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HYBRID CLASSIFICATION SCHEMES FOR HEART MURMUR DETECTION TO ASSIST PHONOCARDIOGRAM BASED SIGNAL ACQUISITION

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ABSTRACT

The main contribution of this paper has been to introduce nonlinear classification techniques to extract more information from the PCG signal. Especially, Artificial Neural Network classification techniques have been used to reconstruct the underlying system's state space based on the measured PCG signal. This processing step provides a geometrical interpretation of the dynamics of the signal, whose structure can be utilized for both system characterization and classification as well as for signal processing tasks such as detection and prediction.

Keywords: Neural Network, Phonocardiogram, Classifier

SUBJECT CLASSIFICATION: Bio medical Signal Processing

METHOD/APPROACH: Hybrid classification schemes

1. INTRODUCTION

The human auditory system remains a "black box," despite many years of physiological research. The PCG signal is traditionally analyzed and characterized by morphological properties in time domain, by spectral properties in the frequency domain, or by non-stationary properties in a combined time-frequency domain. The different methods and a novel analysis algorithm for dynamic assessment of cardiac acoustics signal, such as PCG but not limited to, will improve the associated researchers for better understanding of PCG signal nature and its reflection on integrative clinical diagnosis of cardiomyopathy. Heart sounds are caused by turbulence in blood flow and vibration of cardiac and vascular structures. Murmurs are caused by turbulent blood flow and there are a number of different murmurs which may be detected by cardiac auscultation.

2. BENEFITS OF THIS WORK

The following benefits are achieved due to the algorithms developed in this work:

(i) The developed risk models in this work shall assist the clinicians to improve their prediction models for individual patients.

(ii) The unsupervised clustering techniques used in this research can discover the internal data structure and verify the nature of the problems or the difficulty of measuring influential parameters.

(iii) Alternative risk categories from the classification process are directly predicted and thus provide more reliable diagnosis. Thus, quality services at affordable costs can be provided and poor clinical decisions can be eliminated.

3. PREVIOUS WORKS

In [2] Neural Networks are broadly applied to a number of fields such as cognitive science, diagnosis and forecasting. [2] Has reported the use of confusion matrix for each classifier to see the type of errors being made. A comparison of supervised (MLP/RBF) versus unsupervised (SOM) classifiers may help in determining more appropriate patient classifications. Carotid End Arterectomy (CEA) is emerging as the commonest arterial procedure performed by vascular surgeons. In [4] the efficacy of CEA in stroke prevention has been proven by randomized controlled trials. However, very few models accurately predict individual patient's risk, especially when the outcome event rates are low. Estimating risk for a high risk group of patients often has a wide confidence interval, thus the mean of the distribution cannot be relied on for estimating an individual patient's risk. The minimum mean squared error (MSE) was compared for each network for training and cross validation sets. In [10] an investigation of four different classification models on cardiovascular data for estimation of patient risk in cardiovascular domains is presented. Experimental results are provided showing the performance of particular models. Poor clinical decisions can lead to disastrous consequences which are therefore unacceptable. Healthcare organizations must also minimize the cost of clinical tests. They can achieve these results by employing appropriate computer-based information and/or decision support systems [10]. Several essentially different classification models were employed on cardiovascular data. These models are useable, however, among other problems,

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labeling high risk patients as low risk patients in many cases should be avoided. Further investigation, including a simultaneous use of more classification models, continues so that this can be achieved. [11] Introduce and formalize the multilevel classification problem, in which each category can be subdivided into different levels. The framework in a Bayesian setting is analyzed using Normal class conditional densities. Within this framework, a natural monotonicity hint converts the problem into a nonlinear programming task, with non-linear constraints. In most disease handbooks, not only are unrelated diseases listed, but versions (or severities) of a given disease are also provided. An example is the heart condition. In most disease handbooks, not only are unrelated diseases listed, but versions (or severities) of a given disease are also provided.

