ADAPTIVE NEURO FUZZY CLASSIFIER FOR HEART SOUNDS

Hussnain Ali1, Talha J. Ahmed2, Shoab Khan3
College of Electrical & Mechanical Engineering, NUST, Pakistan
1hussnainali@gmail.com, 2teejay.ahmed@gmail.com, 3kshoab@yahoo.com

ABSTRACT
Classification of heart sounds for correct medical diagnosis without any human intervention is the most vital aspect of automatic heart auscultations. Various classifier designs based on statistical, artificial Neural Networks, Hidden Markov and other methods have been proposed earlier however performance of these classifiers is erratic under different circumstances. Highly nonstationary nature of heart sound signals demand intelligent systems that combine knowledge, techniques and methodologies to distinguish heart sounds of patients with different pathologies in a manner similar to a physician.

This paper proposes an aboriginal approach for the classification of heart sounds using neuro-fuzzy techniques. The basic aim of research has been on design of complementary hybrid intelligent system able to possess humanlike expertise which is able to adapt itself and perform better in changing environment. Classifier design is based on neuro-fuzzy principles for their ability to incorporate human knowledge by using variety of computing techniques synergistically. From the envelogram of the phonocardiogram different distinguishing features are extracted which are used as input to the classifier. Network is then trained with about sixty percent of the total data available while the remaining data is used in testing and validation. Classifier output is very encouraging with high rate of correct identification of S1s, S2s, S3s, murmurs and stenosis. Results are far better than conventional classifiers under different circumstances.

KEY WORDS
Phonocardiogram (PCG), envelogram, neural network, fuzzy, hybrid system, ANFIS

1. Introduction
The two major audible heart sounds in a normal cardiac cycle are the first and the second heart sounds, S1 and S2 respectively. A normal cardiac period thus comprises of S1, the systolic period, S2 and the diastolic period in this sequence in time. Presence of other sounds such as S3, S4, ejection clicks, opening snaps, gallops, splits, murmurs and stenosis into the normal cardiac cycle indicate pathologies. Task of a classifier is to interpret these heart sound signals accurately as well as indicate any abnormalities. This however is a complex job due to highly nonstationary nature of the heart sounds and its variability from person to person. Moreover, many a times a segment of a heart sound signal shows characteristics of different segments which makes correct classification very difficult.

Fuzzy logic provides a systematic calculus to deal with such imprecise information linguistically, and it performs numeric computation by using linguistic labels stipulated by membership functions. Selection of fuzzy if-then rules forms a basis of fuzzy Inference System which effectively models human expertise to assign a degree of association to every segment of the signal with the corresponding heart sound.

Although the fuzzy inference system has a structured knowledge representation in the form of fuzzy if-then rules, it lacks the adaptability to deal with changing conditions. Incorporating neural network learning concepts in fuzzy inference system results in an adaptive knowledge-base neuro-fuzzy classifier.

In our design we have used fuzzy inference system (FIS) whose membership functions are tailored (adjusted) using a back propagation algorithm in combination with a least squares type of method which results in Adaptive Neuro Fuzzy Inference System (ANFIS). ANFIS tunes the parameters of the membership functions in a way that best allows the associated fuzzy inference system to track the given input/output data. This adjustment allows fuzzy system to learn from the data it is modeling while the parameters associated with the membership functions change through the learning process.

From the phonocardiogram, envelogram is computed using any appropriate technique such as mean Shannon energy, amplitude demodulation, rectification, low pass filtering, Hilbert Transform or Wavelet decomposition. We computed envelograms from average Shannon Energy of the signal. Thresholds are set in order to limit noise and clarify zero segments as well as envelope boundaries of the envelogram. Different features of the envelogram such as amplitude, duration, mean frequency and average energy of envelopes are used as classifying agents for distinguishing heart sounds. These features form set of input sequences to the classifier. Moreover, these classifying agents set linguistic labels thereby governing the rule base of the fuzzy inference system. For instance: usually S1 is the loudest heart sound with low frequency, longer duration and highest energy content. Similar linguistic labels for other sounds allow classification of up to four different
kinds of heart sounds through a Sugeno-type fuzzy inference system.

