AN APPLICATION OF NEURAL NETWORK ANALYSIS IN DIAGNOSIS OF MECHANICAL FAILURE OF A TOTAL ARTIFICIAL HEART

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Abstracts A neural network based upon the back propagation algorithm was designed and applied to acoustic power spectra of electrohydraulic total artificial hearts in order to diagnose mechanical failure of devices. The trained network distinguished spectra of the mechanically damaged device from those of the undamaged device with overall success rate of 63%. Moreover, the network correctly classified more than 70% of spectra in the frequency bands of 0-100 Hz and 700-950 Hz. Consequently, the neural network analysis was useful for the diagnosis of mechanical failure of a total artificial heart.

Keywords Neural Network Analysis, Diagnosis, Total Artificial Heart, Mechanical Failure, Acoustic Power Spectrum

1. INTRODUCTION

The auditory organ is an important part of human body, which senses pressure fluctuation of the environment as sound. Humans hear sound to get information of surrounding and react properly with this information. Furthermore, humans generate sound and use it in many fields to make themselves happier. For instance, acoustics has been used in the medical science as follows. The extracorporeal shock wave lithotripsy that breaks urinary stones uses ultrasound. In the stethoscopy and percussion, physicians hear the sound of patients' bodies to diagnose many diseases. The ultrasonography that depends on the acoustics and techniques of the digital signal processing has become an indispensable tool for the diagnosis of human diseases. Diagnostic procedures using sound are noninvasive and have a major advantage upon other invasive diagnostic methods for the invasive diagnostic tools might damage patients.

Sounds from artificial organs have a lot of information that indicate the state of those artificial organs. Therefore, many biomedical researchers have introduced acoustical methods to assess the function of artificial organs. Among several kinds of artificial organs, performances of artificial valve prostheses and total artificial hearts should be assessed thoroughly for these are vital for human lives. The invasive assessment tools such as monitoring blood flow, blood pressure, or driving current of artificial organs have the risk of infection due to additional percutaneous lines. Therefore, sound has been used earlier as a diagnostic method of these artificial organs.

Much work has already been done using acoustics for assessing the performance of artificial cardiac valves. In 1969, Hylen used sound spectrum analysis to quantify valvular dysfunction in mechanical valvular prostheses [4]. In the decade of 80's, acoustical evaluations of bioprosthetic valves were developed individually by Stein, Sabbah, and Longhini [10, 8 , and 6]. They found the difference of sound spectra between normal and degenerated bioprosthetic valves. Less work, however, has been done on acoustically assessing the function of artificial hearts. Sheng showed the acoustical analysis was useful in detecting failures of the pneumatic total artificial heart in 1986 [9]. Lee found in 1994 that higher harmonics around

1300 Hz were shifted in a damaged electromechanical total artificial heart that consisted of mechanically mismatched rack and pinion compared to an undamaged electromechanical total artificial heart [5]. Also, in 1994, Hinrichs presented her work on the sound spectrum analysis of electromechanical artificial heart as the thesis for her degree of master of science in the University of Utah [3]. Hinrichs showed that peak frequency of the sound spectrum among 400 and 500 Hz increased in a damaged electromechanical total artificial heart that had scratched ball bearings. However, Lee and Hinrichs observed a limited part of the total spectrum to diagnose damaged devices. A general method that can use a broad frequency band to get more information from the whole spectrum is needed.

The artificial neural network is suited for the analysis of sound spectrum as a whole unit. Given the fact that the artificial neural network resembles the structure of the human neural network, this implies the ability of the artificial neural network to distinguish similar patterns into groups that have distinct characteristics. Neural networks have been applied successfully to classification and pattern recognition problems of character recognition, etiology of low back pain, and sonar signals from underwater objects [7, 1, and 2]. Once trained, a network may be used to correctly classify input that it has never seen before and it can be used in predictive applications. In theory, a network with a back propagation algorithm work in any application in which an input-output relationship exists. Therefore, the network architecture based on a back propagation algorithm was chosen and applied for distinguishing sound spectra of electrohydraulic total artificial hearts (EHTAHs).