Also chose a risk matrix that is 0 along the diagonal and 1 everywhere else, hence the risk is the probability of error. The general problem presents no additional difficulties. The recent wavelet thresholding based denoising methods proved promising, since they are capable of suppressing noise while maintaining the high frequency signal details. In [12] various thresholding techniques have been studied for adaptive noise elimination and we presented a new type of Thresholding Neural Network (TNN) structure for adaptive noise reduction, which combines the linear filtering and thresholding methods. The wavelet shrinkage methods rely on the basic idea that the energy of a signal (with some smoothness) will often be concentrated in a few coefficients in wavelet domain while the energy of noise is spread among all coefficients in wavelet domain in [12]. In [12] they have presented a new type of thresholding neural network (TNN) structure for adaptive noise reduction, which combines the linear filtering and thresholding methods. We created a new type of soft and hard thresholding functions to serve as the activation functions of TNNs.

4. OBJECTIVES OF THIS WORK

Inference from the reported works, reveal that an integrated classification technique that combines the descriptive and predictive tasks along with cluster analysis and anomaly detection is lacking. Monitoring the heart rate of a patient for abnormalities involves building a model of the normal behavior of the heart rate and raises an alarm when an unusual heart behavior occurred. This would involve the study of both normal and abnormal heart behavior. The following are the objectives of this work:

i. This work focuses on developing such an integrated analysis and applies the same to cardiovascular clinical domain. Both normal and abnormal heart behavior analysis is carried out in this research.

ii. Another observation from the reported work is that, the analysis and algorithms have large dependence on observational data and less use of empirical data. The drawback of this is that complete control of the quantity of the data obtained is not possible. In this work, the above drawback is overcome by making uniform utilization of both observational and empirical data.

5. CLASSIFICATION

Classification, which is the task of assigning objects to one of several predefined categories, is a pervasive problem that encompasses many diverse applications. Classification is the task of learning a target function *f* that maps each attribute set *x* to one of the predefined class labels *y.* The target function is also known informally as a classification model.

5.1 Classification models

These are essentially simple mathematical models defining a function or a distribution. Sometimes models are also intimately associated with a particular learning algorithm or learning rule. A common use of the phrase ANN model really means the definition of a *class* of such functions (where members of the class are obtained by varying parameters, connection weights, or specifics of the architecture such as the number of neurons or their connectivity).

5.2 Employing Artificial Neural Networks

Perhaps the greatest advantage of ANNs is their ability to be used as an arbitrary function approximation mechanism which 'learns' from observed data. However, using them is not so straightforward and a relatively good understanding of the underlying theory is essential.

i. Choice of model: This will depend on the data representation and the application. Overly complex models tend to lead to problems with learning.

ii. Learning algorithm: There are numerous tradeoffs between learning algorithms. Almost any algorithm will work well with the *correct hyper parameters* for training on a particular fixed dataset. However selecting and tuning an algorithm for training on unseen data requires a significant amount of experimentation.

iii. Robustness: The model, cost function and learning algorithm are selected appropriately such that the resulting ANN extremely robust.

With the correct implementation, ANNs can be used naturally in online learning and for large dataset applications. Their simple implementation and the existence of mostly local dependencies exhibited in the structure allows for fast, parallel implementations in hardware. In this research, the Multi-layer Perceptron Neural Network with Back-propagation as the training algorithm is employed (figure 1) and the neural network is trained with the selected significant patterns for the effective prediction of heart attack. The results obtained illustrate that the designed prediction system is capable of predicting the heart attack effectively.

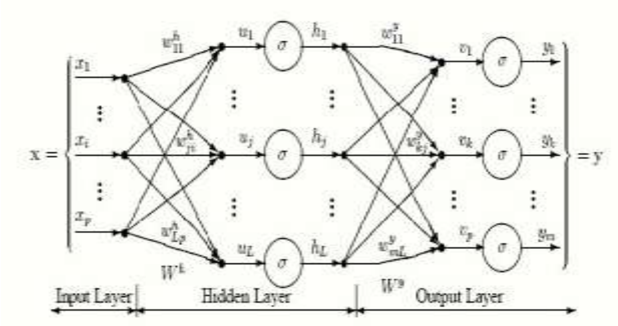

Figure 1 Multilayer Perceptron Neural Network Structure

6. CLASSIFICATION OUTPUT AND FEATURES WEIGHT ASSIGNMENT

Consider a decision matrix, where tf_{ij} is the frequency of the i^{th} input (term) in the j^{th} category and 'm' is the number of categories. A variable transformation that is defined by

