

A Method Based on Wavelet Packet Decomposition and Memory Antibody Clone Hybrid Clustering for Diagnosis of Clinical Heart Disorders

Ting Tao^{a+}, Haibin Wang^a, Yu Fang^a, Jinqun Liu^a and Xiaochen Wu^b

^a School of Electrical and Information Engineering, Xihua University, Chengdu 610039, China

^b Cardiothoracic Surgery, Chengdu Military General Hospital of PLA, Chengdu 610083, China

Abstract. In this study, a method based on wavelet packet (WP) decomposition and memory antibody clone hybrid clustering (MACHC) for diagnosis of clinical heart disorder (HD) is proposed. From considering the fact that the frequency ranges of the normal and heart diseases sound are different from each other, the wavelet packet decomposition (WPD) at level 4 is used to split the frequency bandwidths of the clinical heart sound (CHS) signals. And then the WP energy (WPE) with the frequency information through the range of CHS signals is calculated. WPEs at the terminal nodes from (4,0) to (4,11) are selected and two parameters maxWPE and minWPE are used as the features. Furthermore, the MACHC technique is employed as the identification tool to classify the normal sound and CHSs. Finally, the performances of this method are evaluated in 156 samples that contain 42 normal and 114 abnormal subjects for clinical HDs. The results show that this technique is useful and effective to detect CHSs. The validation of the proposed method is measured by using the sensitivity, specificity and accuracy parameters. Over 94.91% sensitivity, 100% specificity and 96.25% accuracy rate are obtained

Keywords: clinical heart disorder (HD), clinical heart sound (CHS) signals, wavelet packet (WP) decomposition, WP energy (WPE), memory antibody clone hybrid clustering (MACHC) technique

1. Introduction

According to the researches most of human deaths in the world are due to heart disease (HD), for this reason, early detection of HD is one of the most important medical research areas [1]. Nowadays, the techniques used for detection of HD are usually classified into non-invasive and invasive. However, physicians have employed these techniques especially based on experience and information, take auscultation of HS signals for example, auscultation is a fundamental tool in the diagnosis of HD, but it is through either a conventional acoustic or an electronic stethoscope which needs long-term practice and experience. Moreover, keeping long time on HS auscultation makes clinical physicians auditory fatigue; thereby it will influence the accuracy of auscultation.

With the rapid development of computer science and digital signal processing technology, HD can be analyzed in an automatic way. The HS signals should be segmented into some specific features for the automatic analysis and classification in this case. From many researches, HS analysis methods can be divided into five branches, the time domain, frequency domain, time-frequency domain, and energy and pathology analysis. In the spectral analysis, the wavelet decomposition (WD) or wavelet packet decomposition (WPD) were commonly used. Moreover, the advantage of WPD is that it is possible to carry out more elaborate investigations on the piecewise variations of features in signal spectrum [2]. The

* * Corresponding author. Tel.: +86 15828596287;
E-mail address: taoting96@sina.com.

characteristic and correlation information with advances in digital signal processing in the above five branches each other, gives aid not only to doctor, but also to an inexperienced or non-clinical experience person to monitor the heart condition easily.

At present, the studies of the HDs diagnosis system have made some progress, but for clinical physicians, the practical clinical use is extremely limitation. In addition, the common deficiency existed in these HD intelligent diagnosis systems are as follows: (1) It is commonly associated with the standard heart sound dataset; (2) It is always applied to single HD (such as a pure mitral valve disease, or pure aortic valve disease); (3) The clinical value is not so evident. In view of these facts, the objective of this paper is to present a clinical HDs diagnosis method based on WP decomposition and MACHC classifier. Usually, clinical HDs are complex and various, meanwhile, the complicated CHSs contain many valuable pathologic information. To study and analyze the clinical HDs, we should collect the HSs and take the diagnosis techniques into clinical application. This paper is organized as follows. We proposed a brief review on CHSs signals, followed by the HS signals in part 2. The proposed clinical HDs detection techniques are given in part 3, and in part 4, the experimental classification results are shown. Finally, in part 5, remarks and future work can be found.

