Preprint
UCRL-JC-143052

Processing of Prosthetic Heart Valve Sounds from Anechoic Tank Measurements

J. V. Candy, A. W. Meyer

This article was submitted to
The 8th International Congress on Sound and Vibration, Hong Kong, China, July 2-6, 2001

U.S. Department of Energy

Lawrence
Livermore
National
Laboratory

March 20, 2001

This work was performed under the auspices of the United States Department of Energy by the University of California, Lawrence Livermore National Laboratory under contract No. W-7405-Eng-48.

PROCESSING OF PROSTHETIC HEART VALVE SOUNDS FROM ANECHOIC TANK MEASUREMENTS

James V. Candy, Alan W. Meyer

University of California, Lawrence Livermore National Laboratory
P.O. Box 808, L-156
Livermore, CA 94551
candy1@llnl.gov

Abstract

People with serious cardiac problems have had their life span extended with the development of the prosthetic heart valve. However, the valves operate continuously at approximately 39 million cycles per year and are therefore subject to structural failures either by faulty design or material fatigue. The development of a non-invasive technique using an acoustic contact microphone and sophisticated signal processing techniques has been proposed and demonstrated on limited data sets. In this paper we discuss an extension of the techniques to perform the heart valve tests in an anechoic like. Here the objective is to extract a "pure" sound or equivalently the acoustical vibration response of the prosthetic valves in a quiet environment. The goal is to demonstrate that there clearly exist differences between values which have a specific mechanical defect known as *single leg separation* (SLS) and non-defective valves known as *intact* (INT). We discuss the signal processing and results of anechoic acoustic measurements on 50 prosthetic valves in the tank. Finally, we show the results of the individual runs for each valve, point out any of the meaningful features that could be used to distinguish the SLS from INT and summarize the experiments.

INTRODUCTION

The development of a non-invasive technique to detect the potential structural failure of a prosthetic heart valve while still operating in a patient is critical both for the patient's life especially since he/she is a poor candidate for surgery. Heart valves operate continuously at approximately 39 million annual cycles and are subject to structural failures. Here we discuss the analysis of a particular heart valve, the Bjork-Shiley Convexo-Concave (BSCC) which was implanted nationally in 32,000 patients. The prosthetic heart valve tests were motivated by the need to understand the heart valve dynamics and sounds emitted sounds by the valves in a moderately quiet, reverberation free environment. The results of identifying the sound in the spectral domain can then be extrapolated to improve the overall processing of clinical data already available as well as indicate salient spectral features which could potentially be incorporated into a classification scheme to distinguish a fractured valve from one that is not [1-6]. Thus, the BSCC valves were to be tested in an anechoic test tank to eliminate the reverberations and other artifacts experienced in the human body.

The BSCC prosthetic heart valve is shown below in Figure 1. Here we see the basic valve components: the flange, disk occluder, inlet strut and the outlet strut. Both the closing and opening valve positions are shown with the inlet strut excited strongly during the closing cycle and the outlet strut excited weakly directly during the opening cycle. The outlet strut is subject to fracturing, since it must be bent to insert the disk during valve assembly and consists of a thin piece welded to the flange. Next we discuss the signal processing used to extract the valve sounds from anechoic tank measurements.

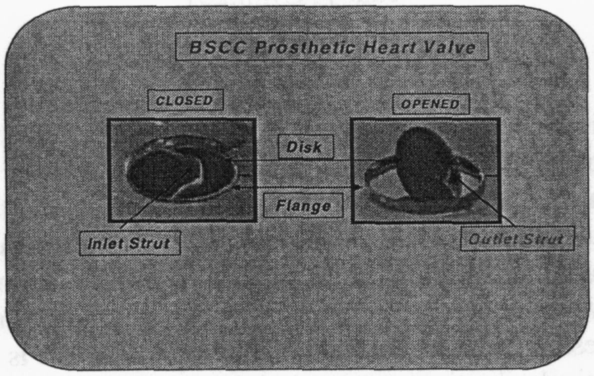

Figure 1. Bjork-Shiley Convexo-Concave Prosthetic Heart Valve Components with Closed Position Showing Inlet Strut and Opened Position Showing Outlet Strut.

