final classifier.

Once the lattice parameters, spectrogram and peak frequency histogram are estimated for a given valve, they are stored in the data base and made available to the various classifiers on demand. Besides the peak histogram, the spectral power in various bands are averaged over the ensemble and used as components of feature vectors along with the reflection coefficients themselves, which have proved to be reliable features for other applications [9,10]. So we see that the parametric approach offers reasonable estimates of desirable features which can ultimately be used to classify heart valve conditions. Next we discuss the detailed development of the Beat Monitor -- a pre-classification algorithm primarily aimed at rejecting "bad" beats.

3.: Processing of Acoustic Heart Valve Transients

Classifying the heart valve condition from the acoustic signatures requires unambiguous data, selection and extraction of the significant features, and development of a classification algorithm which identifies the valve condition with the best sensitivity and specificity. It is important to acquire noise free, uncontaminated signals in the appropriate frequency range to provide enough information to classify the signals. Poor data will significantly hamper the attempts to predict the heart valve condition because the classifiers will be based on random noise instead of signal information related to valve condition. Thus, it is essential not only to extract the opening transients, but to assure that the beats extracted have an adequate signal-to-noise ratio to provide the classifier high quality resonance information as features. We

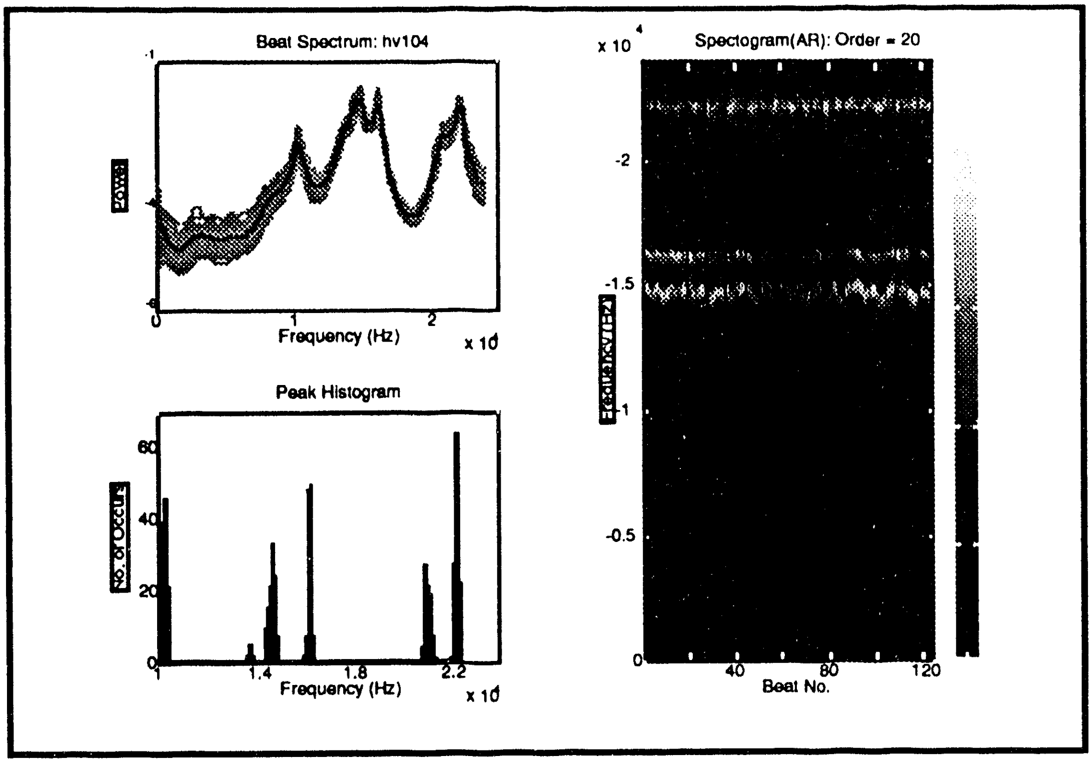

Figure 2. Clinical Spectrogram Estimates: Estimated Power Spectral/Average, Frequency Peak Histogram and Beat Spectrogram.