2. Heart sound signals

The two major HSs heard in the normal heart are the first HS (S1) and the second HS (S2). S1 is caused by turbulence caused by the closure of mitral and tricuspid valves at the start of systole, and S2 is caused by the closure of aortic and pulmonic valves, marking the end of systole. There is also a third and a fourth HS, S3 and S4. They can occur in normal persons or be associated with pathological processes. Because of their cadence or rhythmic timing S3 and S4 are called gallops, which are low frequency sounds that are associated with diastolic filling. The HS patterns used in this study could be classified into the following types, i.e., the normal sound, the Congenital heart disease (CHD) sounds, Rheumatic heart disease (RHD) sounds, Valvular disease (VD) sounds. Furthermore, the CHD cases are mainly comprised of ventricular septal defect, atrial septal defect, patent ductus arteriosus and tetralogy of fallot; the RHD cases are mainly mitral stenosis, aortic insufficiency and tricuspid regurgitation. Typically, basic normal sounds occur in the frequency range of 20–200Hz, while some heart murmurs characteristically have the frequencies between 200 Hz and 700 Hz. Therefore, the HSs with the frequency band of 20–700 Hz were considered in spectral analysis [3], Fig.1 depicts a schematic block diagram of the proposed method.

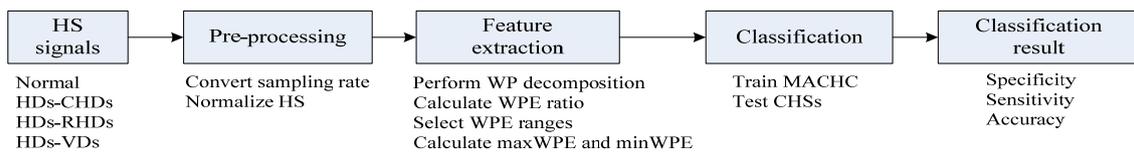


Fig. 1: A block diagram of the clinical HDs detection method.

The over diagnosis algorithm can be divided into five procedures: a brief review of CHS signals, pre-processing, and feature extraction by WP decomposition, classification by MACHC classifier and classification results. Each procedure of HDs identification algorithm is introduced as following.

3. CHS analysis procedure

3.1. Pre-processing

In this paper, the CHS signals with deferent sampling frequencies and intensities were used. Thus, suppose the original HS signal recorded using a stethoscope with 16-bit accuracy and 44.1 kHz sampling frequency. At first, signal $x_{2004}(t)$ is decimated by factor 22 from 44.1 kHz to 2004 Hz, and then the normalization is applied and the resultant signals can be expressed by

$$x_{norm} = \frac{x_{2004}(t)}{\left| \max_{t_x} (x_{2004}(t_x)) \right|} \quad (1)$$

3.2. Feature Extraction

Wavelet transforms (WT) are finding inverse use in fields as telecommunications and biology. Because of their suitability for analyzing non-stationary signals, such as the CHSs signals which have the nature of the complex and highly non-stationary, thus they have become a powerful alternative to Fourier methods in many medical applications, where such signals abound. The main advantages of wavelets are that they have an optimal time-frequency resolution in all the frequency ranges. Furthermore, owing to the fact that windows are adapted to the transients of each scale, but wavelets lack the requirement of stationarity [4].

WP analysis is an extension of the discrete wavelet transform (DWT) and it turns out that the DWT is only one of the much possible decomposition that could be performed on the signal. In a similar way to WT, WPs can be expressed by

$$\begin{cases} w_{2^s f}(2^{s-1}t-l) = \sqrt{2} \sum_{k \in \mathbb{Z}} h(k-2l)w_f(2^s t-k) \\ w_{2^{s+1} f}(2^{s-1}t-l) = \sqrt{2} \sum_{k \in \mathbb{Z}} g(k-2l)w_f(2^s t-k) \end{cases} \quad (2)$$

Where f is the frequency index, s is the scale index, l is the position index, and $[h(k), g(k)]$ are the low pass (LP) and high pass (HP) filters with $g(k)=(-1)^k h(1-k)$. Therefore, due to the orthonormal property, the WP coefficients at different scales and positions of a signal can be calculated efficiently as follows [2]:

$$\begin{cases} c_{2^s f, l}^{s-1} = \sum_{k \in \mathbb{Z}} h(k-2l)c_{f, k}^s \\ c_{2^{s+1} f, l}^{s-1} = \sum_{k \in \mathbb{Z}} g(k-2l)c_{f, k}^s \end{cases} \quad (3)$$

The advantage of wavelet packet analysis is that it is possible to combine the different levels of decomposition in order to achieve the optimum time-frequency representation of the original [4]. The tree structures for the three-scale WT and WP decompositions are shown in Fig. 2.