2. Phonocardiogram Database

Online database available from “e-general medical” for research purposes is used throughout the study. It contains about sixty phonocardiograms including that of normal and pathological subjects. The data is sampled at 11025Hz and low pass filtered out using Chebyshev (type 1) filter with a cutoff frequency of 882 Hz [1]. Frequency components higher than this cutoff value are usually associated with noise. This database had an added advantage of a good SNR since noise reduction was not the aim of the study.

3. Signal Manipulation

3.1 Envelogram Computation

Average Shannon Energy is computed as:

\[ \text{Shannon Energy}_{avg} = -\frac{1}{N} \sum_{t=1}^{N} \left[ x^2(t) \cdot \log(x^2(t)) \right] \]

where ‘x(t)’ is the original time sampled signal and ‘N’ is window size which is taken to be time interval between two zero crossings of the signal [1]. Advantage of using variable window size rather than fixed window size in calculating average Shannon energy is that it enhances signal details by computing separate envelopes for murmurs and major heart sounds. This makes envelopogram inspection in classifier dependent upon envelope features rather than only the shape of envelopes [2].

Figure 1 shows PCG of a normal subject along with its Shannon Energy Envelogram (highlighted) computed using the above mentioned formula with variable window size.

3.2 Envelopogram Features

Physical attributes, features or characteristics of the computed envelopogram are the classifying agents to distinguish different heart sounds and formulate rules for the fuzzy inference system.

3.2.1 Amplitude. Amplitude of envelopes corresponds to the intensity levels of heart sounds. It is one of the key classifying agents since usual intensity levels are highest for S1 followed by S2, S3 and then S4.

3.2.2 Frequency Content. Time-frequency variability of the signal helps in differentiating different heart sounds very efficiently so is the width/duration of envelopes of the envelopogram. Trends are similar; S1 has lowest frequency content and wider lobe/envelope while murmurs have highest frequency content and smallest envelope duration.

3.2.3 Energy. Since S1 is most audible of heart sounds, total energy of the S1 segment is relatively highest followed by S2, S3, S4 and least for murmurs. Ratio of energy of individual envelopes to the width of respective envelopes proves to be a better classifying agent in cases of split sounds and is hence used in parallel with total energy of individual envelopes.

3.2.4 Zero segments. Zero segments are parts of the envelopogram where energy of the signal is nearly zero. In noisy conditions a threshold is often set, below which energy of the envelopes is forced to zero; hence rejecting extra envelopes. Duration of zero segments correspond to systolic and diastolic periods. Generally diastolic period is much greater than systole; therefore they are used as reference indicators for S1s and S2s.

4. Classifier Design

Figure 2 shows structural architecture of the ANFIS designed for the classifier. It consists of five layers with layer 1 and 3 being adaptive layers. Four input nodes [\( \alpha \), \( \beta \), \( \gamma \), \( \lambda \)] are the classifying agents (envelopogram features) of the classifier and represent amplitude, width, energy and energy to duration ratio of the envelopes respectively. The first layer is used to generate the membership grades for each set of input data vectors. Membership functions of all the inputs are described by asymmetric curves and are modeled by product of two sigmoidal curves to map input space to the resulting membership value. These asymmetric functions are very useful in modeling actual situations and to counter for uncertainty of real measurements. First input (amplitude) is designed using three linguistic labels. Murmur classification cannot be achieved from the amplitude information of the envelope since murmurs can have any intensity level depending upon the nature of pathology. Remaining three inputs, however, are assigned four membership functions each to categorize S1, S2, S3 and murmurs accordingly. Figure 3 shows the resulting fuzzy inference system while Figure 4 depicts the shape of the evolved input membership functions of the four inputs after network training. Each of the fifteen membership functions are mathematically described as:

\[ \mu_{A_i}(\alpha) = \frac{1}{(1 + e^{-a_i(\alpha-b_i)})(1 + e^{-\epsilon_i(\alpha-d_i)})} \]
where $A$ is the linguistic label for the input $a$ while $[a,b,c,d]$ is the set of premise parameters for the node $i$. These adjustable parameters are associated with the IF part of the fuzzy rule and are used to modify the shape of the membership functions.