$$tf'_{ij} = tf_{ij} * \log\frac{m}{dfi'} \quad \ldots (1)$$

is proposed in this research to assign weight to the frequency of occurrence of i^{th} i/p. In eqn. (1) df_i is the number of categories in which the i^{th} input appears and is known as the category frequency. This transformation is known as the inverse category frequency transformation. Input feature category that occurs in every category assigned zero weights, while those that occur in one category have maximum weight, i.e., log m. Such normalization reflects the observation that the features that occur in every category do not have any power to distinguish one output from another, while those that are relatively rare, do. The proposed medical decision support system is based on a time series clustering and requires time series with relative high positive correlation to be put together. For this purpose the following transformation is chosen:

$$\text{sim} = \begin{cases} \text{Corr} & \text{if corr } \geq 0 \\ 0 & \text{if corr} < 0 \end{cases}$$

For predicting the behavior of one time series from another, it is necessary to consider strong negative as well as strong positive correlation. In this case, the following transformation $\text{sim} = |\text{vcorr}|$ is appropriate with the assumption that only magnitude is to be predicted and not direction.

7. APPROXIMATION OF CLASSIFIERS USING KERNEL FUNCTIONS

In this work, the approximation of classifiers is done using Gaussian kernel function. The parzen window method is used to approximate. The closeness of the approximation is studied by varying the smoothing parameter. The code is shown as follows:

Input:

Smoothing parameter h [varies between 0.05 and 0.2].

N: the no. of points generated from a pseudorandom generator according to *p*(*x*).

Output:

Plot of the approximation varied w.r.t. (N,h)

Code:

```
n=rand(1,N)*2;

Privy=0;

p=[];

for m=-0.5:h:2.5

newp=0;

for a=1:size(n,2)

X=(n(a)-m)/h;

newp=newp+(1/sqrt(2*pi))*exp(-(x)^2/2);
```

```
end
newp=(1/h)*(1/size(n,2))*newp;
p=[p newp];
end
x=[zeros(1,length(-0.5:0.01:-0.01)),ones(1,length(0:0.01:-
                        0.01)),ones(1,length(0:0.01:2))*0.5,zeros(1,length(2.01:0.01:2.5))];
xax=-0.5:0.01:2.5;
m=-0.5:h:2.5;
plot(m,p,'r',xax,'k');
```

The output obtained by executing the above code snippet for different values of smoothing parameter 'h' and 'N' is shown in figure 2 to figure 7.

