QUANTIFICATION OF CAVITATION IN MECHANICAL HEART VALVE PATIENTS

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ABSTRACT

Mechanical heart valves (MHV) are used to replace native valves in patients with various heart valve diseases. However, the patients remain at risk of blood cell damage, thromboembolic events and material failure of the MHV. A phenomenon known as cavitation has been identified as a likely cause of a series of MHV failures and has been shown in vitro to occur near MHVs. It is thought that cavitation damages blood components, leading to both clot formation and possibly cerebral embolization in MHV patients. A non-invasive in-vivo technique to quantify the level of cavitation present in MHVs would be useful to help cardiologists determine the amount of anticoagulant medication to prescribe for their patients. Recent work has shown some promise towards achieving this goal of cavitation quantification by signal processing of acoustic measurements of heart sounds.

In this paper, two algorithms for cavitation quantification are investigated for robustness and usability. Both algorithms separate the deterministic energy from the random (non-deterministic) energy in the acoustic signal. However, the energy is calculated using different methods. These algorithms are investigated for the purposes of determining robustness, usability and implementation issues that need to be addressed in order to ensure accuracy and utility of this approach in a hospital setting.

INTRODUCTION

Mechanical heart valves (MHV) are used throughout the world to replace native valves in patients with heart valve dysfunctions [1]. The issue of cavitation was first introduced when damage at MHVs was observed. Cavitation has been shown in vitro to occur near MHVs in several studies using high-speed visualization [2]. Cavitation bubble implosion produces high-speed micro jets and high-pressure shock waves that can cause mechanical damage to the valve structure and blood elements, when it occurs near the surface of a MHV. It is thought that this damages blood components, leading to both clot formation and possibly cerebral embolization in MHV patients [1, 3].

For in vivo studies, the cavitation near MHVs has to be detected acoustically since blood is not a transparent fluid. The acoustic evidence of cavitation is defined by the high-frequency pressure fluctuations (HFPFs) associated with transient bubble collapse [1]. These HFPFs can be detected acoustically with the use of a high sensitivity hydrophone by applying it on the patient's chest since a hydrophone can record high frequency sounds. The sound measured at valve closure includes a mechanical resonance component coming from the MHV and a cavitation component. To obtain the part of the signal that characterizes the cavitation, the mechanical resonance component has to be removed from the signal. Garrison et al. proposed to remove this component from the signal by using a high-pass filter [1]. This was the first method that could be applied for the in vivo investigation of cavitation [2]. Recently, Johansen et al. determined that different designs of MHVs had different closing-sound characteristics implying that *a priori* knowledge of the valve mechanical resonance was required to choose the cut-off frequency of the high-pass filter [1, 2]. Consequently, Johansen et al. proposed a different approach which was to decompose the cavitation and valve mechanical resonance components by separating the HFPF signal into a deterministic and a non-deterministic part. They suggested that the cavitation bubble implosion creates random (non-deterministic) pressure fluctuations since the number and size of bubbles varies from beat to beat. Also, they assumed that the mechanical resonance occurring at valve closure is deterministic since valve closure is cyclic [1].

In this paper, two methods proposed by Johansen are implemented and analyzed to determine their robustness, usability and implementation issues. In addition, recommendations are provided to improve the accuracy and utility of the algorithms.

METHODOLOGY

It has been suggested in [2] and [4] by Johansen and colleagues that the cavitation can be quantified by separating the acoustic pressure signal into deterministic and non-deterministic components. The deterministic component represents the valve closing sound. The non-deterministic component is the information of interest since it contains the signal information originating from cavitation. Johansen's algorithm suggested that the non-deterministic energy can be obtained by subtracting the deterministic energy from the total energy [2, 4].

$$E_{non-\det} = E_{total} - E_{\det} \tag{1}$$

where $E_{non\text{-}det}$ represents the non-deterministic signal energy, E_{total} represents the total signal energy and E_{det} represents the deterministic signal energy.