The second layer of ANFIS calculates the firing strengths of the rules. Output of each node is the product of all incoming signals from the input space $[a,b,c,d]$ to that node and is given by:

$$w_i = \mu_{A_i}(a) \cdot \mu_{B_i}(b) \cdot \mu_{C_i}(c) \cdot \mu_{D_i}(d), \quad i = 1, 2, 3, 4$$

Layer 3 calculates the normalized firing strengths of the rules:

$$\bar{w}_i = \frac{w_i}{\sum_i w_i}, \quad i = 1, 2, 3, 4$$

Layer 4 yields the parameters of the consequent part of the rule. Every node in this layer is adaptive and characterized with a node function $f_i$ of the form:

$$f_i = p_0 + p_1 x + p_2 y + p_3 z + p_4$$

where $[p_0, p_1, p_2, p_3, p_4]$ are adjustable consequent parameters associated with THEN part of the fuzzy inference rules.

Output of the fourth layer is given by:

$$O_i = \bar{w}_i f_i, \quad i = 1, 2, 3, 4$$

Fifth layer represented by a single node calculates the overall output as the sum of the contributions of each rule.

$$Overall\ Output = \sum_i \bar{w}_i f_i$$

5. Computation Methodology

5.1 Input Space

Multidimensional input space requires a fuzzy partition or in other words division of the input into rule patches. A number of partitioning techniques exist, for example; fuzzy grid, adaptive fuzzy grid, multi-level fuzzy grid, tree or scatter partitioning methods etcetera. We used both grid partitioning and subtractive clustering techniques, however beside the fact grid partitioning shows an exponential growth in number of rules with increase in number of variables, grid partitioning gave us better results.

Since our model is based on ANFIS, grid partitioning develops itself into adaptive grid partitioning. We start with uniformly partitioned grid but as the network is trained and premise membership functions are tuned, the grid evolves. Four input variables formulated 192 rules by grid partitioning in our case.

5.2 Membership Function Determined from Fuzzy Grid

Three input variables were partitioned using fuzzy grid which resulted in 9 membership functions for each. The membership functions for these variables are as follows:

- Amplitude
- Frequency Content
- Envelope Energy

Output membership function is the product of the membership function of each input variables.

Figure 2. Five layer ANFIS architecture of the Classifier
5.2 Learning Algorithm

Neuro-adaptive learning techniques provide a method for the fuzzy modeling procedure to learn and compute the membership function parameters that best allow the associated fuzzy inference system to track the given input/output data. For faster convergence we have used hybrid learning algorithm to identify parameters of Sugeno-type fuzzy classifier. It applies a combination of the least-squares method and the backpropagation gradient descent method for training FIS membership function parameters. More specifically, in the forward pass of the hybrid learning algorithm, node outputs go forward until layer 4 and the consequent parameters are identified by least squares method. In the backward pass, the error signals propagate backward and the premise parameters are updated by gradient descent [2].

5.3 Network Training

Network is trained using phonocardiograms of normal as well as of pathological subjects suffering from problems like stenosis, ejection clicks, gallops, sound splits and regurgitation. During this training/learning phase, several input patterns are presented to the network combined with the expected outputs (target). By the hybrid learning algorithm and a corresponding error criterion, the internal weights \( w \) are altered, until the network output pattern matches the predefined output within the error limit. Sample size used in training the network for the correct classification of S1s, S2s, S3s and murmurs was 86, 86, 40 and 250 envelopes respectively. It required only 15 epochs for the error to converge to \( 1 \times 10^{-5} \) units as shown in figure 5. On the other hand, we tested that any simple neural network without fuzzy inference system gives a high error rate as well as shows slows convergence.

5.4 Output

Since ANFIS we constructed has Sugeno type fuzzy inference system, therefore output of the classifier is a single linear function obtained using weighted average defuzzification. This linear function gives output levels which indicate degrees of association of an envelope with different heart sounds. Output is then interpreted as S1, S2, S3 or murmur according to its degree.

