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In Search of an SVD and QRcp Based Optimization Technique of ANN for Automatic Classification of Abnormal Heart Sounds

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***Abstract*—**Artificial Neural Network (ANN) has been extensively used for classification of heart sounds for its discriminative training ability and easy implementation. However, it suffers from overparameterization if the number of nodes is not chosen properly. In such cases, when the dataset has redundancy within it, ANN is trained along with this redundant information that results in poor validation. Also a larger network means more computational expense resulting more hardware and time related cost. Therefore, an optimum design of neural network is needed towards real-time detection of pathological patterns, if any from heart sound signal. The aims of this work are to (i) select a set of input features that are effective for identification of heart sound signals and (ii) make certain optimum selection of nodes in the hidden layer for a more effective ANN structure. Here, we present an optimization technique that involves Singular Value Decomposition (SVD) and QR factorization with column pivoting (QRcp) methodology to optimize empirically chosen over-parameterized ANN structure. Input nodes present in ANN structure is optimized by SVD followed by QRcp while only SVD is required to prune undesirable hidden nodes. The result is presented for classifying 12 common pathological cases and normal heart sound.

***Keywords*—**ANN, Classification of heart diseases, murmurs, optimization, Phonocardiogram, QRcp, SVD.

I. INTRODUCTION

AUSCULTATION, the technique of listening to heart sound, is used as a primary detection tool for diagnosis of heart valve disorders since invention of stethoscope in 1816 by Lannec [1]. Certain heart diseases are best detected only by auscultation [2]. It has been reported that a disturbing percentage of medical graduates cannot properly diagnose heart conditions using stethoscope [3]. The poor sensitivity of human ears in the low frequency range of the heart sounds makes this task even more difficult. Phonocardiogram (PCG), the digitized recording of heart sound is proven to be very useful in the description and understanding of heart sounds as it provides a visual display of the recorded waveform [4], [5] and allows computer aided signal processing techniques to characterize them.

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Heart sounds are usually divided into normal and abnormal heart sounds, the later indicating a pathological case. A heart sound cycle primarily consists of first heart sound ($S1$) followed by second heart sound ($S2$). The intervals between $S1$ and $S2$ (systole), and $S2$ and $S1$ (diastole) of the next cycle are usually silent for normal cases. These two distinct normal heart sounds are often described as lub and dub (or dup), and occur in sequence with each heart beat. In an abnormal heart sounds there could be several other sounds in the phonocardiogram signal besides primary heart sounds. Abnormal heart sounds called murmurs; if present in the cardiac cycle, refer to different pathological conditions [6] as per location, shape, duration and other associated features. Murmurs are generally high-frequency, noise like sounds that arise when the velocity of blood become high when it flows through an irregularity. The PCG signal has been widely used to detect the cardiac abnormalities. Different features of PCG signals like intensity, frequency content, split information, time relations etc. can give an idea of the underlying pathology, if any and the state of the heart function [7].

A variety of methods have been reported for the classification of heart diseases. Sharif *et al.* have reported a classification technique based on the instantaneous energy and frequency estimations of heart sound signal [8]. They have

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reported an accuracy of 70% for classification of normal heart sound, mitral stenosis and mitral regurgitation. Time-frequency analysis techniques like wavelet transform have also been widely used for this purpose [9]-[13]. Ian Cather presented ANN as a discriminative model for classification of 5 different heart sounds taken from 48 recordings of 9 different subjects using wavelet based feature extraction technique [9]. Ölmez *et al.* have given a classification technique that utilizes Daubechies-2 wavelet detail coefficients at the second decomposition level for classification of 7 different heart sounds collected from 28 subjects using ANN [10]. Reed *et al.* described a computer-aided diagnosis mechanism for 5 different pathological cases using a seven level wavelet decomposition, based on a Coifman fourth order wavelet kernel [11] and ANN classifier model. A classification of heart sound technique that uses same method as proposed by Ölmez *et al.* [10], is developed by Gupta *et al.* [12] for classification of 3 different heart sounds (normal, systolic murmur and diastolic murmur) recorded from 41 volunteers. Omran *et al.* [13] presented a wavelet based feature extraction technique using ANN as a model for classifying 10 different heart sounds with accuracy of 98%.

At present, the wavelet transform is popular in extracting feature vectors from heart sound signal because of its ability to characterize time-frequency information which is important in this context [14]-[17]. Artificial Neural Network (ANN) is normally used as a classifier [9]-[13] to discriminate the heart sound signal using these features. The popularity of ANN as a classifier is because (i) ANN can be used to generate likelihood-like scores that are discriminative in the state level (ii) ANN can be easily implemented in hardware platform for its simple structure (iii) ANN has the ability to approximate functions and automatic similarity based generalization property (iv) complex class distributed features can be easily mapped by ANN.