Calculation of the deterministic energy

The first step consists of finding the deterministic energy. It is found the same way in both [2] and [4]. It is defined as

$$E_{\det} = \frac{N}{f_s}\left(\int_0^{\frac{f_s}{2}} \left|\mathbb{F}\left(p_{ea}[n]\right)\right|^2 df\right) \tag{2}$$

where N is the number of samples, f_s is the sampling frequency, $p_{ea}[n]$ is the ensemble average, and $\mathbb{F}$ is the Fourier transform. The ensemble average is calculated according to

$$p_{ea}[n] = \frac{1}{HC}\sum_{m=1}^{HC} p_{xy}[n,m] \tag{3}$$

where HC is the number of heart beats measured, and $p_{xy}[n,m]$ represents the n^{th} sample of the m^{th} heart beat of the pressure signal.

In order to obtain the ensemble average of the heart beats, the starting point of each heart beat needs to be known. To obtain that value, the original signal is segmented at the beginning of each heart beat using the method suggested in [5]. Then, each heart beat is truncated for all beats to have the same length. The end part of the beats is truncated since no important information is located there. The truncated heart beats are then superimposed one over the other and then averaged to obtain an average heart beat signal. This eliminates unwanted noise as well as reduces the signal parts that do not repeat from beat to beat. Finally, the energy is calculated from the energy density spectrum to obtain the deterministic energy.

Calculation of the total energy (Method 1)

The second step consists of determining the total energy. It is calculated according to

$$E_{total} = \frac{N}{f_s}\left(\frac{1}{HC}\sum_{i=1}^{HC}\int_0^{\frac{f_s}{2}} A_i(f)\,df\right) \tag{4}$$

where $A_i(f)$ is the amplitude spectrum squared of the i^{th} heart beat [2].

As in the previous sub-section, the signal is segmented at the beginning of each heart beat followed by the truncation of each beat to make them the same length. Then, the energy density spectrum is determined for each heart beat. Finally, the energy is calculated from each energy density spectrum signal followed by a calculation of the mean energy representing the total energy.

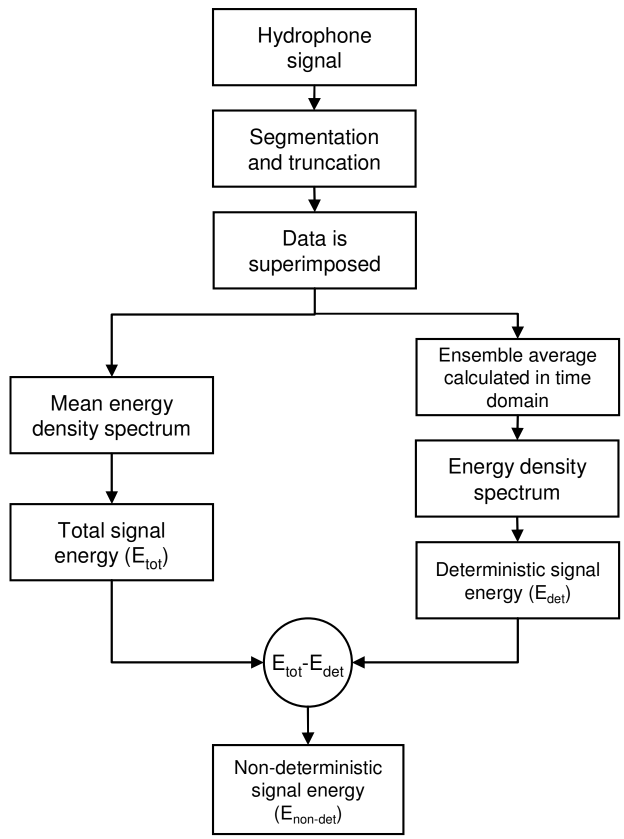

Figure 1: Non-deterministic energy block diagram using method 1

The final step consists of subtracting the deterministic energy from the total energy to obtain the non-deterministic energy, as stated in equation (1). Figure 1 is a block diagram summarizing Johansen's algorithm using method 1 to find the total energy [2].