SIGNAL PROCESSING

In this section we discuss the basic signal processing performed on the raw heart valve transient response measurements after they had been acquired at the facility. The extraction of data consists of the following steps: pre-processing, spectral estimation, peak frequency estimation, and valve signal estimation [7,8].

Pre-processing of the data is necessary to reduce the measurement noise and potential artifacts for performing the subsequent spectral estimation. Trends (linear) are removed from the data and they are piecewise windowed, that is, they are tapered on each end using a 2% tapering window (Blackman) to assure no end effect artifacts (Gibb's phenomena) in the spectra. Following the tapering, the data are half-windowed, which means that a typical window

(Blackman here) is cut in half with its maximum at the origin. This type of window assures the energy in the transient is preserved approximately. Once this is accomplished the data are ready for spectral estimation and screening.

Of the 100 transient responses gathered, we chose to use the "best" set of 25 spectra to represent the ensemble statistically. The approach was to estimate the spectra and use the median absolute deviation (MAD) statistic to select the best spectra [10]. We used a nonparametric approach and applied the minimum variance distortionless response (MVDR) method known to produce reliable spectra along with its inherent smoothing. The MVDR is a data adaptive technique which essentially provides unity gain in the center of each Fourier bin and minimizes the noise by producing a data adaptive taper [7,8,9] rather than the default rectangular taper inherent in the bin structure. It is particularly effective when SNR are low and smoothing is necessary.

The *Peak Frequency Histogram* estimate is performed by simply detecting the spectral peaks of each of the 25 best transient spectra and estimating their distribution using a histogram. This display is quite helpful in finding the predominance of valve spectral peaks and can be very useful for analysis and comparisons.

The "closest to the median" (*CTM)* signal, which is assumed to represent the response of the particular valve under test, is determined by a robust statistical approach. After the best 25 spectra have been selected using the MAD statistic, the sample median spectrum is determined by simply estimating the median amplitude in *each* bin. The resulting median spectra estimate is then used as the reference to determine which of the individual spectra is closest to it, which is precisely what the MAD algorithm provides. The transient signal (beat) is identified and taken as the best representative of the particular valve's transient response. The CTM signal is used in subsequent analysis to study the valve performance. For instance, we compare the ensemble of CTM spectra (overlay plot) to demonstrate the similarity of each spectrum of the INT and SLS class and perform peak comparisons. Performing this same procedure on the CTM ensemble of the INT and SLS class we can obtain the universal or UCTM for each resulting in two signals to perform analysis. Thus, the UCTMs are taken in this analysis to be representative of the INT and SLS classes. The UCTM is used in the final step to perform comparative analyses as well as time-frequency estimation using a parametric processor. By observing the time-frequency spectrum, we can see how the valve frequency response changes as a function of time.

MAD Statistic and MVDR Spectral Estimation Estimation

In this section we briefly discuss the basic theory behind both the MAD and MVDR estimators. The MAD statistic is a robust/resistant estimate of the population standard deviation that we apply to prune outliers from the spectral ensembles [6,10]. When the data arise from non-normal distributions characterized by long tails, the MAD estimator will more efficiently estimate population standard deviation than the sample standard deviation (SD). The gain in efficiency depends is particularly great in the case of outliers, a common form of non-normality.

The equations for SD and MAD are:

$$s = \sqrt{\frac{1}{n-1}\sum_{i=1}^{n} x_i - \bar{x}^{2}} \tag{1}$$

and $m \equiv \text{Median } x_i\big|_1^n;\quad M \equiv K \times \text{Median}\big|\text{x}_\text{i} - m\big|_1^n$.