Though ANN enjoys several advantages, it has inherent difficulties like problem of overfitting. During training redundant input data might force solution to be trapped in local minima resulting non-convergence of ANN structure. Redundancy within the features increases modeling complexity without improving discrimination performance. Since, there is no unanimity in selection of features for characterizing phonocardiogram signals for disease identification, a scheme that in the first place includes all the features that seems reasonable and then removes redundancy may prove to be useful. The problem of ANN is its empirically chosen structure of the network i.e., the number of hidden units and their interconnections are chosen arbitrarily. No such method exists which allows one to decide the necessary structure for a given application or size of training set [10]. The performance decreases if solution traps in local minima for multi layer perceptron (MLP). In the ANN based classification over parameterization or redundancy in the structure is commonly seen for using excessive number of hidden nodes and a method to select an optimum number of nodes in classifier design will be of interest. This is also required for real time hardware implementation that reduces storage and time complexity. In this work, we propose an optimization of the ANN structure for classification purpose, which uses SVD followed by QRcp. The network is optimized sequentially i.e. first the unnecessary input nodes are pruned followed by deletion of hidden nodes from the ANN structure. Similar optimization technique has been successfully used by the authors in their previous work but in the context of modeling and prediction [18]. Here we show its effectiveness in the classification problem for detecting abnormality in the phonocardiogram signal. For the implementation of automatic classification of valvular heart diseases, it is necessary to detect primary heart sounds properly that serves as a reference marker to extract features from the corresponding cycle for use in classifier model. In one of authors' previous work [19], such a method is described which does not need auxiliary input like electrocardiogram signal and another work [20] makes a binary decision on heart sound whether pathological or not in a Digital Signal Processor based system. We use that segmentation technique [19] here to facilitate feature extraction in the wavelet domain. We always begin with an over-parameterized model that ensures we do not to miss any important feature or nodes and let the optimization strategy to do the necessary selection. The result shows significant reduction in ANN structure with improved classification for normal heart sound and 12 common pathological cases on a database of 104 different phonocardiogram recordings.

The paper is organized as follows: Section II presents a brief description about the QR, QRcp factorization and SVD, Section III discusses the database that is used in the work, Section IV presents the methodology, Section V gives the results and performance of the optimization technique, Section VI presents a discussion on the optimization method followed by principle conclusions in Section VII.

II. Theoretical Background

A. QR and QRcp Factorization

Consider, a model represented by $y=Ax$ where $A = [a_1,\ldots\ldots\ldots,a_i,\ldots\ldots,a_N] \in \mathbb{R}^{m\times N}$ contains N ($< m$) feature vectors a_i, $i=1,..,N$, y is the output vector, x is the N parameter vector. The n ($< N$) most significant features vectors satisfy, $y = \overline{A}\overline{x} + e$, where $\overline{A}$ subset of A and $\overline{x}$ the least square (LS) estimated n parameter vector and e defines the uncertainty. QR factorization [18] can be used for efficient LS estimation of above.

1) QR Factorization: QR factorization of A given by $A = QR$, where $Q = [q_1\ldots.., q_i,\ldots\ldots.,q_N] \in \mathbb{R}^{m\times N}$, $Q^TQ = I_N$, and R is an upper triangular matrix. The columns of Q span the same subspace as the columns of A matrix. The number of nonzero diagonal elements R_{ii} ($i\leq min(m,N)$) of R indicates the rank of A. $\left|R_{ij}\right| = 0$ denotes a_j being redundant, as it has no component in the q_j vector space.

2) QR factorization with column pivoting (QRcp): QRcp can be used to pivot the columns of a matrix in order of maximum Euclidian norm in successive orthogonal directions, while QR factorization is performed on the matrix. The column vector of A matrix with $max(a_i^T a_i)$, $i=1$ to N, is first selected, and is swapped with a_1. The subsequent columns of A are pivoted using the Gram-Schmidt orthogonalization concept [21]. If q_1 be the unit vector in the direction of a_1, the second vector is the one maximizing $(a_j-q_1^T a_j q_1)^T (a_j-q_1^T a_j q_1)$, where $j= 2$ to N, which is swapped with a_2 and likewise. At the i-th stage of selection the rotated vectors (a_j^*) are

$$a_j^* = a_j - (q_1^T a_j q_1 + ...q_{i-1}^T a_j q_{i-1}) \quad (1)$$

$i=2$ to N, $j=i$ to N, and the i-th selected vector is the one maximizing $a_j^{*T} a_j^*$. The subsequent rotation within the QR decomposition will be with respect to this vector and so on. The selection procedure is repeated until n vectors are selected. The column swappings are recorded in a permutation matrix called P.