2. MATERIALS AND METHODS

Two EHTAHs of the Artificial Heart Research Laboratory in the University of Utah were used, one undamaged and the other damaged by scratching the inner race of the bearings. Acoustic data were acquired under two separate conditions, one in a water tank and the other in postmortem sheep.

First, the in vitro experiment was performed. An EHTAH was submerged in a water tank and a microphone (model #106B50, PCB Piezotronics, Incorporated, Depew, New York) was set 15 cm apart from the center of the EHTAH. The EHTAH was set to run at 6000 rpm, bidirectionally at 50% systole and 60 beats per minute.

Second, the animal experiment was done. After removing the natural heart, the EHTAH was implanted in the animal's chest cavity. Aquasonic 100 ultrasound transmission gel was placed on the fifth intercostal space and the microphone was then placed on top of the gel. The EHTAH was set to run at 6000 rpm, bidirectionally at 50% systole and 60 beats per minute.

The voltage signals that indicated the vibration of bearings were acquired through an analog-to-digital converter and saved into an IBM compatible personal computer. The sampling interval was 70 μsec and the duration of data acquisition was 0.5 sec. The discrete Fourier transform was performed on the acoustic data and the log power spectra of the EHTAH sound were acquired with the frequency interval of 1 Hz. The number of acoustic data in the in vitro test was 25 for the damaged and 23 for the undamaged. In the animal experiment, the number of acoustic data was 13 for the damaged and undamaged respectively. The high frequency portion of every power spectrum above 1 kHz was removed since it had insignificantly low power. All 74 power spectra were normalized to have the same total power. The number 10 was added to each power value and divided by 10 to make each power value lie between 0 and 1. To determine which part of a spectrum was critical to the network in the successful classification, the rectangular window of which bandwidth was 100 Hz was applied to the normalized power spectrum and the window moved with an interval of 50 Hz. Consequently 19 windowed spectra were acquired from each power spectrum.

The designed neural network consisted of an input layer, one hidden layer, and an output layer. The input layer contained 100 nodes and 100 points representing the log power value in each 1 Hz band of the sound spectrum were used as input values into the neural network. The output of the neural network consisted of 1 node that could take on a value of 0 to 1 depending on whether the EHTAH was undamaged or not. The number of nodes in the hidden layer was empirically determined to be 20. A neural network architecture based on a back propagation using log-sigmoid function was chosen. The network was implemented with the MATLAB software package (Math Works Inc.) on an IBM compatible pentium 100 MHz personal computer. The network was trained with three different training data sets. First, 10 pairs of data were selected among power spectra of the in vitro experiment, that is, 10 spectra for the

TABLE 1. The number of testing data sets which the trained network correctly classified.

	training with in vitro data			training with animal data			training with mixed data		
window No.	in vitro (28)	animal (26)	total (54)	in vitro (48)	animal (6)	total (54)	in vitro (38)	animal (16)	total (54)
1	25	18	43	36	5	41	34	16	50
2	24	8	32	30	5	35	36	10	46
3	13	17	30	29	6	35	23	14	37
4	11	15	26	21	4	25	16	16	32
5	19	8	27	21	5	26	19	9	28
6	19	11	30	17	6	23	19	7	26
7	18	12	30	16	6	22	16	10	26
8	16	14	30	24	6	30	16	11	27
9	18	11	29	21	5	26	12	7	19
10	14	8	22	15	4	19	9	8	17
11	19	12	31	19	5	24	27	10	37
12	20	13	33	22	6	28	28	11	39
13	12	4	16	16	5	21	16	7	23
14	12	5	17	10	5	15	13	4	17
15	26	14	40	44	6	50	37	13	50
16	27	18	45	47	6	53	38	11	49
17	27	16	43	48	5	53	38	12	50
18	27	15	42	47	5	52	38	12	50
19	18	6	24	11	2	13	23	3	26
overall rate	69%	46%	58%	54%	85%	58%	63%	63%	63%

damaged and undamaged each. Second, 10 pairs of data were chosen from the animal experiment. Last, 5 pairs of data were used from the in vitro and animal experiment respectively. The network was trained for 100,000 iterations and the sum squared error decreased below the predetermined error goal of 0.01. The trained network was then tested using both 20 training and 54 testing data sets. Criteria of the classification success were the output value above 0.8 for the damaged and below 0.2 for the undamaged.