The constant K is adjusted so that MAD gives nearly the same result as SD when the data are exactly normal. Both SD and MAD are estimating the same thing, the population standard deviation σ. If the data are normal, then the SD (n>10) estimates σ with optimal efficiency as show by its variance.

$$\text{Var(SD)} = \frac{\sigma^2}{2n} \tag{2}$$

On the other hand when the data come from a non-normal and long-tailed distribution the efficiency of the SD degrades significantly. The usual measure of the non-normality of long-tailed distributions is the *kurtosis*. Distributions with excess kurtosis (the normal has zero kurtosis) are more peaked at the center and have longer tails than the normal. When we include the effects of kurtosis on the variance of SD becomes:

$$\text{Var(s)} = \frac{n\sigma^2}{2}\left|1+\frac{\gamma_2}{2}\right| \tag{3}$$

In practical terms this means the SD gives a poor estimate when the data are contaminated with outliers, while the MAD statistic provides a estimate. The application of MAD to our problem is given by:

$$P_{MAD}(f) = \left|P(f) - \hat{P}_{median}(f)\right|. \tag{4}$$

where $\hat{P}_{median}$ is the sample median spectral estimate over the ensemble of transient or beat measurements. The MAD statistical estimate returns the beat numbers of the valve transient responses in a rank ordered list with the first entry corresponding to the CTM. MAD is applied to the resulting CTM ensembles, one for SLS and one for INT, to produce the UCTM representing the overall class response and spectra.

The MVDR spectral estimator originated from the work of Capon [11] and has also been labeled by various names such as the maximum likelihood method (MLM) and the minimum variance (MV) [7]. Note that the power spectrum estimation is equivalent to filtering a signal with a bank of narrow bandpass filters. In classical methods these bandpass filters are fixed, whereas in the MVDR method each filter is *data adaptive*, since it is designed to be optimum in the sense of rejecting as much out-of-band signal power as possible. The MVDR method solves the optimization problem at *each* spectral frequency bin creating an individual bandpass filter based on the spectral information residing in the bin, that is, it solves the problem of finding a set of filter weights $\{w(n)\}$ at each spectral bin that minimizes the overall power except at the narrowband frequency. Formally, we search for the set of optimal weights satisfying

$$\min_{\underline{W}} \quad J = \underline{W}^T R_{zz} \underline{W} \qquad \ni \qquad \underline{V}^T(f_m)\underline{W} = 1, \tag{5}$$

where J is the energy cost function, z is the data, R_{zz} is the data covariance matrix (NxN), $\underline{W}$ is the set of weights (N-vector) to be estimated and $\underline{V}(f)$ is the discrete vector of Fourier bins given by $\underline{V}^T(f_m) \equiv \left[1\; e^{-jf_m} \cdots\; e^{-j(N-1)f_m}\right]$. The solution to this problem is easily determined using Lagrange multipliers [2,3] to yield the set of optimal weights as

$$\underline{W} = \frac{R_{zz}^{-1}\underline{V}(f_m)}{\underline{V}^T(f_m)R_{zz}^{-1}\underline{V}(f_m)} \tag{6}$$

with corresponding power spectrum estimate

$$P(f) = \underline{W}^T R_{zz} \underline{W} = \frac{1}{\underline{V}^T(f_m)R_{zz}^{-1}\underline{V}(f_m)} \tag{7}$$

Note that the weight in Eq. 6 *changes* at each specified bin (f_m) since it changes through the term $\underline{V}(f_m)$, thereby making the MVDR data adaptive. Thus, in practice the MVDR estimator essentially constrains the narrow bandpass filter to pass all frequencies in the bin at f_m (gain constrained to unity) and minimizes any other energy not at that frequency. This completes the discussion of the signal processing of the heart valve sounds for eventual classification and comparison. Next we discuss the results of this effort.