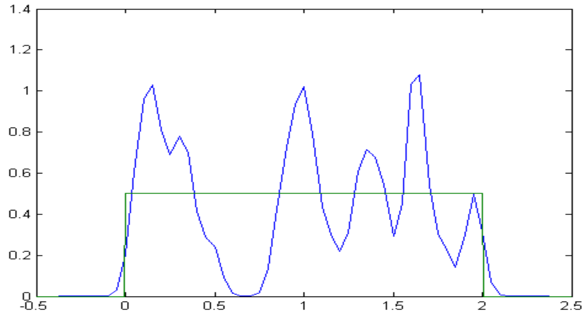

Figure 2 Approximated pdf for h=0.02 and N=32

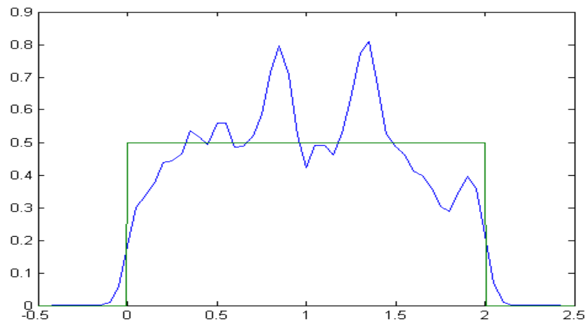

Figure 3 Approximated pdf for h=0.02 and N=256

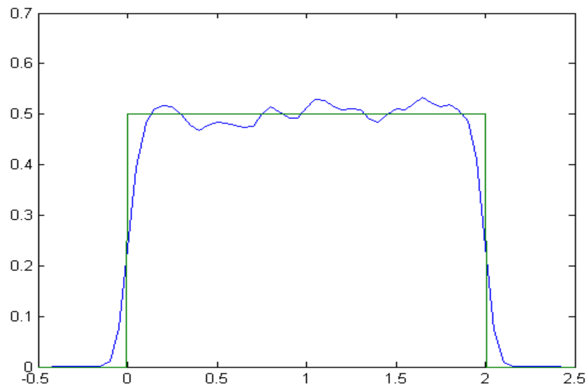

Figure 4 Approximated pdf for h=0.02 and N=5000

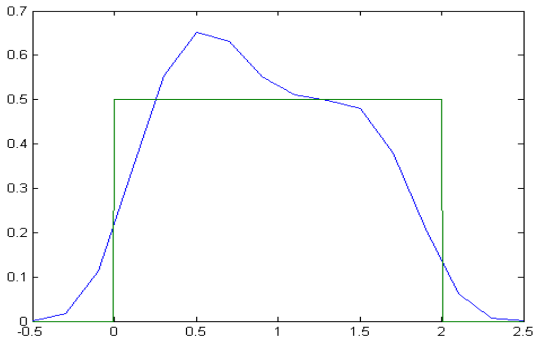

Figure 5 Approximated pdf for h=0.2 and N=32

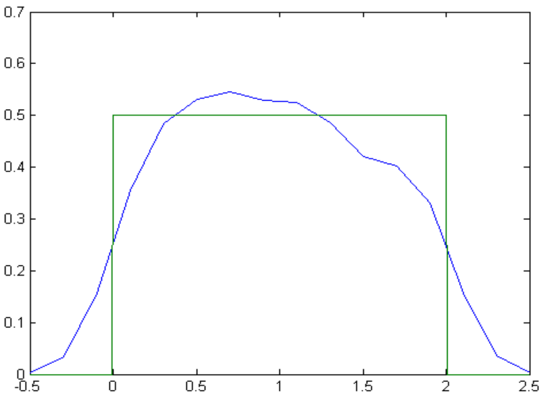

Figure 6 Approximated pdf for h=0.2 and N=256

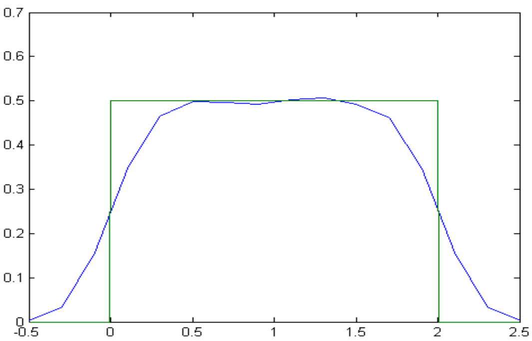

Figure 7 Approximated pdf for h=0.2 and N=5000

8. PROPOSED HYBRID B00STING CLASSIFIER USING NEURAL NETWORK

In this work, a hybrid boosting classifier is implemented with improved classification results. The error on the training data set is minimized in the proposed work. The error is bounded by exp ($-2K\gamma^2$) and drops exponentially fast with *K*. This is illustrated in appendix-1. In this research, the Multi-layer Perceptron Neural Network with Back-propagation as the training algorithm is employed and the neural network is trained with the selected significant patterns for the effective prediction of cardiovascular risks. The data collected is pre-processed for normalization and fed to the neural network for training. Data is fed into the network through an input layer; it is processed through one or more intermediate hidden layers and finally fed out of the network through an output layer.