B. Singular Value Decomposition

SVD of a $p\times q$ matrix H, is given by $H = UWV^T$ where $U\in \mathbb{R}^{p\times p}$, $V\in \mathbb{R}^{q\times q}$, $U^TU=I$, $V^TV=I$, W is the diagonal matrix with decreasing matrix. The $p\times q$ matrix $W = [diag\{w_1, w_2, ..., w_m\} : 0]$, $m=min(p,q)$, $w_1 \geq w_2 .... \geq w_m \geq 0$ and $w_1, w_2, ..., w_m$ are the singular values of H. The left singular matrix (U) and the right singular matrix (V) form a basis for the column space and row space respectively. The matrix H contains the energy: $E_H = \sum_{i=1}^{p}\sum_{j=1}^{q} h_{ij}^2 = \| H \|_F^2 = w_1^2 + w_2^2 + ... + w_p^2$; h_{ij} represents for j-th element of i-the row of H, F is the Frobenius norm.

III. Database

The heart sound recordings for normal and abnormal heart conditions were obtained from various resources, maximum being provided by Maulana Azad Medical Institute, Delhi, India. In total 832 cycles from 104 recordings of 104 volunteers are collected for 12 different pathological problems and normal heart conditions. Heart sound signals were recorded by the cardiologists at different auscultation locations as necessary for various pathological cases using electronic stethoscopes like 3M™ Littman electronic stethoscope, interfaced to the computer and were stored in 16 bit, PCM, Mono audio format with 8012Hz sampling frequency. The data is not associated with any particular age group.

IV. Methodology

The three successive stages followed in characterization of phonocardiogram signals are: preprocessing or segmentation, feature extraction and classification. This is decision making process, is shown as a flowchart in Fig. 1.

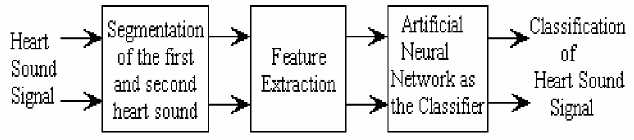

Fig. 1 Different stages for the classification of heart sound

A. Preprocessing (Segmentation) of Phonocardiogram Signal

Preprocessing stage involves segmentation of heart sound cycle from a continuous phonocardiogram signal. In a normal heart sound cycle, usually two major heart sounds (first heart sound, S1 and the second heart sound, S2) are noticed and these segment the cycle into two major parts, the systole and the diastole. The S1 denotes the start of systole and S2 denotes the start of diastole. The complete cardiac cycle can be extracted from different established segmentation methods [9]-[13], [19], [22], [23]. Here, it is obtained from our previous work [19] which does not use any auxiliary input like electrocardiogram signal.

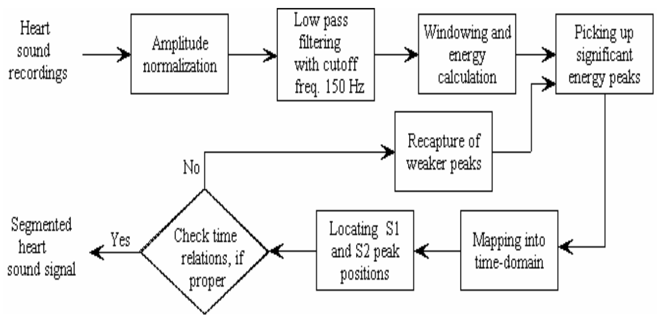

Fig. 2 Block diagram of the segmentation method

Fig. 2 represents the block diagram of segmentation algorithm which is primarily based on the use of frequency content present in the PCG signal, calculation of energy in different time windows and timing relations of various signal components. A number of medical domain features e.g. normal split-sound duration, frequency content of $S1$ and $S2$ etc. are exploited in the algorithm.

B. Feature Extraction Process

In time-frequency domain wavelet based feature extraction technique has been successfully used to get meaningful features from non-stationary heart sound signals [9]-[13]. We use wavelet based feature extraction technique mentioned in [10], [12] where Daubechies-2 wavelet is used for determining the wavelet coefficients. Wavelet detail coefficients and approximation coefficient at the sixth level for a normal subject are shown the Fig. 3.