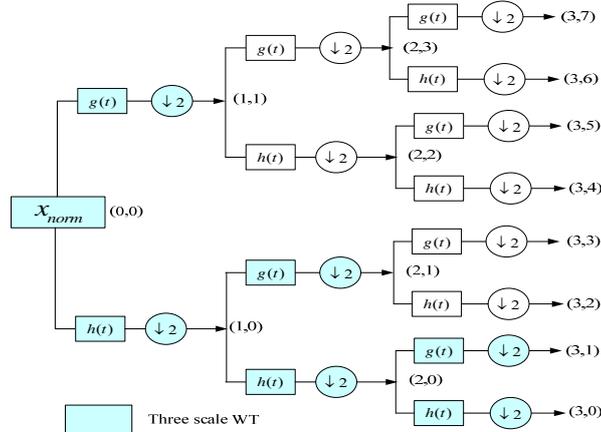


Fig.2. three-scale WP decompositions and WT

The WPE provides the useful information for CHS signals analysis. In this paper, the energy (E) throughout a certain frequency range of CHS signals was considered as features. The normalized E can be calculated as

$$\begin{cases} E_{ij} = \sum_{m=1}^n |x_{jm}|^2 \\ E = \frac{E_{ij}}{\left(\sum_{j=0}^l |E_{ij}|^2 \right)^{\frac{1}{2}}} \end{cases} \quad (4)$$

Where E_{ij} is the energy of the reconstructed signals, and X_{jm} ($j=0,1,\dots,2i-1, m=1,2,\dots,n$) is the amplitude of the reconstructed signals, i is the decomposition level (4), j is the selected position index is the position index and $j=0,1,\dots,11$.

So the feature extraction comprises of the following steps:

- WP decomposition

The decomposition structure tree at level 4 was used for WP decomposition of CHS signals. Daubechies Db10 type wavelet was used as a wavelet filter. Hence, we could obtain 16 WP coefficients. And the resultant resolution of a terminal node, i.e. (4, l), l=0,1,...,15 where fs is the sampling frequency (2004Hz) and S is the level index (4), see Table I .

- Calculate WPE and select the useful WPE ranges

The WP decomposition calculation is followed by the WPE calculation. Because CHSs with the frequency band of 0–751.5 Hz would be considered for classifying between normal sound and HDs, WPEs at terminal nodes (4,0) to (4,11) were selected as a terminal node (4,11), e.g., 688.875-751.5Hz, to cut off the HF component over 751.5 Hz, see Table 1.

Table.1: The frequency ranges from the nodes (4,0) to (4,11)

Node	Frequency ranges (Hz)	Node	Frequency ranges (Hz)
(4,0)	0-62.625	(4,6)	375.750-438.375
(4,1)	62.625-125.250	(4,7)	438.375-501.000
(4,2)	125.25-187.875	(4,8)	501.000-563.625
(4,3)	187.875-250.500	(4,9)	563.625-626.125
(4,4)	250.500-313.125	(4,10)	626.125-688.875
(4,5)	313.125-375.750	(4,11)	688.875-751.500

- Extract features

Two features maxWPE and minWPE are defined by the max value and min value of WPE, and these two feature values are respectively at the nodes (4,0) and (4,8), with the frequency band 0-62.625 Hz and 501-563.625 Hz. These two features are expressed as

$$\begin{aligned} \max WPE &= \max(E) \\ \min WPE &= \min(E) \end{aligned} \tag{5}$$

3.3. Classification.

This section introduces the classification procedure for detecting HDs. To discriminate between normal HS and several HDs by the extracted features maxWPE and minWPE, the MACHC classifier was applied, this technique is described briefly as following.

In recent years, the artificial immune system (AIS) as a new research area of computational intelligence, which provides a powerful information processing capabilities and problem solving paradigm. The AIS has been successfully applied to transformer fault diagnosis, image recognition, data mining and other fields, but in the field of detection for clinical HDs, this application is still rarely. So in this study, a MACHC algorithm was proposed, which used clone selection (CS) algorithm of AIS and improved Gustafson-Kessel (G-K) clustering algorithm to achieve the recognition and classification of CHSs.

