

Detection of Mechanical Heart Valve Thrombosis Using Support Vector Machine

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Abstract: Thrombosis on the valve that prevents the movement of mechanical heart valves is a fatal disease requiring urgent intervention. Thrombosis is detected by echocardiographic findings and/or CT images. In this study, it has been tried to determine the formation of thrombosis by listening method which has been used for controlling the functionality of the heart valves for years. For this, firstly heart sounds of patients with thrombosis and normal mechanical heart valves were recorded. Then, the first and second heart sounds (S1 and S2) were separated from the recorded sounds. After the frequency spectrum of S1 and S2 were found using autoregressive spectrum estimation methods, six features were obtained regarding the frequency components. Then, the features obtained are classified by support vector machine methods. The average accuracy is 95.18% as a result of running the classifier 500 times using 3-fold cross validation. The maximum accuracy value was found to be 100% by using the 3-fold cross validation.

Keywords: Mechanical Heart Valve, Heart Sounds, Support Vector Machine

1. Introduction

Natural heart valve diseases occur as a result of deformation of the valves of the heart that connect the atrium to the ventricles and the ventricles to the artery. These problems are most commonly encountered in mitral and aortic valves. Although drug therapy is considered in the initial stages of the disease, it can be treated only by surgical intervention in the event of an advanced valve deformation. Heart valve is either repaired or replaced by a prosthetic (mechanical or biological) valve in surgical intervention. Approximately 50% of the 140,000 valve replacement operations performed worldwide each year are mechanical heart valve replacement. Mechanical heart valves are especially recommended for younger patients with longer life expectancy than for bioprosthetic valves [1].

Blood clot accommodation on the mechanical valve is called mechanical heart valve thrombosis. Thrombosis formation restricts or completely prevents the heart valve movement. Mechanical valve thrombosis is an important complication with high risk of death and requires urgent diagnosis and thrombolytic or surgical treatment. Although improvements in the structure and design of mechanical heart valves have improved the hemodynamic properties and durability of mechanical valves, thrombotic complications are still the leading cause of postoperative disease and death. The incidence of thrombotic complications varies between 0.03-6% depending on the quality of the anticoagulant drug usage, the used mechanical valve and the location of the valve [2-7].

In the literature, it is seen that studies are performed for both biological and mechanical prosthetic valves. The number of

studies on bioprostheses is quite high compared to mechanical prostheses. Here only the details of the work carried out for mechanical valves will be mentioned. One of the first studies in the literature was performed by Hysten to evaluate the dysfunction of the caged-ball mechanical heart valve using heart sounds. In this study, it was observed that high frequency components of heart sounds recorded from aortic area disappeared when dysfunction occurred [8]. Koymen et al. emphasized that the rate of closure of the valve will slow down in thrombosed mechanical valves and this deceleration shifted the frequency components of the heart sound to the lower bands [9]. Baykal et al. examined the heart sounds of patients with AVR by recording from 12 different recording area. They compared the ratio of energies of the high frequency components to the low frequency components of the S2 sounds and the frequency components of the heart sounds. In their study, they observed that the energy ratio of the sounds changed according to the recording area but the frequency components of the heart sound was independent from the recording area [10]. Sava et al. examined the effects of chest-lung and heart-valve systems on the spectral components of mechanical heart valve sounds [11]. The spectral characteristics of mechanical heart valve sounds with five normal and one dysfunction using MUSIC (Multiple Signal Classification) and FOS (Fast Orthogonal Search) methods was obtained. Then, it has been shown that the maximum frequency of the heart sounds may be an effective parameter for the determination of mechanical heart valve dysfunction [12]. Heart sounds were monitored daily after heart valve replacement performed in four different centers. As a result of this study, the differences in frequency spectrum of heart sounds obtained from 13 patients with mechanical valve dysfunction were clearly observed [13]. The split interval, time between the closures of the leaflets, in mechanical heart sounds was investigated. As a result, it was stated that there was a short-term, clear separation in the normal mechanical valve sounds and the absence of this split found to be a sign of dysfunction in the mechanical heart valve [14]. In the 2007 study of the same team, the splits of the heart sounds of