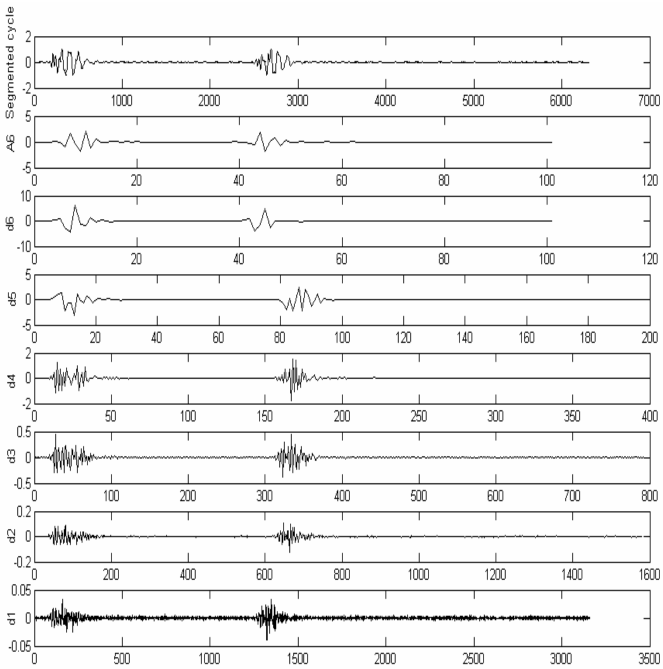

Fig. 3 Wavelet detail coefficients at the first-six decomposition levels (d^1-d^6) and the wavelet approximation coefficients at the sixth level (a^6) for a normal PCG signal

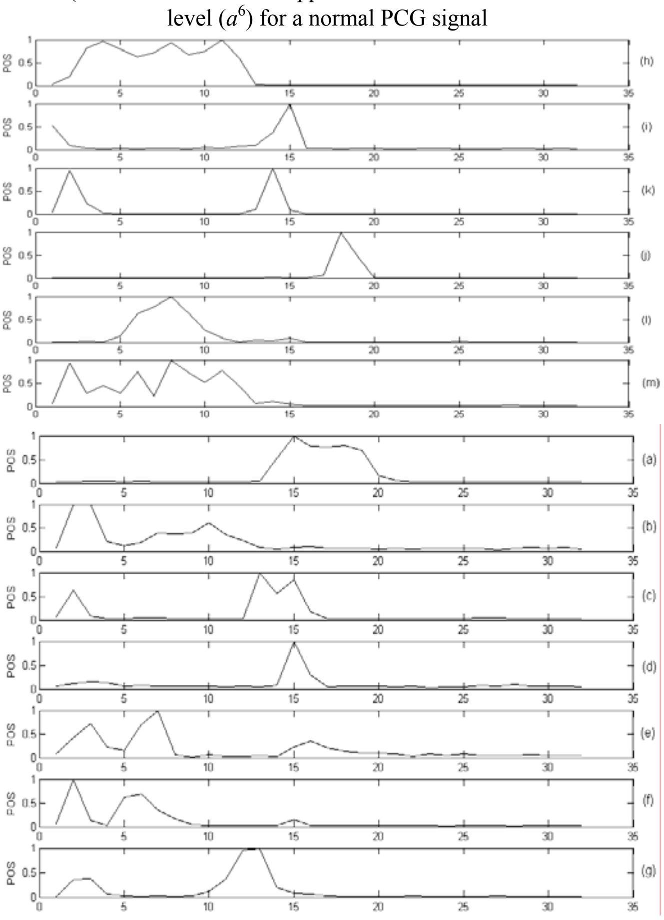

Fig. 4 Feature vector for (a)aortic insufficiency (b) aortic stenosis (c) atrial septal defect (d) coarctation of aorta (e) ejection click (f) early systolic murmur (g) late systolic murmur (h) mitral regurgitation (i) mitral stenosis (j) normal (k) opening snap (l) pulmonary stenosis (m) pan systolic murmur

Fig. 4(a-m) represents wavelet detail coefficients at the second decomposition level for all the cases under study : aortic insufficiency, aortic stenosis, atrial septal defect, coarctation of aorta, ejection click, early systolic murmur, late systolic murmur, mitral regurgitation, mitral stenosis, normal, opening snap, pulmonary stenosis, pan systolic murmur respectively.

The signal formed by wavelet detail coefficients at the second decomposition is regrouped into 32 sub-windows. Fig. 4 shows that the elements of the feature vectors that formed by the square of the signal within these sub-windows. In this study, total 52 subjects, four subjects each for 1 pathological or normal case are used for training purpose. Each recording contains 8 cycles of heart sound. Training set contains total feature vectors belong to each class. 416 (52×8) feature vectors, in which 32 (52×8/13 = 32)

Another 52 different recordings of 52 subjects are applied in same way for testing purpose. It is also containing 416 feature vectors, and is different from training data set.