The algorithm aiNet originally proposed by De Castro et al. [5] was developed for data compression and clustering. The aiNet which is AIS based unsupervised clustering algorithm and used for data reduction purposes in a supervised manner in this paper. But in this study, the training data set of each class is known and can be used by aiNet for constituting the memory cells which are used for classification purposes. The training samples are called Ag while memory units are called Ab. The resulting memory antibodies (Ab) which carry the same class information are used to obtain optimal cluster centres. The improved Gustafson-Kessel algorithm is applied to classify the testing data based on the obtained optimal cluster centres. The improved Gustafson-Kessel algorithm extends the Fuzzy C-means algorithm by employing an adaptive distance norm, in order to detect clusters with different geometrical shapes in the data set. The following notation was adopted in [5-7] and also used here:

- X data set composed of D_p patterns (feature vectors) of dimension p ;
- C matrix containing all the N_t network cells ($C \in R^{(N_t \times p)}$);
- M matrix of the N memory cells, each of dimensions $p (M \subseteq C)$;
- N_c total number of clones generated by the stimulated cells at each iteration;
- Dgb (dissimilarity) matrix with elements d_{ij} of Ag-Ab affinity;

Dbb (similarity) matrix with elements s_{ij} of Ab-Ab affinity;
 vbD the highest affinity cells selected for cloning and mutation;
 qi percentage of the matured cells to be selected;
 tp,s natural death and suppression threshold, respectively.

The aiNet learning algorithm can be described as follows:

1. At each iteration step, do:

1.1. For each antigen i , do:

1.1.1. Determine the class of the Ag_i , $i=1, \dots, m$, and call the memory cell Ab_j , $j=1, \dots, n$, of that class and calculate the affinity of the given antigen to all the network cells according to the Euclidean distance metric in shape space, d_{ij} , and it was expressed as

$$d_{ij} = \|Ag_i - Ab_j\| \quad (6)$$

1.1.2. Select the r_s (or r_s % of the) highest affinity network cells;

1.1.3. Clone these r_s selected cells. The number of progeny of each cell, N_c , being proportional to their affinity: the higher the affinity, the larger the clone size;

1.1.4. Increase the affinity of these N_c cells to Ag_i by reducing the distance between them, and The total number of clones N_c was calculated according to the following equation:

$$N_c = \sum_{j=1}^n \text{round}(n - d_{ij} \cdot n) \quad (7)$$

Where n is the total amount of antibodies in Ab, $\text{round}(\cdot)$ is the operator that rounds the value in parenthesis towards its closest integer and d_{ij} is the distance between the given antigen Ag_i and the selected antibody j given by Equation (6).

1.1.5. Calculate the affinity of these improved cells by Euclidean distance metric with antigen i ;

1.1.6. Re-select q_i of the most improved cells and put them into a partial matrix M_p of memory cells;

1.1.7. Eliminate those cells whose affinity is inferior to threshold tp (affinity threshold), yielding reduction in the size of the M_p matrix;

1.1.8. Determine the network cell-cell (Ab-Ab) affinity, s_{ij} ;

1.1.9. Eliminate those cells whose affinity s_{ij} is inferior to threshold ts , leading to another possible reduction in M_p (clonal suppression);

1.1.10. Concatenate the original network cell matrix with the partial matrix of memory cells;

1.2. Determine the whole network inter-cell affinities and eliminate those cells whose affinity with each other is inferior to threshold ts (network suppression);

1.3. Replace r of the worst individuals by novel randomly generated ones;

2. Test the stopping criterion. If the stopping criterion is reached, save the memory cell Ab for that class.

In the above algorithm, Steps 1.1.1 to 1.1.7 describe the clonal selection and affinity maturation processes as proposed by [8] in their computational implementation of the clonal selection principle. Steps 1.1.8 to 1.3 simulate the immune network activity. The learning algorithm aims at building a memory set of network cells that recognize the data, and hence represent their structural information. The resulting memory cells (Ab) constitute the training samples in the improved Gustafson-Kessel (G-K) clustering algorithm, and Gustafson and Kessel extended the standard fuzzy c-means algorithm by employing an adaptive distance norm, in order to detect clusters of different geometrical shapes in one data set [9].