8.1 OBSERVATIONS

The clinical information is correlated with the cardiovascular risk using the ANN in this work. The error curve, neural network mapping curve and the convergence plots are shown in figure 8 to figure 10. In figure 8, the x-axis denotes the range of variations of parameter about its nominal value and in this work, the variations was chosen as x€ [-6,6]. The results are shown for first 500 epochs. Figure 9 indicates that, the neural network is able to map with the required data with lesser error for most of the data points. However, when the data points are much closer to the nominal value, the network exhibits an increased error and therefore, the number of epochs must be increased.

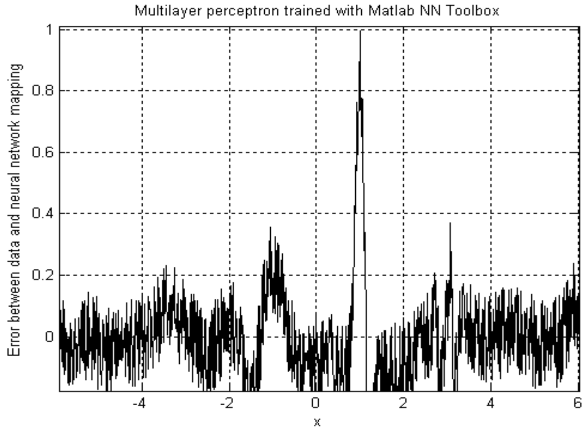

Figure 8 Error plot between target data and neural output

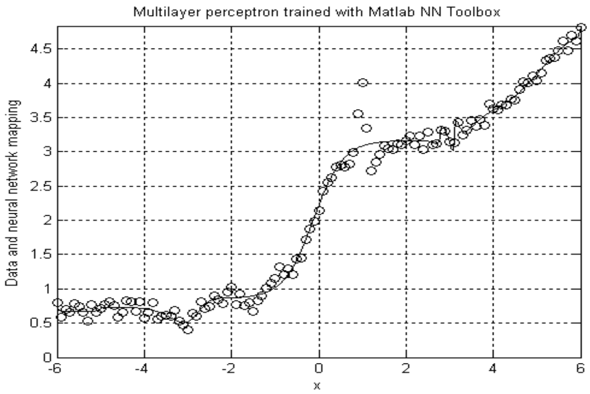

Figure 9 Mapped output points over the range of trained input data set

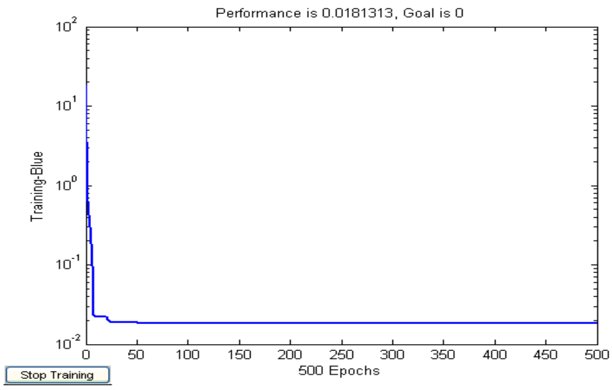

Figure 10 Training curve for the first 500 epochs

APPENDIX-1

The error on the training data set is given by

$$P_e^N = \frac{1}{N}\sum_{j=1}^{N} I(1 - y_i f(x_i)) \le \frac{1}{N}\sum_{j=1}^{N} exp(-y_i F(x_i))$$

This by the definition of the combined classifier is written as

$$\frac{1}{N}\sum_{i=1}^{N} exp\left(-y_i F(x_i)\right) = \frac{1}{N}\sum_{j=1}^{N} \exp\left(-y_i \sum_{k=1}^{K} \alpha_k \phi(x_i;\theta_k)\right)$$

$$= \sum_{j=1}^{N} \frac{1}{N} \prod_{k=1}^{K} \exp\left(-y_i\, \alpha_k \phi(x_i;\theta_k)\right) \qquad \dots (2)$$