C. *Artificial Neural Network*

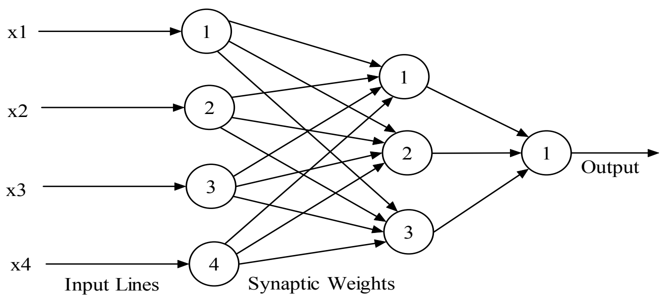

Fig. 5 Neural Network Architecture

Artificial Neural Network employed for heart sound modeling uses Multi-layer Perceptron (MLP) mechanism with back propagation algorithm. MLP has been successfully used to solve complex and diverse classification problems [24], [25]. In this case, the problem is to classify the feature vectors into several heart sound classes. The network consists of an input layer, one hidden layer and an output layer similar to Fig. 5. Here, the number of nodes in the input layer equals to 32 feature dimensions or less depending on selection made on input features whereas number of nodes in output layer is always 13, the number of heart sounds to be classified. The number of nodes in the hidden layer is usually chosen empirically to find a superior performance of the system. We start with a relatively large number and let the proposed algorithm select the final number of hidden nodes. The network uses nonlinear hyperbolic tangent activation function with training goal set at 0.003, learning rate 0.9 and a momentum term 0.9. For training data target output is set to 1 and 0 is set for the rest of the classes.

D. Design of Optimum Networks using SVD and QRcp

1) Input nodes: For classification of phonocardiogram signal, 32 input features from each pattern are used as input to ANN. Note that, all these 32 features are not containing same amount of information and few of them may be redundant. Thus, the determination of the optimum number of inputs which does not contain redundant information, involves subset selection from feature set of candidate inputs. In this study, SVD followed by QRcp factorization is applied for subset selection of input features.

As an example, Fig. 6 shows a prototype neural network structure with 3 input nodes, 6 hidden nodes, and one output node. For each deletion of input feature a corresponding node of ANN is also deleted. This ensures exclusion of the associated links that are attached with pruned node. Fig. 6(a-c) illustrates this fact where the prototype ANN's second input node is removed when identifying by subset selection method that the corresponding feature does not carry further significant information for input of ANN. Assume ($p\times q$) matrix A is the training input data set where q is the dimension of input feature elements and p is the set of input data. In our case, to begin with A is a 416×32 matrix, the no. 416 coming from total number of phonocardiogram cycles used (52 subjects, each 8 cycle) and 32 is the number of feature vector. The algorithm for the input feature vector selection procedure is as follows:

Step-1: Let $p\times q$ input information set A with $p\geq q$, the objective is to find a $p\times g$ subset A_1 ($g<q$) of A, which contains significant part of the information of A.

Step-2: Assume SVD of A is presented by $A=UWV^T$ where $U\in\mathbb{R}^{p\times p}$, $V\in\mathbb{R}^{q\times q}$, $U^TU=I$, $V^TV=I$, $W\in\mathbb{R}^{p\times q}$ .W is the diagonal matrix with decreasing order. The $p\times q$ matrix $W = [diag\{w_1, w_2,.......,w_m\} : 0]$, $m=min(p,q)$, $w_1 \geq w_{2\ldots\ldots\ldots} \geq w_m \geq 0$ and $w_1, w_2,\ldots\ldots\ldots,w_m$ are the singular values of A. The left singular matrix (U) and the right singular matrix (V) form a basis for the column space and row space respectively.