The classification procedure conducts the following steps:

Step 1 Give the testing data set Z which was defined as $Z=[Ag_1 \dots Ag_m]^T$, where $Ag_k=[ag_{1,k}, ag_{2,k}]$ and $k=1, \dots, N$. Choose the parameter ρ_i , the condition number threshold β , the weighting parameter $\gamma > 1$, and number of clusters $1 < c < N$, norm-inducing matrix A . Set the fuzziness exponent $m=2$ and termination tolerance $\epsilon > 0$. Initialize the partition matrix $U(0)=[\mu_{i,k}]_{c \times N}$ and compute the covariance matrix F_0 of the hole data set. Repeat for $l=1, 2, \dots$

Step 2 The cluster centers, choose $k=1, \dots, N$

$$V_i^{(l)} = \frac{\sum_{k=1}^N (u_{ik}^{(l-1)}) z_k}{\sum_{k=1}^N (u_{ik}^{(l-1)})}, 1 \leq i \leq c \quad (8)$$

Step 3 Compute the cluster covariance matrices.

$$F_i^{(l)} = \frac{\sum_{k=1}^N (u_{ik}^{(l-1)})^m (z_k - V_i^{(l)})(z_k - V_i^{(l)})^T}{\sum_{k=1}^N (u_{ik}^{(l-1)})^m} \quad (9)$$

Add a scaled identity matrix:

$$F_i = (1 - \gamma)F_i + \gamma(F_0)^{1/n} I \quad (10)$$

Extract eigenvalues λ_{ij} and eigenvectors ϕ_{ij} ,

find $\lambda_{i,\max} = \max_j \lambda_{ij}$ and set:

$$\lambda_{i,\max} = \lambda_{ij} > \beta, \forall j \text{ for which } \lambda_{i,\max} / \lambda_{ij} \geq \beta \quad (11)$$

Reconstruct F_i by:

$$F_i = [\phi_{i,1} \dots \phi_{i,n}] \text{diag}(\lambda_{i,1} \dots \lambda_{i,n}) [\phi_{i,1} \dots \phi_{i,n}]^{-1} \quad (12)$$

Step 4 Compute the distances.

$$D_{ikA_i}^2 = (z_k - V_i^{(l)})^T [\rho_i \det(F_i)^{1/n} F_i^{-1}] (z_k - V_i^{(l)}) \quad (13)$$

Step 5 Update the partition matrix.

$$u_{ik}^{(l)} = \frac{1}{\sum_{j=1}^c (D_{ikA_i}(z_k, V_i) / D_{jk}(z_k, V_j))^{2/(m-1)}} \quad (14)$$

$$\text{Until } \|U^{(l)} - U^{(l-1)}\| < \varepsilon \quad (15)$$

Step 6 Achieve the visualization of the classification results.

4. Experiment classification results

In order to evaluate the performance of the proposed methodology, the information of the normal and abnormal subjects is shown in Table2.

Table2. The information of these two kind subjects

	Normal	Abnormal		
		CHD	RHD	VD
Number	42	68	40	6
No. of Male	30	39	14	4
No. of Female	12	29	26	2
Age ranges(years old)	19-25	2-47	22-70	50
Mean age(years old)	21	11	50	51

The experimental study was performed with 156 cases that consist of 42 normal subjects and 114 abnormal. The abnormal sounds are classified into three types, such as CHD, RHD and VD. From this table, we can see the incidence of CHD in the group of children is higher than the adults, and the male is more than the female; while the incidence of RHD in the group of adults is higher, and the female is more than the male. And according to the heart auscultation, there are four important areas used for listening to HSs, so for any subject, there are four experimental data, they are respectively from aortic, pulmonic, tricuspid and mitral areas. In the training processing; 55 abnormal and 21 normal subjects were selected for detection the clinical HDs. Remaining of the data set was used as a test set, and in the test set, the abnormal subjects (59) are from CHD patients, meanwhile, the rest of the CHD, all the RHD and the VD are as training data.

The training parameters of aiNet were chosen as following: The total number of clones N_c is 15, the highest affinity network cells vbD is 4, the matured cells to be selected q_i is 0.1, tp_s natural death and suppression threshold are 1 and 0.001, respectively.