have developed a sophisticated Beat Monitor that utilizes the spectral content of acceptable opening transients to accept/reject subsequent openings. The Monitor depicted in Figure 2 uses the opening heart valve beat sounds to develop a parametric model and then predicts the acoustic response on a beat-to-beat basis. The algorithm, first captures an ensemble of acceptable beats (during training), estimates an "average" parametric model, and then screens subsequent beats using the model. This processor is based on testing the residual sequence, which is the difference between the measured and predicted acoustic signal, for the statistical property of "whiteness". This scheme relies on the underlying fact that if the parametric model reliably represents or "fits" the data, then the residual sequence contains no other information about valve acoustics (resonances). Therefore, the sequence should be purely random or "white". Should the residual sequence test statistically white, then theoretically the estimated model fits the data and nothing has changed; however, should it test non-white, then something has changed and a further, more detailed investigation must be pursued (see Refs. 11, 12, 13 for more details). Theoretically, the heart valve Beat Monitor is implemented using the $AR(N)$ model whose parameters are estimated using the Levinson recursion [6] to "fit" the model to pre-selected beats yielding the "inverse" or residual filter, that is,

$$H_{INV}(z) = \frac{E(z)}{Y(z)} = \frac{\sigma}{A(z)}, \tag{6}$$

or equivalently in the time domain with q^{-k}, the delay or k-step time delay operator for the ith heart sound $y_i(n)$

$$(1 - A_i(q^{-1}))\varepsilon_i(n) = \sigma_i y_i(n), \tag{7}$$

Once the valve sound is processed by the residual filter, its estimated correlation is tested for statistical whiteness using the correlation estimates

$$\hat{\rho}_{\varepsilon\varepsilon}(k) = \frac{R_{\varepsilon\varepsilon}(k)}{R_{\varepsilon\varepsilon}(0)} \tag{8}$$

$$R_{\varepsilon\varepsilon}(k) = E\{\varepsilon^2(n)\}$$

to perform the *whiteness test* given by

$$\left[\rho_{\varepsilon\varepsilon}(k) \pm \frac{1.96}{\sqrt{K}}\right] \quad , \tag{9}$$

where k is the lag variable and K is the number of samples in the signal. Here 95% of the normalized correlation samples must lie within the bounds (or equivalently 5% can exceed the bounds) for the sequence to be deemed white.

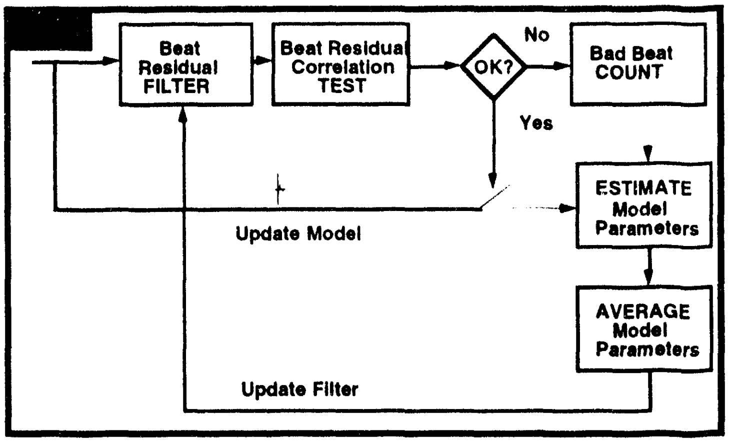

Figure 2. Mechanical Heart Valve Beat Monitor Structure Diagram.

A typical Beat Monitor design is shown in Figure 3. The raw data is processed beat-by-beat. First, the parametric model is designed using the *AIC(N)* to estimate the order for a given beat (shown in the Figure as N=17), next the prediction error is tested for whiteness according to Eq. 9. The results of the Whiteness Test are also shown in the Figure indicating a white prediction error sequence (3.5% out of bounds). The corresponding power spectra (raw and estimated) show good agreement assuring that the major spectral properties of the heart valve sound have been captured by the parametric model.

Utilizing this design, each beat is processed by the estimated model and if tested statistically white, the model fits the beat and it is deemed acceptable, processed and incorporated in the spectrogram for the heart valve under examination. During the "training phase" of the Beat Monitor, any beat that is deemed white is also further modeled and averaged with the previous beat models to train the algorithm and produce a set of average coefficients for the given valve (patient). To check the feasibility of this approach designed to reject "bad" beats based primarily on the spectral content of good beats during a recording session, we applied it to the "gold standard" data set, that is, a set of acoustic data in which the heart valve condition (INT or SLS) is known a-priori. The results are shown in Figure 4. Here we see a plot of whiteness Percentage Out versus Beat Number with a 5% Whiteness Threshold and a 10% Acceptance Threshold. The accompanying tables show the percentage of beats deemed "good" for the particular valve number and class. The Monitor passes a large percentage of the beats for both classes (INT or SLS) of known valve condition showing that the collected data is highly repeatable. This completes the section, on pre-classification processing of opening sounds. Each of the acceptance levels (%) as well as a count of the number of acceptable beats relative to those available is logged into the data base header for future classification. Next, we investigate, more specific problems associated with the opening sounds.