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15 patients with five different types of mechanical heart valves was determined with Morlet wavelet function and evaluated statistically. It has been emphasized that splits of closure sounds may help in finding mechanical valve function disorders [15]. The frequency spectrum were determined for the normal situation by recording the early period of heart sounds of each patient. The patients were then asked to record heart sounds with a device every day. The valve functions of the patients were checked with fluoroscopy when a difference was observed in the spectrum of early records and subsequent records. As a result, all 25 dysfunction could be understood from the power spectrum densities obtained with FFT, but one for the normal condition was received incorrectly [16]. The statistical difference between the normal and dysfunctional mechanical heart valve sound split intervals have evaluated. They evaluated statistically the split time and split time change obtained from mechanical heart valve sounds with 184 normal bileaflet, 10 tilting disc and 10 dysfunction. Also they found the limit values for the split time that determine the dysfunction [17]. Zhang et al. concluded that a combination of spectral and time-scale features of heart sounds recorded from paravalvular leakage, valve obstruction and normal patients can be used to detect these dysfunctions [18]. By using the frequency spectrum of the heart sound signals produced in an artificial environment by five commercial mechanical heart valves, the thrombosis occurring in the mechanical heart valve, the weight and diameter of the thrombosis were classified by artificial neural networks [19]. A new method to classify the heart sounds recorded from patients with mechanical heart valve problems (paravalvular leakage, valve obstruction, valve stenosis, valve stenosis and paravalvular leakage) have been proposed. Instead of standard spectrum detection algorithms, they tried local discriminant bases and Hilbert Huang Transform bases feature extraction algorithms and obtained higher classification accuracy with these features [20]. Similarly, in another study, the same team stated that the classification accuracy in the properties obtained with kernel Fisher discriminant analysis reached 95.6% [21].

The frequency components of heart sounds recorded from in vitro test environment was examined. For this purpose, they obtained separate recordings for different hydrodynamic conditions and different thrombosis simulations and removed their spectral properties with periodogram. In conclusion, it was emphasized that the formation of thrombosis may be found in spectral properties [22].

2. Material and Method

In this section, the details of data acquisition, feature extraction and classification will be explained. The first process to be performed on the raw data after data acquisition is normalization and filtering. The stage after normalization and filtering is to obtain some meaningful information about the biological system in which the signals are recorded. Knowing the structure of the biological system in order to extract this meaningful information is important as our problem. Heart sounds are periodical and have two parts with each heart cycle. At the same time, these sounds are synchronized with ECG signals. Using a number of algorithms based on these biological information, the heart sounds recorded from each patient were first divided into heart cycles and then S1 and S2 sounds. The frequency spectra of the S1 and S2 heart sounds were obtained and the frequency dependent 6 features were obtained for each heart sound and the features obtained for each heart cycle were averaged. As a result, a total of 12 features were obtained for each patient, 6 of them from the first heart sound and 6 of the second heart sound. The resulting properties were used for the classification. In order to increase the reliability of the

classification, training and testing procedures were carried out using a 3-fold cross validation. In addition, this classification process performed with 3-fold verification was repeated 500 times and its accuracy was tested for all possible situations. The general

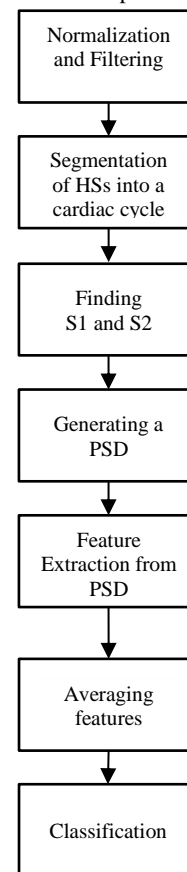


Fig. 1. General block diagram of system

block diagram of signal processing and feature extraction is given in Figure 1. Detailed information about the methods is given in the subsections.

2.1. Patients and Data Acquisition

For this study, normally functioning heart sounds of 14 patients with MVR were recorded for 30 seconds after surgery. In addition, heart sounds of a patient who was admitted to the hospital with complaints of dyspnea and had thrombosis was recorded 4 times before thrombolytic treatment and 4 times after thrombolytic treatment. Clinical information of the patients is given in Table 1. E-Scope II electronic stethoscope manufactured by CardionicsTM was used to record heart sounds and surface electrodes were used to record ECG signals BiopacTM's MP35 data acquisition module was used to convert these two signals into digital and transfer them to the computer. The sampling frequency of the signal is selected as 5000 samples / second. The BSL PRO 3.7 software (the computer interface of the data acquisition module) was used to view and register the signals.

2.2. Segmentation of Heart Sounds

The first step in the signal processing is the normalization of the recorded raw heart sound signals. Filtering is then carried out to remove noise. The second stage of signal processing is the segmentation of the heart sound signals. Heart sound signals are periodic signals. Each record of 30 seconds has approximately 30 heart cycles. ECG signals recorded with heart sound signals are used to segment heart sound signals into periods. The R peaks of the ECG signal are the beginning of each period. The R peaks of

the ECG signals must therefore be detected first. Then, the periods of the raw heart sound signals are determined using the R peaks of the ECG signals as the time reference. Thus, approximately 30