The classification results of the testing data are given in Table3.

Table.3: Testing results of the proposed methodology

	Normal	Clinical HDs
The number of samples	21*4=84	59*4=236
Correct number	84	224
Incorrect number	0	12
Sp (%)		100
Se (%)		94.9153
Acc (%)		96.25

The classification rates of the proposed clinical HDs identification method were evaluated by the terms of specificity (Sp), sensitivity (Se) and accuracy (Acc) with respect to the testing data. From the results, it is evidently that the proposed clinical HDs detection method may be validated on the classification between normal sound and clinical HDs. Furthermore, the visualization of the classification results of the clinical HDs is shown in Fig. 3.

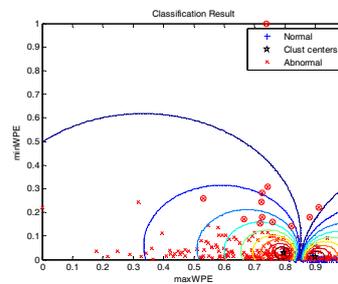


Fig.3: The visualization of the classification results

In Fig. 3. The cluster centres are remarked with “☆”, “+” remarks the normal, “x” and the feature data classified incorrectly will be remarked with “o”.

5. Remarks and future work

In this paper, a clinical HDs diagnosis method based on WP decomposition and MACHC classifier was described. The maximum value and the minimum of WPE were verified useful for identification of clinical HDs.

In this study, the future works are concluded as follows: Firstly, only maximum and minimum values of WPE were considered to identify between normal sound and clinical HDs. Therefore, the detailed HDs analysis and classification associated with abnormal cases via more valuable and effective parameters, such as mean, variance, high-order statistics, and others, will be continued in our future works. Secondly, the WPD at level 4 in this paper is used, and combine the clinical data to find the optimal level of WPD will be made in the future work. Thirdly, for the classification technique MACHC, use the convenient and efficient methods to determine the training parameters of aiNet is a key problem in the following steps, and finally, with the development of the clinical database, we will make detection of the different disorders in the abnormal subjects.

6. Acknowledgements

Thanks to the Innovation Fund of postgraduate, Xihua University (No.yejj201161), the Technological Support Project of Sichuan (No.2012FZ0019), and the Scientific & Technological Innovation Seeding Project of Sichuan (No.2011-048), and also thanks to the corresponding author of Xiaochen Wu.

7. References

- [1] Akay, M., Akay, Y. M., & Welkowitz, W. (1992). Neural networks for the diagnosis of coronary artery disease. *International Joint Conference on Neural Networks, IJCNN*, (Vol. 2, pp.419–424).
- [2] Samjin Choi, Detection of valvular heart disorders using wavelet packet decomposition and support vector machine, *Expert Systems with Applications* 35(4) (2008) 1679–1687.
- [3] Zhongwei Jiang, Samjin Choi, Haibin Wang, A New Approach on Heart Murmurs Classification with SVM Technique, *International Symposium on Information Technology Convergence*, 2007, pp:240-244.
- [4] I. Turkoglu, A. Arslan, E. Ilkay, An intelligent system for diagnosis of the heart valve diseases with wavelet packet neural networks, *Computers in Biology and Medicine* 33 (4) (2003) 319–331.
- [5] L.N. De Castro, F.J. Von Zuben, aiNet: an artificial immune network for data analysis, *Draft*, 2001.
- [6] Abdulkadir Sengur, An expert system based on principal component analysis, artificial immune system and fuzzy k-NN for diagnosis of valvular heart diseases, *Computers in Biology and Medicine* 38(3) (2008) 329–338.
- [7] Abdulkadir Sengur, Ibrahim Turkoglu, A hybrid method based on artificial immune system and fuzzy k-NN algorithm for diagnosis of heart valve diseases, *Expert Systems with Applications* 35(3) (2008) 1011–1020.
- [8] De Castro, L. N., & Von Zuben, F. J. (2000a). The Clonal Selection Algorithm with Engineering Applications, *In Workshop Proceedings of the GECCO2000*, 36-37.
- [9] D.E. Gustafson and W.C. Kessel. Fuzzy clustering with fuzzy covariance matrix. *In Proceedings of the IEEE CDC*, San Diego, pages 761-766. 1979