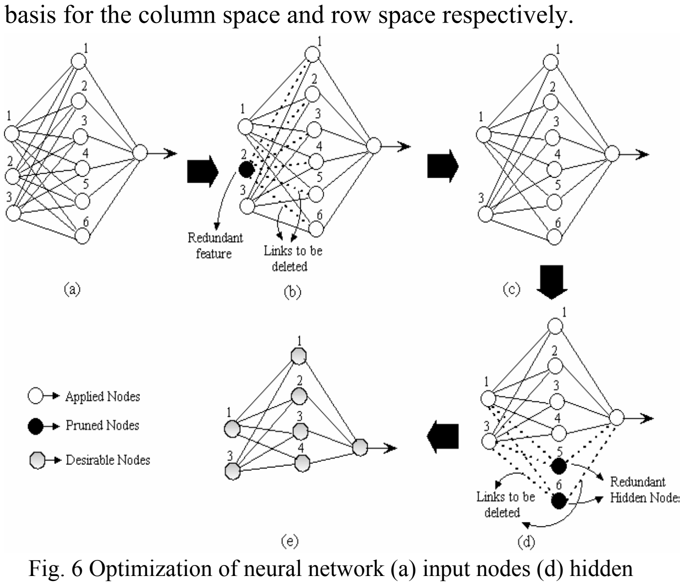

Fig. 6 Optimization of neural network (a) input nodes (d) hidden nodes

Step-3: The matrix A contains the energy: $E_A=\sum_{i=1}^{p}\sum_{j=1}^{q}a_{ij}^2=\|A\|_F^2 = w_1^2+w_2^2+\ldots\ldots\ldots+w_p^2$; a_{ij} represents for j-th element of i-th row of A, F is the Frobenius norm. If g of m singular values of A are dominant, that is s_{g+1}, $s_{g+2\ldots\ldots\ldots\ldots}, s_m$ are insignificantly small, the significant information of A will be contained in $A_1=\sum_{i=1}^{g}u_iw_iv_i^T$. The A_1 subset selection from A requires a significant jumps in the distribution of the singular values (i.e. $w_i >> w_{i+1}$ where, $1\geq i\geq p$).

Step-4: Now which of the candidates input of A constitute the optimal set A_1, are selected by the QRcp factorization. The QRcp factorization is performed on matrix V which is consisting of q columns.

Step-5: QRcp factorization produces the $q\times q$ permutation matrix P, where $[Q^TV^TP = R]$. The permutation matrix P stores the sequence of selection for subset A_1 of A. It is worth to mention it again that the QRcp factorization is done on the basis of Gram-Schmidt orthogonalization process (section II) which takes care of removing the redundancy that exist between the features.

Step-6: The training feature set is selected according to the sequence of permutation matrix. Accordingly, the test feature set is also rearranged as the same sequence as stored by matrix P. After pruning the most redundant column as indicated by P matrix from train and test data set, the performance of the classification accuracy is tested. If the performance is not degraded, then the next redundant input feature will be deleted from train and test data both. Note that training is done purely in offline basis. Therefore the best performance of the network can be retained after successive exclusion of feature parameters.

2) Optimum number of hidden nodes: In post hidden layer stage of ANN, the links are connected with output layer. It is desirable to eliminate those links which are redundant, that does not carry additional significant information. In the proposed method, the chosen neural network is a homogeneous network where all the input nodes are connected with all the hidden nodes. For getting optimum size of network, SVD technique is used to determine how many hidden nodes should be used. That is, the links between the hidden layer stage and output stage can be eliminated without degradation of classification performance. In our case, a 3-layer neural network is used for classifying heart sound. Usually, number of hidden nodes of ANN is chosen empirically by the programmer. Although the optimum number of hidden nodes can be less than any chosen value to classify with maximum accuracy.

Fig. 6, where the 3 input features, 6 hidden nodes and 1 output nodes are used shows the selection of optimum network. Fig. 6(c) represents a network with optimum input features. Fig. 6(d) shows that out of 6 hidden nodes, 2 hidden nodes are redundant and their connecting links are also undesirable. The undesirable links and nodes are shown by dotted line and black circle respectively in the Fig. 6.

Moreover, Fig. 6(e) represents that these undesirable links are pruned. A neural network with optimum size is shown in Fig. 6(e). The procedure of taking optimum number of hidden neurons is calculated as follows.

Step-1: A neural network, which is considered, may be exhaustive or over-parameterized but the same should not be underparameterized. In this work, initially we started with an overparameterized model i.e. 32 dimensional input, 416 number of input data and 115 hidden nodes.

Step-2: Let the k number of hidden nodes and p number of input data sets are used in the network. For each of the p input data sets to the network, the k pseudo-outputs of the hidden layer are computed. Therefore, a $p \times k$ matrix D is formed corresponding to the p sets of input data. In our case, initially $p = 416$ and $k = 115$ are taken.

Step-3: SVD technique is applied on matrix D. $D = U_D W_D V_D^T$ where, W_D is the diagonal matrix with decreasing order, U_D and V_D are the left singular and the right singular matrices respectively. The number of dominant singular values of W_D will indicate the number of nodes that should be retained. The rank of D also indicates the number of dominant singular values. If t is the number of dominant singular values of k, then $t \leq k$. The dominant singular values will be a number where a significant jump is noticed in the W_D matrix.

For optimizing ANN, the SVD and QRcp factorization are used because these techniques find the collinearity between the different input variables (or links that carry information) and eliminate these collinearity of the variables. The robustness characteristic of the SVD and QRcp factorization provides the advantage of this method.

V. Results

The performance of the proposed method is evaluated for data set having 832 cycles of 104 volunteers for normal heart sound and 12 different pathological problems. These pathological problems include aortic insufficiency, aortic stenosis, atrial septal defect, coarctation of aorta, ejection click, early systolic murmur, late systolic murmur, mitral regurgitation, mitral stenosis, normal, opening snap, pulmonary stenosis, pan systolic murmur. The database is divided in two sections each of which consists of 416 patterns (32 patterns × 13 classes). One set of 416 patterns are used for training data set while other set is taken for testing purpose. The input layer consisted of 32 nodes because it has to accommodate 32 features, while the output layer was set to 13 nodes for the classifying 13 different heart sounds.