ANALYSIS INTACT AND SLS VALVES

In this section we show the results of MVDR spectral estimator applied to the opening sounds measured in both SLS and INT valves during anechoic testing. The following figure shows the ensemble spectra indicating the reliability of the measurement system and valve to reproduce the sound. The plots also show the corresponding CTM spectra for each valve along with the individual valve peak frequency histogram estimates and CTM spectra superimposed to indicate how to weight the histogram amplitudes, that is, high count and high amplitude indicate a strong and repeatable resonance. Observing each of these plots show the correlation between the valve and it peak response. Valve similarity can be deduced by carefully sorting similar responses; however, we choose to use the CTM signal to represent the individual valves and the *universal* CTM (UCTM) to represent the class for analysis purposes.

We concentrate on analyzing the opening sounds of the INT and SLS valves tested in the tank. Typical results for intact valve opening sounds are shown in Figure 2 below. A typical ensemble is shown in the Figure 2a along with its corresponding median spectral estimate. The associated Peak Frequency Histogram is shown in Figure 2b indicating dominant resonant peaks at approximately 12, 18, 22, 32, and 55 kHz, that is, over more than 10 counts in the histogram. The valve transient CTM signal is shown in Figure 2d along with its corresponding spectra in

Figure 2c. The results appear quite good for this valve in the sense that the ensemble bounds are small with the variance significantly smaller below 60 kHz. These results indicate that our mechanism appears to excite the valve sufficiently to make these measurements in a reasonable manner.

To compare the spectral response of the valves of either the INT or SLS class, we create a CTM ensemble for each class. These results are shown in Figure 3 below. In Figure 3a we see the ensemble of CTM spectra for both the INT valves along with their corresponding Peak Frequency Histogram estimates below in Figure 3b. The results for the SLS opening sounds are shown in Figure 3c and Figure 3d. The peak-valley differences are shown in the color coded lists of these figures. It is interesting to note from this figure that if we first mentally "smooth" the spectra ignoring resonant peaks that the resulting overall spectra have similar shapes which is not unexpected because other non-fractured parts of the valve still vibrate under both INT and SLS conditions. We notice an initial peaking of both spectra around *10* to *15 kHz,* peaking in the *20 kHz* band with a linear decay up until *40 kHz*, a broad response follows with peaking between *40* and *60 kHz* and from *60 kHz* on the spectra flattens out (high frequency noise). A more detailed observation of the figure indicates that the INT spectra are similar with dominant resonant peaks (histogram) at 4, 6, 8, 17, 29, 30, 40, 50 kHz (above 3 counts), while those for the SLS spectra (above 3 counts) are 4, 7.4, 12.4, 21.6, 53 kHz.

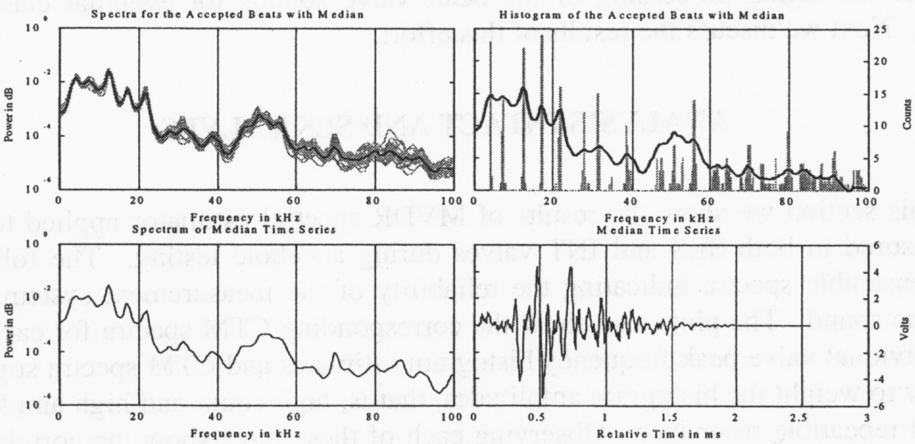

Figure 2. Typical MVDR Spectral Estimation for INTACT Valve No. 1 Opening Sounds: (a) Ensemble and Median Spectra. (b) Peak Frequency Histogram Estimates with Median Spectra. (c) CTM Transient Spectra . (d) CTM Signal.