3. RESULTS

The results that the trained network worked in classifying testing data sets are shown in Table 1. As expected, the performance of the network was better on the training set and the network recognized 100% of training data sets in all of three different trainings. When the testing data sets were applied to the network, however, the overall classification success rate was decreased to 58% (590/1026) in the training of in vitro data, 58% (591/1026) in the training of animal experiment data, and 63% (649/1026) in the training of mixed data. Analyzing the overall classification success rate of the training with in vitro data, the rate for testing data sets of the in vitro experiment was 68% (365/532) and the rate for testing data sets of the animal experiment was 46% (225/494). In the case of the training of animal experiment, the network successfully classified 54% (494/912) of the in vitro testing data sets and 85% (97/114) of the animal testing data sets. Trained with mixed data, the network was able to correctly differentiate 63% (458/722) of the in vitro testing data and 63% (191/304) of the animal testing data.

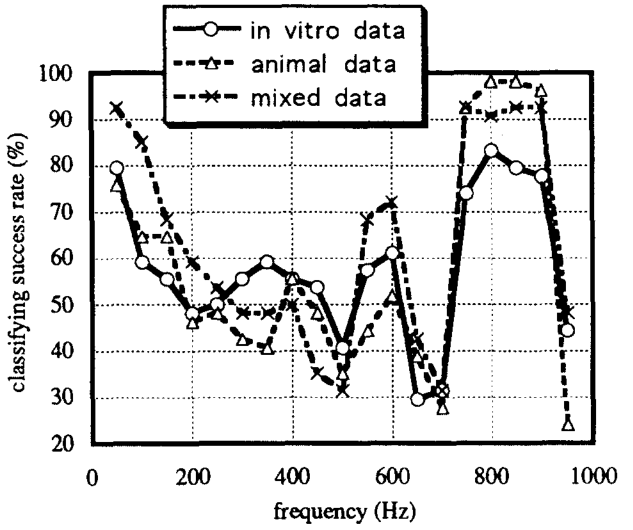

Fig.1 Classification success (percentage of total numbers correctly identified in the testing data set) when window was applied.

Analysis of the results in the specific frequency band shows that certain frequency ranges were important to the network in successful classification (Fig. 1). For all three training cases, the classification success rates were over 70% in 5 frequency bands. The first band lies in low frequency range (0-100 Hz) and the other 4 bands are located continually through 700-950 Hz.

4. DISCUSSION

The results of this study indicate that the mechanically damaged EHTAH produce different acoustical power spectra from those of the undamaged one. This difference is difficult to discriminate visually, but can be discerned using sophisticated classification techniques, such as neural network analysis.

Our data demonstrated that similar acoustic power spectra could be differentiated using the classification technique of neural network analysis. Comparing the results of 3 different trainings, the case of using mixed data was better than the others. We thought that one of the reason for this fact was the acoustic characteristics of the animal chest. When sound wave transmits through the animal chest, it traverses at least 4 different tissue layers. Characteristics of the sound wave such as amplitude and phase will change at boundaries of those layers. Moreover, the anatomical geometry of the animal chest is not so simple that the coherency of the sound wave that is detected at the surface cannot be maintained due to reflective waves. Nevertheless, the acoustic power spectra can be classified successfully on the condition that training data sets include data of the animal experiments.

Moreover, it was possible to show that the certain frequency bands were important to distinguish sound spectra of EHTAHs. These bands can be used in classifying acoustic power spectra of other EHTAHs. However, this cannot be generalized to include sound spectra from other kinds of damage. It should be understood that this specific location of frequency bands ought to be applied only to specific cases since the damage to the EHTAH in this study was confined to bearings only. The physical meaning of these bands is still unknown. A more intensive study is needed to reveal the underlying mechanism of acoustic power spectra from mechanically damaged EHTAHs.

In conclusion, EHTAHs with the mechanically damaged bearings produce similar, but not identical acoustic power spectra compared to undamaged EHTAHs. The difference was successfully classified using the artificial neural network and this technique can be used in distinguishing damaged EHTAHs from undamaged EHTAHs. Also it is possible that this technique is modified to detect the degree of damages for the output value of the artificial neural network can be varied continuously from 0 to 1.

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