Table 1. Clinical information from patients included in this study

	Treatment	Sex	Age	Brand	Valve Function	Number of Records
1	MVR	F	27	Sorin	Normal	1
2	MVR	M	46	Sorin	Normal	1
3	MVR+TRA	F	47	Sorin	Normal	1
4	MVR+TRA	M	62	Sorin	Normal	1
5	MVR+TRA	F	58	Sorin	Normal	1
6	MVR+TRA	M	70	Sorin	Normal	1
7	MVR+TRA	F	37	Sorin	Normal	1
8	MVR+TRA	F	35	Sorin	Normal	1
9	MVR+TRA	M	63	Sorin	Normal	1
10	MVR+TRA	F	37	Sorin	Normal	1
11	MVR	F	30	St. Jude	Normal	1
12	MVR	F	60	St. Jude	Normal	1
13	MVR	F	41	St. Jude	Normal	1
14	MVR+TRA	F	36	St. Jude	Normal	2
15	MVR	F	54	Sorin	Normal	4
				Abnormal		4

MVR: Mitral Valve Replacement, AVR: Aortic Valve Replacement, TRA: Tricuspid Ring Annuloplasty

heart cycles were obtained depending on the pulse rate within the 30 second heart sound records. Then, the first and second heart sounds (S1 and S2) are separated from each heart cycle ECG signals as the time reference. These S1 and S2 were used to find spectral features explained in next chapter.

2.3. Spectral Features

Parametric spectrum estimation methods are designed to remove the distortions in the spectrum obtained by conventional methods and are especially effective in detecting the spectra of short data parts. A parametric method, Auto Regressive (AR), is used to find the frequency components of the S1 and S2 signals. After finding the frequency components of the S1 and S2, the spectral features defining the heart sounds are extracted from the obtained frequency components. For this the spectral features used for biological valve sounds by Durand et al., 1990 are arranged for mechanical valve sounds [23]. These features are

F1 : The frequency of the first dominant spectral peak (Hz).
DF1 : The bandwidth at 0.707 of the dominant spectral peak (Hz).

Q1 : Quality factor of F1 (Q1 = F1/DF1).

AREA : Total area of the spectrum.

A20–100 : Area in the 20–100 Hz band.

A100–200: Area in the 100–200 Hz band.

This spectrum estimation and feature extraction process are repeated for each heart cycle and each heart sounds (S1 and S2) obtained from the heart sound signals recorded from a person. Then, the average of the features obtained for each heart cycle gives the final features of the one person to be used in the classification. Detailed information on the recording, processing and feature extraction step of heart sounds can be found in [24].

2.4. Support Vector Machine

The method is a supervised machine learning algorithm used by Vapnik and Cortes in 1995, which is used in pattern recognition

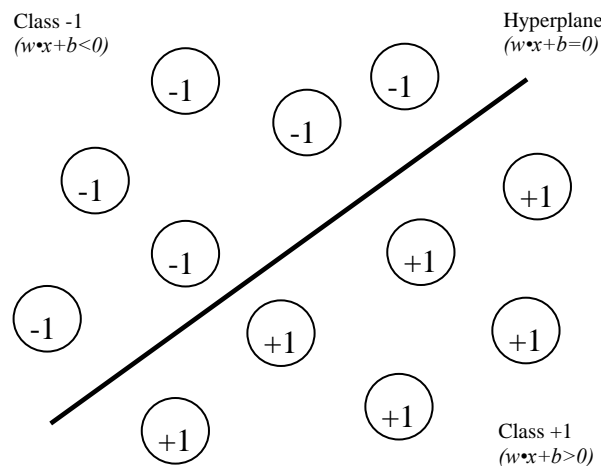


Fig. 2. Linear classifier defined by the hyperplane $H(w \cdot x + b = 0)$ [26]

and regression analysis. In the classification process, the SVM performs two patterns in one plane by dividing the two patterns by drawing a border from the farthest point to the two patterns. In this way, two patterns are shown in the two-dimensional plane [25]. The dot product $w \cdot x$ is defined by:

$$w \cdot x = \sum_{i=1}^n w_i x_i \quad (1)$$

All of the training models are classed correctly as shown in Figure 2. The $H(w \cdot x + b = 0)$ equation shown in Figure 2 represents the linear classifier. The regions divided into two classes by means of this equation ($w \cdot x + b > 0$) + classes, ($w \cdot x + b < 0$) - are defined in the hyperplane to represent the classes. The x_k pattern class is specified as follows:

$$\text{class}(x_k) \begin{cases} +1 & \text{if } w \cdot x_k + b > 0 \\ -1 & \text{if } w \cdot x_k + b < 0 \end{cases} \quad (2)$$

The class of each data in the test data is formed according to the sign of the equation ($w \cdot x + b$) [27].