CONCLUSIONS

We found the 25 spectra for each valve (with one exception) to be tightly clustered demonstrating that the pruning process was effective. Visual inspection of the ensemble CTM spectra show significant between-valve variation in the spectral fine structure, but general similarity in the peak locations. Visual comparison of the two UCTMs for INT and SLS reveal some differences. By differences, for example, we mean the appearances of a peak in one spectrum and a valley in the other class. Spectral classifiers are based on difference features, which are sometimes readily observed by visual inspection or are more subtle and must be found by a sensitive spectral feature selectors [5]. Even though the opening sounds contain more direct information about the outlet strut fracture [6], they are plagued by noise because their intensity is low yielding a much lower SNR than the closing sounds. Note that UCTMs were calculated for the purposes of summary and display only and do not necessarily indicate that the spectra lack useful classification features. We include the UCTMs for the opening sounds INT and SLS valves and also for the closing sounds shown in Figure 4 below. The arrows and bullets mark locations where the INT and SLS UCTMs differ offering some expectation that there is potential information available in these signatures to perform a successful classification. Note that we used the criteria of placing a bullet on either UCTM spectra when a peak of one corresponds to a valley of the other.

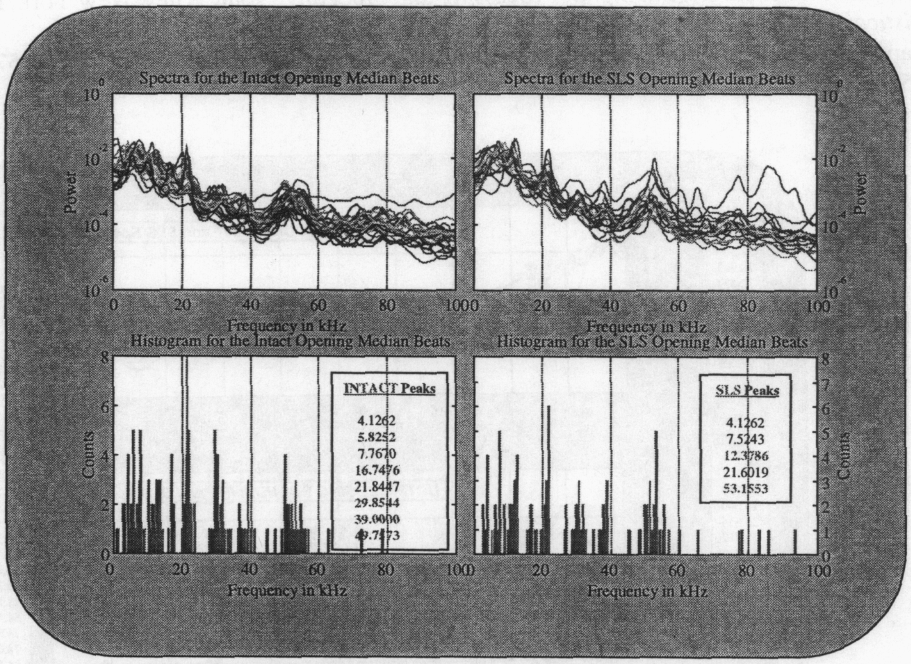

Figure 3. Ensemble CTM Opening Sound Spectra for Tested INTACT and SLS Valves: (a) INT Valves Ensemble CTM Spectra. (b) INT Valves Peak Frequency Histogram Estimates. (c) SLS Valves Ensemble CTM Spectra. (d) SLS Valves Peak Frequency Histogram Estimates.

This work was performed under the auspices of the Department of Energy by the Lawrence Livermore National Laboratory under contract W-7405-Eng-48.