However

$$w_i^{(K+1)} = \frac{w_i^K \exp\left(-y_i \alpha_k \phi(x_i;\theta_k)\right)}{Z_K} = \frac{w_i^{K-1} \exp\left(-y_i \alpha_k \phi(x_i;\theta_{k-1})\right) \exp\left(-y_i \alpha_k \phi(x_i;\theta_k)\right)}{Z_K Z_{K+1}}$$

$$= \frac{\prod_{k=1}^{K} \exp\left(-y_i\, \alpha_k\, \phi(x_i;\theta_k)\right)}{N \prod_{K=1}^{K} Z_K} \qquad \dots (3)$$

Thus, $\sum_{i=1}^{N} \frac{\prod_{k=1}^{K} \exp\left(-y_i \alpha_k \phi(x_i;\theta_k)\right)}{N \prod_{K=1}^{K} Z_K} = 1$ $\qquad \dots (4)$

Combining the above equations results

$$P_e^N \le \prod_{K=1}^{K} Z_K \qquad \dots (5)$$

By the respective definition we have

$$Z_k = \sum_{i=1}^{N} w_i^{(k)} \exp\left(-y_i \alpha_k \phi(x_i;\theta_k)\right) = \sum_{(y_i \alpha_k \phi(x_i;\theta_k))<0} w_i^{(k)} \exp(\alpha_k) + \sum_{(y_i \alpha_k \phi(x_i;\theta_k))>0} w_i^{(k)} \exp(-\alpha_k)$$

$$Z_K = P_K \exp(\alpha_k) + (1 - P_K) \exp(-\alpha_k) \qquad \dots (6)$$

Also,

$$\alpha_k = \frac{1}{2} \ln \frac{1 - P_k}{P_k} \qquad \dots (7)$$

Combining (6) and (7)

$$Z_K = 2\sqrt{P_K(1 - P_k)} \qquad \dots (8)$$

Hence (5) can be written as

$$P_e^N \le \prod_{k=1}^{K} \left\{2\sqrt{P_K(1 - P_k)}\right\} = \prod_{k=1}^{K} \left\{\sqrt{1 - 4\gamma_k^2} \le \exp(\;) - 2\sum_{k=1}^{K} \gamma_k^2\right\}$$

Where by definition $\gamma_k \equiv \frac{1}{2} - P_K$

or $\gamma_k \ge \gamma > 0.$

9. CONCLUSION

The features extracted from the heart sound signal in this work shall reduce the existing higher dependency on experience and inter-observer variation. Future direction of study shall focus on schemes to classify and assess heart murmurs from the extracted information to and relate the same to different heart valve pathologies. This paper reports the signal analysis of heart sounds and murmurs. A large number of, partly nonlinear, features was extracted and used for distinguishing innocent murmurs from murmurs caused by Aortic Stenosis using recurrence quantification analysis. In general, the presented nonlinear processing techniques have shown considerably improved results in comparison with other PCG based techniques and be of great supplement to modern health care. The work is a noninvasive investigation of blood pressure changes. The work proposes that a heart monitor with electrocardiographic and phonocardiogram (present work) processing fusion will offer improved clinical decision making.

10. REFERENCES

[1] S.M. DEBBAL, F.BEREKSI-REGUIG, “Frequency analysis of the heartbeat sounds”, Biomedical Soft Computing and Human Sciences, Vol.13, No.1, pp.85-90 (2008).

[2] TanveerSyeda-Mahmood, FeiWang, “Shape-based Retrieval of Heart Sounds for Disease Similarity Detection”, San Jose.

[3] SreeramanRajan, RajamaniDoraiswami, Raymond Watrous, “Wavelet Based Bank Of Correlators Approach for Phonocardiogram Signal Classification”, 1998 IEEE.

[4] Hideaki Shino, Hisashi Yoshida, Kazuo YanaKensuke Harada, JiroSudoh, and EishiHarasawa, “Detection and Classification of Systolic Murmur for Phonocardiogram Screening”, 18th Annual International Conference of the IEEE Engineering in Medicine and Biology Society, Amsterdam 1996.