<table>
<thead>
<tr>
<th>PCG Samples</th>
<th>S1s</th>
<th>S2s</th>
<th>S3s</th>
<th>Murmurs</th>
<th>Correct Classification</th>
</tr>
</thead>
<tbody>
<tr>
<td>NORMAL</td>
<td>12/12</td>
<td>12/12</td>
<td>0/0</td>
<td>1/1</td>
<td>100%</td>
</tr>
<tr>
<td>PCG with S3</td>
<td>12/12</td>
<td>13/13</td>
<td>12/12</td>
<td>0/0</td>
<td>100%</td>
</tr>
<tr>
<td>Early systolic</td>
<td>13/13</td>
<td>12/12</td>
<td>0/0</td>
<td>36/36</td>
<td>100%</td>
</tr>
<tr>
<td>Ejection Click</td>
<td>10/10</td>
<td>10/10</td>
<td>0/0</td>
<td>10/10</td>
<td>100%</td>
</tr>
<tr>
<td>Normal Split</td>
<td>6/6</td>
<td>6/6</td>
<td>0/0</td>
<td>0/0</td>
<td>100%</td>
</tr>
<tr>
<td>Diastolic Fixed S2 Split</td>
<td>12/12</td>
<td>12/12</td>
<td>0/0</td>
<td>0/0</td>
<td>100%</td>
</tr>
<tr>
<td>Early Aortic Stenosis</td>
<td>18/18</td>
<td>18/18</td>
<td>0/0</td>
<td>34/34</td>
<td>100%</td>
</tr>
<tr>
<td>Diastolic Atrial Gallop</td>
<td>16/16</td>
<td>16/16</td>
<td>0/0</td>
<td>12/12</td>
<td>100%</td>
</tr>
<tr>
<td>Opening snap</td>
<td>7/7</td>
<td>7+6/14</td>
<td>0/0</td>
<td>0/0</td>
<td>95.2%</td>
</tr>
<tr>
<td>Diastolic Phys. S2 Split</td>
<td>6/6</td>
<td>6/6/6/6+4</td>
<td>0/0</td>
<td>200/227</td>
<td>88%</td>
</tr>
<tr>
<td>Pan Systolic</td>
<td>7/7</td>
<td>7/7</td>
<td>0/0</td>
<td>83/83</td>
<td>100%</td>
</tr>
<tr>
<td>TOTAL</td>
<td>119/119</td>
<td>129/130</td>
<td>12/12</td>
<td>376/403</td>
<td>92.1%</td>
</tr>
<tr>
<td>Relative Percentage</td>
<td>100%</td>
<td>99%</td>
<td>100%</td>
<td>93%</td>
<td></td>
</tr>
</tbody>
</table>

Table 1. Results
5.5 Network Testing and Results

Network is finally tested with ten different sets of phonocardiograms. Results obtained are highly commendable as shown in Table 1. Since correct classification of S1 and S2 sounds is the most important task of a classifier, we are achieving almost 100 percent results not only for normal cases but also for pathological ones.

6. Conclusion

In this paper we have incorporated neuro-fuzzy techniques to classify different types of heart sounds. The main advantage of the model is its simplicity and high accuracy. Results achieved are very impressive for classifier’s versatility to compute accurate results for different pathological cases. The design can be further improved by increasing the dimension of input space in such a way that characteristic features of the PCG formulate a better rule base to accommodate for even more pathological cases. Since the present model is based on the Shannon Energy envelogram features of the PCG, ANFIS can further be applied to time-frequency distribution of the PCG signal to make the design more versatile. Moreover the knowledge-base can further be streamlined by training the network with data which is fully representative of the input data space features. Incorporating sophisticated clustering algorithms and understanding their relationship with input space to form rules and fuzzy sets associated with the final model will give a better understanding of the underlying workings of the model. We have tried to design hybrid intelligent classifier to incorporate soft computing to biomedical signal processing whose role model is human mind.

References