REFERENCES

[1] T. D. Plemons, S. Shreck, R. S. Interbitzen. "Stability of the BSCC Heart Valve Outlet Strut Resonance Frequency Under Changing Physiological Conditions and Observation Times," *Proc. IEEE 7th Symposium of Computer-Based Medical Systems*, NC, 1994.

[2] A. C. Eberhardt, and C. E. Chassaing, R. S. Interbitzen, and D. W. Wieting. "Acoustic Evaluation of Progressive Failure of BSCC Heart Valves," *Proc. IEEE 7th Symposium of Computer-Based Medical Systems*, NC, 1994.

[3] J. V. Candy and H. E. Jones. "Classification of Prosthetic Heart Valve Sounds: A Parametric Approach," *J. Acoustic. Soc. Amer.*, **97** (6), pp 3675-3687, 1995.

[4] J. V. Candy, Ed. "Final Report for BP Panel on Anechoic Study Results," **LLNL-Report**, UCRL-ID-126508, 1996.

[5] A. L. Warrick, J. V. Candy and A. E. Brown. "Parametric Signal Processing of Anechoic Data From Prosthetic Heart Valve Testing," *Circuits, Systems Signal Proc.* **17**, pp 123-136, 1998.

[6] R. O. Duda and P. E. Hart. *Pattern Classification and Scene Analysis.* John Wiley, New York, N. Y., 1973.

[7] S. Kay. *Modern Spectrum Estimation: Theory and Applications.* Prentice-Hall, Engelwood Cliffs, N. J., 1988.

[8] J. V. Candy. *Signal Processing: The Modern Approach.* McGraw-Hill, New York, N.Y., 1988.

[9] M. Hayes. *Statistical Digital Signal Processing and Modeling.* John Wiley, New York, N. Y., 1996.

[10] *Statistical Toolbox.* MathWorks Inc., Boston, MA., 1995.

[11] J. Capon. "High Resolution Frequency Wavenumber Spectral Analysis," *Proc. IEEE*, **57**, pp 1408-1418, 1975.

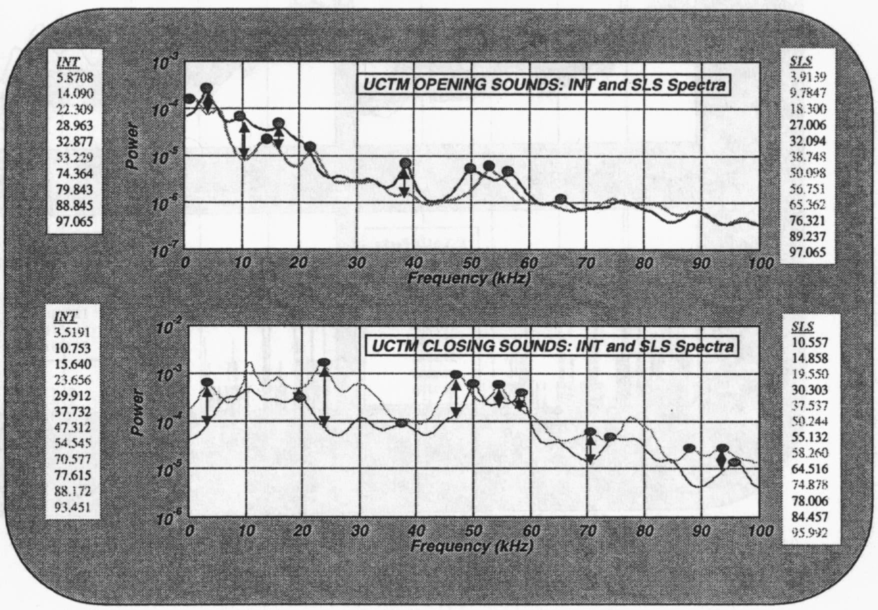

Figure 4. Opening and Closing Sound UCTM Spectra Showing Similarity and Differences in Peaks and Valley.