Calculation of the total energy (Method 2)

It has been suggested in [4] that the total energy of the signal can be calculated from the energy density spectrum of the raw data

$$E_{total} = \frac{N}{f_s} \int_0^{\frac{f_s}{2}} G(f)\, df \qquad (5)$$

where G(f) is the amplitude spectrum squared of the raw data (output of the hydrophone). Figure 2 represents the block diagram summarizing Johansen's algorithm using method 2 to find the total energy [4].

Segmentation algorithm

As stated in the first sub-section, the original hydrophone signal is segmented to superimpose the heart beats in order to determine the ensemble average of the beats. The segmentation algorithm proposed in [2] and [4] was a cross-correlation of each heart beat with a chosen template to line up the heart beats. That segmentation algorithm was implemented; however, the results could not be reproduced. Other heart sound segmentation methods have been introduced using techniques such as the wavelet transform [6, 7], Shannon energy [6-8], mel-frequency cepstral coefficients (MFCC) [6, 9], and the mel-scaled wavelet transform (MSWT) [9].

The segmentation algorithm used in this paper is the method suggested in [5], using the wavelet transform and Shannon energy techniques in combination with the heart rate approximation to identify the first heart sound component S1.

IMPLEMENTATION AND DISCUSSION

The results in this paper were obtained by testing the algorithms on a pre-recorded stethoscope test signal. That signal was chosen since it was less noisy than all other signals and because a stethoscope signal should not contain a cavitation component since it records low frequency sounds. This means that the non-deterministic energy result should theoretically be near zero. A sampling frequency of 44.1 kHz was used.

The results obtained using the two methods introduced previously are compared in table 1.

The results in table 1 show that the non-deterministic energy is not zero. This is due in part to signal noise which is random and thus contributes to the non-deterministic energy. Some other factors making the non-deterministic energy non-zero come into play and are explained below.

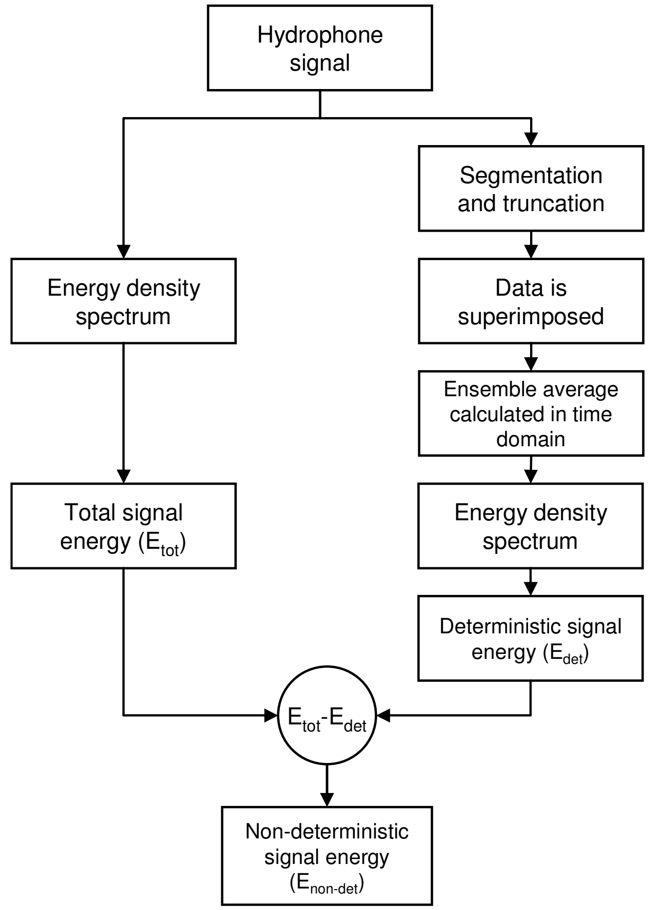

Figure 2: Non-deterministic energy block diagram using method 2

Table 1: Results of the energy obtained with the two methods

Method used	Energy		
	Deterministic energy [V^2]	***Total energy [V^2]***	***Non-deterministic energy [V^2]***
Method 1 [2]	$1.2998*10^7$	$3.9394*10^7$	$2.6396*10^7$
Method 2 [4]	$1.2998*10^7$	$8.3905*10^8$	$8.2605*10^8$