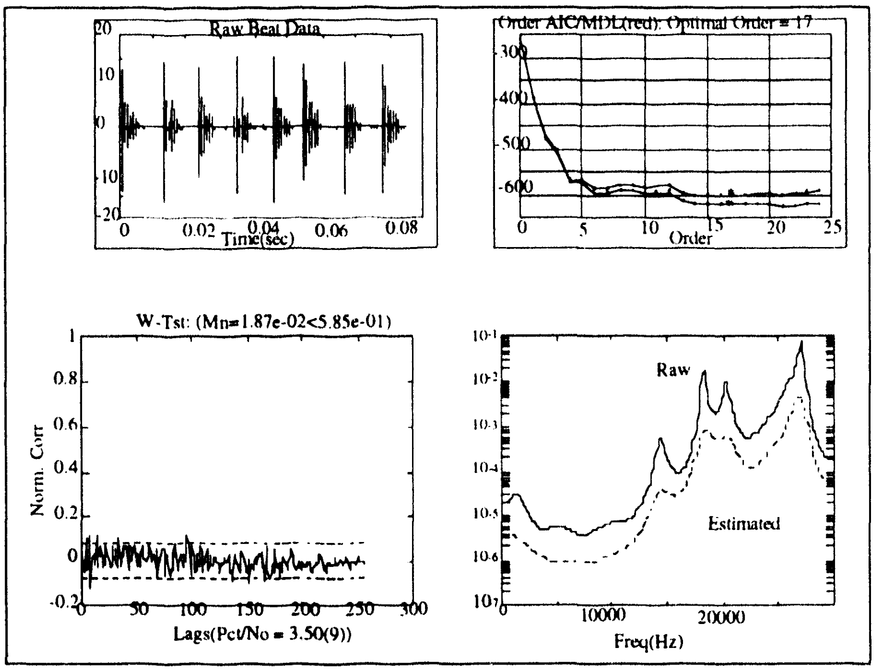

Figure 3. Beat Monitor Residual Filter Design: Raw Opening Signal and Order Testing. Whiteness/Acceptance Testing and PSD Estimates.

INTACT	% Good
153	52*
183	86
187	90
304	85
358	98

SLS	% Good
146	97
315	92
360	92
973	97
60825	93
61483	91

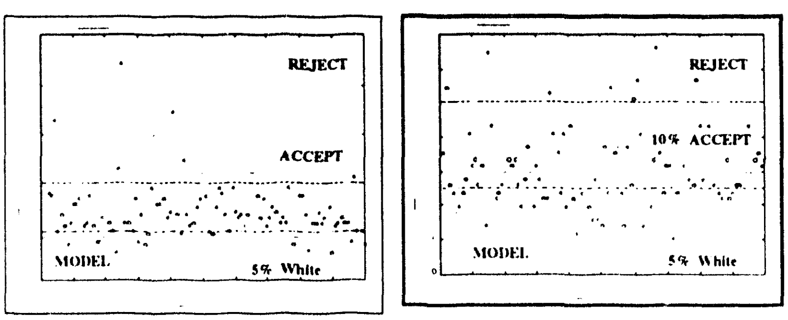

Figure 4. Beat Monitor Performance on "Gold Standard" Data Set.

4.: Summary

We have discussed the development of a parametric approach of feature estimates which are employed in schemes to solve the BSCC prosthetic heart valve classification problem. The features are based on the estimated spectrogram of the periodic valve response, the peak frequency histogram estimated simultaneously from the spectrogram and the lattice parameters (reflection coefficients) estimated directly from the data. The use of these features has proved to be effective in developing a reliable classifier for a related application. Data are currently being gathered and processed in a clinical environment and to date the results appear promising indicating that acoustic data can be used to noninvasively provide information about heart valve outlet strut condition.

We also discussed the overall automated procedure to extract the heart valve opening sounds, the most desired, yet the most difficult, acoustic signal to process and showed a sophisticated automated procedure to achieve the desired results. The detailed development of the corresponding heart valve Beat Monitor followed showing excellent performance on a "gold standard" (known) data set. The Monitor design appears quite effective and is currently being tested to screen changes in valve conditions on a visit-by-visit basis.

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