Table I represents the input features arranged in ascending order of their redundant ability shown by SVD and QRcp based technique. Recognition accuracies of optimized models with lower number of input features are presented in Table II. Fig. 7 describes those singular values of training dataset (matrix A) where a significant jump is found while going from feature no. 28 to 29 in the input features. Therefore, out of 32 input features 28 input features are dominant features.

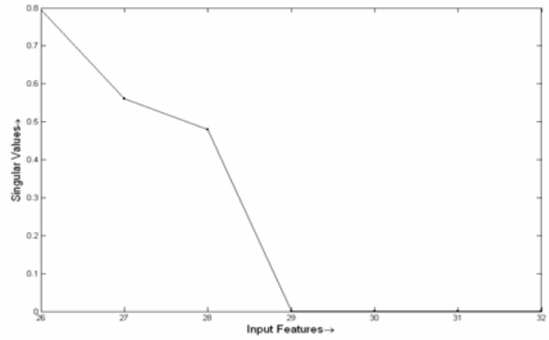

Fig. 7 Singular values of training dataset having 32 input nodes

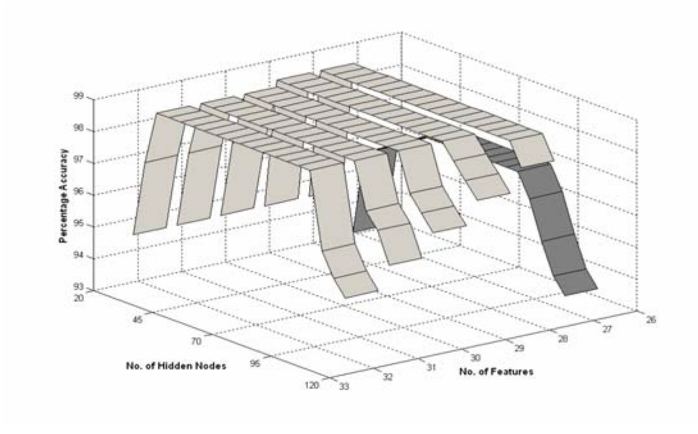

Fig. 8 Performance of ANN for various numbers of input and hidden nodes

The result also validates the same by the Table II where 28 out of 32 input features are efficient because these 28 input features give the same performance accuracy as with 32 input features but classification performance is decreased while less than 28 input features. Therefore, the optimum number of input features can be taken as the feature number where the jump of singular values is achieved. Thus, one can avoid exhaustive search by pruning one by one feature from data set to select effective input features. The reduced models discard the lower features described in Table I. Note that these rank of features is stored in permutation matrix P. At first, a reduced model of 32 features discards the lowest performer (i.e. feature 7) as shown in Table I. If the performance is not degrading then next lowest performer is eliminated from input feature set and the classification performance is tested again. The same procedure is also applied for the next stages of optimization for input features.

An SVD based method is adopted for hidden layer optimization. The rank of W_D matrix shows the minimum number of hidden layer that is required for the application of classifying heart sounds. These numbers of hidden nodes with their corresponding input features are shown in Table II. Further, Fig. 8 represents the graphical illustration of performance of ANN at different number of input features and hidden nodes as described by Table II. Fig. 8 also shows that the performance is duped when the ANN is either overparameterized or under parameterized but unaltered in between of these two cases. We have started with overparameterized model of ANN for each of input dimensional feature sets. Fig. 9 represents the singular values of W_D matrix at the different numbers of hidden nodes. For 32 input feature set a significant jump is noticed in singular values in between 33 to 34 hidden nodes. Therefore, the proposed method shows that the required minimum number of hidden neuron is 33. Similarly from Fig. 9, it can also be noted that 32, 31, 30, 29, 28 will be the minimum numbers of hidden nodes for 31, 30, 29, 28, 27 input features respectively. Furthermore simulation results validate the proposed hypothesis. The classification performance is decreasing when hidden nodes are less than 33. The same can be also applied to lower dimensional optimized input features. Thus, one can avoid trying with various combinations of hidden nodes and use SVD selection numbers directly. For 28 input feature coefficients using 29 hidden nodes the ANN shows the maximum performance as shown by network using 32 feature elements and 60 hidden nodes. Note that, after deletion of input features in overparameterized model the recognition performance increases because of redundant information of input feature coefficients is diminished for each pruned input nodes. The optimized network structure will be now (28-29-13). Therefore, significant reduction of nodes is achieved in compare to standard ANN structure which is empirically used for classifying heart sounds.