Truncation of the heart beats

The two different methods of determining the non-deterministic energy presented previously appear to be the same, but they are theoretically different. The first method of calculating the total energy truncates the heart beats as for the deterministic energy calculation. Therefore, the heart beats are the same length for both the total energy and the deterministic energy. However, in the second method of calculating the total energy, the original hydrophone signal is used and not the truncated signal. Thus the truncated portions of the signal are retained for the total energy calculation resulting in a larger value of total energy. This implies that the non-truncated portions of the signal contribute to the non-deterministic energy and are falsely considered to be cavitation. As a result, it is observed in table 1 that the non-deterministic energy calculated with method 2 is larger than that calculated with method 1. From this observation, one can conclude that method 1 is better than method 2.

Superimposition of the heart beats

The quality of the segmentation of the hydrophone signal has a large impact on how well the heart beats are superimposed. If the segmentation is poorly done, the heart beats will not line up properly.

Figure 3 illustrates the superimposed heart beats for the heart signal used to obtain the results in table 1.

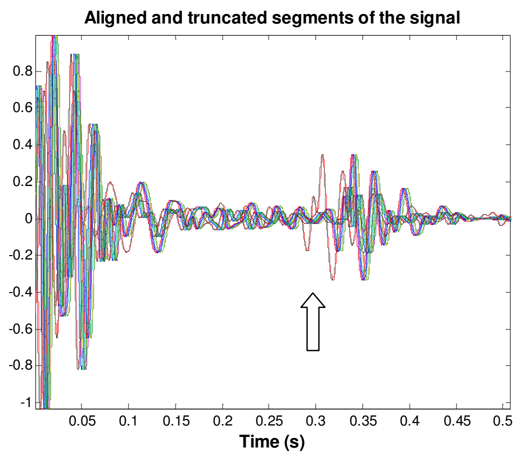

Figure 3: Superimposed heart beats

The arrow in figure 3 points to the heart beats that were not properly lined up with the other beats. They would need to be shifted to the right to be lined up. These misplaced beats have an impact on the energy results. To demonstrate the impact, the beats that did not line up with the other beats were manually removed from the signal and the results obtained are shown in table 2.

Table 2: Results of the energy obtained after manually removing the misplaced beats

Method used	Energy		
	Deterministic energy [V^2]	***Total energy [V^2]***	***Non-deterministic energy [V^2]***
Method 1 [2]	$1.5989*10^7$	$3.3056*10^7$	$1.7067*10^7$
Method 2 [4]	$1.5989*10^7$	$8.3905*10^8$	$8.2306*10^8$

As expected, the non-deterministic energy decreased which confirms that the poorly lined up beats have an impact on the results. Johansen's algorithm is thus very sensitive to the lining up issues and greatly depends on the quality of the segmentation algorithm. It is noted again that the non-deterministic energy calculated with method 2 is larger than that calculated with method 1, confirming the earlier observation.

CONCLUSION AND FUTURE WORK

This paper compared Johansen's two algorithms and the results showed that the first method, illustrated in figure 1, is more robust and accurate than the second method. However, this method still requires improvements. The algorithm implementation demonstrated that it is very sensitive to the lining up issues. Future implementation of an algorithm that determines the quality of the input heart signals could lead to better segmentation results since a cleaner signal is easier to segment than a noisy one. In addition, to further improve the accuracy of the cavitation quantification algorithm, an algorithm to remove or shift the misplaced heart beats is of interest.

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