.[5] Haibin Wang, Jian Chen and Yuliang Hu, Zhongwei Jiang and Choi Samjin, “Heart Sound Measurement and Analysis System with Digital Stethoscope”, 2009 IEEE.

[6] Qiong Li, Jing.Wu, Xin He, “Content-based Audio Retrieval using Perceptual Hash”, International Conference on Intelligent Information Hiding and Multimedia Signal Processing.

[7] M. SabarimalaiManikandan and S. Dandapat, “Wavelet-Based ECG and PCG Signals Compression Technique for MobileTelemedicine”, 15th International Conference on Advanced Computing and Communications.

[8] H Liang, S Lukkarinen, I Hartimo, “Heart Sound Segmentation Algorithm Based on Heart Sound Envelolgram”, Computers Cardiology 1997 Vol24.

[9] S. Kiranyaz and M. Gabbouj, “Generic content-based audio indexing and retrievalFramework”, IEE Proc.-Vis. Image Signal Process., Vol. 153, No. 3, June 2006 285.

[10] Wenjie Fu, Xinghai Yang, Yutai Wang, “Heart Sound Diagnosis Based on DTW and MFCC”, 2010 3rd International Congress on Image and Signal Processing (CISP2010).

[11] J S D Mason and Y Gu, “Perceptually-Based Features in ASR”

[12] P.R. White, W.B. Collis and A.P. Salmon, “Analyzing Heart Murmurs Using Time-Frequency Method”, ISVR, University of Southampton, High field, Hants, U.K.

[13] Zeeshan Syed, Daniel Leeds, Dorothy Curtis, Francesca Nesta, Robert A. Levine, and John Guttag, “A Framework for the Analysis of Acoustical Cardiac Signals”, IEEE Transactions on Biomedical Engineering, Vol. 54, No. 4, April 2007.

[14] Emil Jovanov, Kristen Wegner, Vlada Radivojevic, Dusan Starcevic, Martin S. Quinn, and D. B. Karron, “Tactical Audio and Acoustic Rendering in Biomedical Applications”, IEEE Transactions on Information Technology in Biomedicine, Vol. 3, No. 2, June 1999.

[15] Lie Lu, Hong-Jiang Zhang, and Hao Jiang, “Content Analysis for Audio Classification and Segmentation”, Senior Member, IEEE, IEEE Transactions on Speech and Audio Processing, Vol. 10, No. 7, October 2002.

[16] Robert A. Dennis and Sanjiv S. Gambhir, “Internet Question and Answer (iQ&A): A Web-Based Survey Technology”, IEEE Transactions On Information Technology In Biomedicine, VOL. 4, NO. 2, June 2000.

[17] Dimitar H. Stefanov, Zeungnam Bien, Won-Chul Bang, “The Smart House for Older Persons and Persons With Physical Disabilities: Structure, Technology Arrangements, and Perspectives”, Senior Member, IEEE, Member, IEEE, IEEE Transactions On Neural Systems And Rehabilitation Engineering, VOL. 12, NO. 2, June 2004

[18] Yasemin M. Akay, Metin Akay, WalterWelkowitz, John L. Semmlow, and John B. Kostis, “Noninvasive Acoustical Detection of Coronary Artery Disease: A Comparative Study of Signal Processing Methods”, Student Member. IEEE, Senior Member, IEEE, Fellow, IEEE, IEEE Transactions on Biomedical Engineering. Vol. 40, No. 6, June 1993.

[19] Frank Baumgarte, “Improved Audio Coding Using a Psychoacoustic Model Based on a Cochlear Filter Bank”, IEEE Transactions On Speech And Audio Processing, VOL. 10, NO. 7, October 2002.

[20] Jesper Jensen, Richard Heusdens, and Soren Holdt Jensen, “A Perceptual Subspace Approach for Modeling of Speech and Audio Signals with Damped Sinusoids”, Member, IEEE and Senior Member, Senior Member, IEEE Transactions On Speech And Audio Processing, Vol. 12, No. 2, March 2004.

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