2.4.1. Performance evaluation

Performance evaluation and validation methods used in the system are confusion matrix, classification accuracy, analysis of specificity and sensitivity, and k-fold cross-validation. Mathematical formulas of performance evaluations are explained in the study of Yilmaz N. et al. [26, 28]

2.4.2. Classification parameters

In this study, a system based on SVM classification algorithm was developed in order to determine whether thrombosis that prevents the movement of mechanical heart valves occurred. The reliability of this classifier is ensured by the k-fold cross-validation method. When using this classifier, the training was performed according to the parameters given in Table 2.

Table 2 List of classification parameters

Parameters	Value
Method	SVM
Optimization algorithm	SMO
Validation method	k-fold cross-validation (3-fold CV)
Kernel_Function	Linear

ToIKKT	1.0000e-003
MaxIter	15000
Kernel Cache Limit	5000
The initial value	Random

3. Experimental Results and Discussion

In this study, 12 features obtained from the frequency components of the mechanical heart sounds were classified by the support vector machine classifier in order to determine whether there was a malfunction due to thrombosis in the mechanical heart valve or not. 3-fold cross validation was used to increase the accuracy of the classification. In this way, the system was operated 500 times and the presence of thrombosis in the patient was determined with an accuracy of $95.18\% \pm 5.44\%$ (mean \pm standard deviation). The highest accuracy rate obtained by running classifier 500 times was found to be 100% and the lowest accuracy rate was found to be 68.45% (Table 3). Table 4 shows the correct classification rate, sensitivity, specificity, positive predictive value and negative predictive value of the best results obtained by the running classifier 500 times with 3-fold cross validation.

Because mechanical heart valve thrombosis is a rare disease requiring rapid intervention, it is difficult to find diseased heart valve data. Therefore, the number of studies on the detection of thrombosis of mechanical heart valve is quite low. Most of these studies are based on statistical evaluation of the frequency and time dependent features. [2, 12-18, 22, 29].

Some of the studies on the detection of mechanical heart valve dysfunction with artificial intelligence were performed the data obtained by simulating the formation of thrombosis by applying gel on the mechanical heart valve in an in-vitro test environment, [19, 30]. However, it should not be overlooked that mechanical heart sounds are recorded in vitro, that is, the heart sound signals are not affected by other disturbing signal interferences in the body. Therefore, it is clear that the studies conducted on human beings are more realistic considering the disturbing effects affecting the in vivo recording of heart sound signals.

Only two studies have been reported in the literature in which mechanical heart valve sounds were recorded in vivo and evaluated by artificial intelligence [20, 21]. In these studies, mechanical heart valve voice signals were recorded from patients with paravalvular leakage, valve obstruction, valve stenosis, valve stenosis and paravalvular leakage (VSPL) and normal mechanical heart valve. After that, they have extracted features from mechanical heart sounds using a modified LDB-based scheme and a HHT-based scheme. The features obtained were classified by generic linear discriminant analysis (LDA). They found that frequency spectrum of heart sounds can only be used for detecting paravalvular leakage. They also proposed a new feature extraction algorithm for the correct classification of all diseases. As a result, they have achieved high accuracy classification except VSPL using the feature extraction algorithm they propose.

In our study, only a classification of patients with thrombosis in the mechanical heart valve was performed. In contrast to Zhang et al., thrombosis formation using spectral features was obtained at 100% accuracy [20]. The reason for this difference may be due to difference in features obtained from the frequency spectrum of the heart sounds and may be due to the performance of the classification algorithms used. Because of the fact that there are two classes in our study, classification accuracy may have increased. However, considering other studies in the literature [12, 13, 16, 29] the frequency spectrum can be used as an effective method for the diagnosis of mechanical heart valve thrombosis.

The important point here is to develop an effective, easy-to-use and inexpensive method for the diagnosis of mechanical heart valve diseases and to present them to the patients. For this, it is necessary to verify these studies using more data.

Table 3. Classification accuracy rate obtained by running 500 times with 3 fold cross-validation

Performance Criteria	SVM
Correct Classification Max (%)	100
Correct Classification Min (%)	68,45
Correct Classification Rate (%)	95,18
Correct Classification std (%)	5,44

Table 4. Classification performance for the dataset obtained from

Performance Criteria	SVM
Correct Classification Rate (%)	100
Sensitivity (%)	100
Specificity (%)	100
Positive predictive value (%)	100
Negative predictive value (%)	100

4. Conclusion

In this study, it is aimed to develop a system that can help specialists in the detection of thrombosis on the mechanical heart valve. For this purpose, frequency spectrum of the heart sound signals recorded from people with normal and abnormal mechanical heart valve were analysed and 12 features were obtained from this frequency spectrum. The obtained features were used to identify normal and abnormal heart valves using the Support Vector Machine classifier. In order to ensure the reliability of the system, k-fold diagonal verification was used. Also designed system was operated 500 times. Accuracy rates of the classification system are given in the previous section. Considering the experimental results, we think that the system we recommend can be used as a pre-diagnostic tool for assisting physicians in primary health care facilities.

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