Remarks: The F-Ratio based optimization which uses only inter and intra class variation and no orthogonality information gives a reduced network of 31-60-13 with 97.836% accuracy.

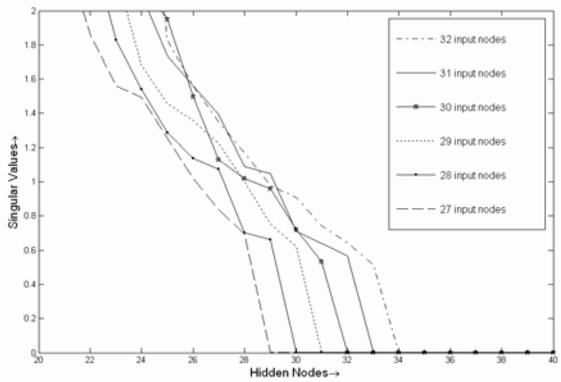

Fig. 9 Singular values of matrix D for different numbers of hidden nodes

VI. Discussions

The proposed method is applied for classification of 13 different heart sounds that includes normal and 12 different pathological cases. In this study, segmentation algorithm is used in time domain by considering biomedical domain features. A time-frequency domain based wavelet transform technique is used for extracting the useful features from segmented heart sound signal. ANN is applied as a classifier model for recognition of normal and 12 different pathological problems. In this study, proposed optimization technique is developed based on SVD and QRcp, which shows the optimum input features and optimum hidden nodes for ANN. Note that, the values for optimum number of input features and hidden nodes obtained from theoretically study is validated by the simulations. For example, proposed method shows the minimum hidden nodes that should be 33 for 32 input features. From Table II, it is cross validated that lower than 33 hidden nodes, the classification performance is degrading for 32 input features. Table II also depicts that, the relation between varying input features with their respective hidden nodes. For 27 input features the classification performance is decreasing because of a useful feature is deleted for reduction of input features. Note that, out of 32 input features 28 input features are effective, which is shown by the proposed method.

VII. Conclusion

An optimization within ANN structure which is used for classifying heart valve disorder is proposed here. SVD followed by QRcp technique is used to optimize input neuron while only SVD is required to optimize hidden nodes. When optimized structure of ANN is used for classifying diseases, it exhibits superior recognition accuracy compared to empirically chosen larger structure. The reduction in ANN size reduces time of testing which in improves user's comfort when employed as a part of a real time device. Furthermore, the optimization of the ANN makes it suitable for implementing in an inexpensive hardware platform.

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TABLE I
RANK OF INPUT FEATURES

Original Position	17	18	19	20	21	22	23	24	25	26	27	28	29	30	31	32
Position after SVD & QRcp	27	28	31	29	30	19	26	32	11	6	13	2	1	5	22	7

Original Position	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16
Position after SVD & QRcp	8	15	16	17	18	9	3	21	10	12	14	4	20	23	24	25

TABLE II
RESULTS FOR CLASSIFICATION

No. of coefficients taken	No. of hidden neurons	Network structure	% of Accuracy	Min. no. of hidden Neurons required
32	115	32-115-13	95.192	33
	105	32-105-13	96.394	
	60	32-60-13	98.798	
	50	32-50-13	98.798	
	33	32-33-13	98.798	
	32	32-32-13	98.076	
	25	32-25-13	94.711	
31	115	31-115-13	95.913	32
	105	31-105-13	97.355	
	60	31-60-13	98.798	
	50	31-50-13	98.798	
	32	31-32-13	98.798	
	31	31-31-13	97.836	
	25	31-25-13	94.711	
30	115	30-115-13	96.634	31
	105	30-105-13	97.596	
	60	30-60-13	98.798	
	50	30-50-13	98.798	
	31	30-31-13	98.798	
	30	30-30-13	97.115	
	25	30-25-13	94.711	
29	115	29-115-13	97.355	30
	105	29-105-13	98.317	
	60	29-60-13	98.798	
	50	29-50-13	98.798	
	30	29-30-13	98.798	
	29	29-29-13	97.115	
	25	29-25-13	94.711	
28	115	28-115-13	98.076	29
	105	28-105-13	98.798	
	60	28-60-13	98.798	
	50	28-50-13	98.798	
	29	28-29-13	98.798	
	28	28-28-13	96.634	
	25	28-25-13	94.711	
27	115	27-115-13	93.750	28
	105	27-105-13	95.192	
	60	27-60-13	97.115	
	50	27-50-13	96.875	
	28	27-28-13	95.673	
	27	27-27-13	94.711	
	25	27-25-13	93.269	