Discrimination of ECG signal based on S-interpolation and Quantum Neural Network

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Abstract: The evolution of health care through the early detection of the disorder, which affects the functioning of the heart. This paper proposes an algorithm that uses blend of statistical methods (S) which sorting and identification of solstice points of the ECG signals and then uses the Interpolation method (I) to extract factors and Quantum Neural Network (QNN) to distinguish between six types of abnormal and normal signals. Extraction of solstice points depends on the shape of the signals. Solstice points are chosen by statistical methods. Then, they are reduced with retain the features of signals. The attributes for six cases of data are categorized by using an algorithm (QNN). The valuation of the accuracy for (QNN) per case is excellent for 42 ECG signals. Classification is based on training and testing chosen data and again through altering the parameter values which are sent to the network, several tests were obtained to get the best results. Classification with a maximal number of the repetitions has been 100 that has increased the speed of this process.

Keywords: ECG Signals, Solstice Points, Interpolation, Quantum Neural Networks

How to cite this article: Hassan AN, Mohsin MJ, Khwayyir HK (2020): Discrimination of ECG signal based on S-interpolation and Quantum Neural network, Ann Trop Med & Public Health; 23(S10): SP231039. DOI: http://doi.org/10.36295/ASRO.2020.231039

Introduction

The system of the (SI-QNN) can be implemented in the majority of the scientific areas, especially the medical area. A lot of research has been done on how to automatically classify ECG signals. Over time the heart’s electric activity (ECG) is changed. Detecting the heart diseases in an early stage and prescribing suitable treatments will prolong life and improve living [1]. the basic ECG wave for a single cardiac cycle. It is divided to elements P, Q, R, S and T. Six categories of ECG beats have been introduced into the system for testing. These cases are normal and five pathologies cases. In Figure 1, one pulse is shown for each category.
The nature of biological signal is not stable and changes arbitrarily over the time, that depending on the different situations of the health, stress cases and mental state for the person. The heart signal also varies from person to person. As well as the speed of heartbeat change depending on the conditions mentioned earlier. All these reasons have made researchers are interested in the analysis and processing of automatic computer ECG. [2]. Propose a system consisting of two techniques, interpolation (SI) and quantum neural networks, which are used to process signals and extract their characteristics and then classify them in order to obtain a diagnosis and distinguish of ECG signals. Thus determine the state of the person's heart whether they are healthy or not, As well as determine the type of disease.

1. Extraction technique of solstice points
Accurate ECG signal analysis is of high importance because it reveals the abnormalities of blood vessels in the heart, and begins to find the distinctive points, which are based here to determine the solstice points for each ECG signal.

2.1 Normalization
Differences in signals in terms of displacement of amplitude and time often occur due to physiological changes from one person to another or because of the difference in the accuracy of measuring instruments, It may occur to the same person due to mental state or muscle strain. Normalization eliminates this difference in order to accurately process data and extract its features. The difference of the input signals in terms of amplitude has been removed for making the mean of the data equal to 0. At the normalization of time, data is emptied into a longer zero matrix, then all data is consolidated according to the maximum value (R-peak) of each signal, where the value (R-peak) is placed in the middle of the matrix. Finally, the beginnings and ends of each signal are deleted in a way that does not affect the signal information.

2.2 Solstice points extraction
Initially, the data is sorted by statistical methods and then get the solstice points and it is repeated this process with the conservation of all points and the removal of duplicate points for each section of the ECG signal. The higher the number of sections per signal, the more the solstice points will be extracted. Then the process of selecting the most distinct points of the solstice points and the most representative of the signal, solstice points number can be determined by the shape and type of the signal. To classify any signal, it is necessary to first perform signal processing techniques on it in order for the features to be extracted for each signal, which is the primary signal. The more accurate the ECG signal analysis, the classification will be accurate and fast. Where the points with the highest and lowest value of ECG signals are identified and determine its location, then the data is divided for each signal into three periods and find the highest and lowest values for each period then applying the same statistical methods to find them (sorting and max and min). Each of these points is a solstice point that can be used after identifying the specific points at which potential cardiovascular anomalies can be detected at a later date. Relying on the ECG signal’s shape form is the basis for the solstice points extraction technique. This technique is done by dividing the data into periods, then the sorting process is performed. From the sorting process, the largest and lowest value is obtained, which represent the sorting process[3]. After that, the process of extracting the reversal points is repeated for each period and collecting the extracted points as distinct points of the signal and without repeating the values of these points. Determining the number of these points depends on the signal type, accuracy, and shape.

2.3 Selection of solstice points
The number of solstice points is equal in each heartbeat and for each category. The matrix of extracted points is considered as new data to be sorted again and by the same previous process in order to reduce the number of points and limit them to the most distinctive points. These resulting points will be sufficient to represent the initial signal.

2.4 Extraction of feature by (SI)

S-Interpolation technique dependent based on the solstice points. It is a technique that extracts coefficients for a third degree equation quickly and accurately, depending on the continuous derivative that this technique enjoys [4]. Four coefficients are extracted between each two points, where each two points are connected by a third degree curve. The number of coefficients extracted in each class is 24 coefficients. After attributes extracted, distinguish between Classes will be very clear and easily. Later, the attributes extracted directly will be the input vector to the quantum neural network.

3. Classification system of ECG signal

In the techniques of signal processing, especially biomedical signal, classification of signals is considered an important area, as the first step is to analyze the signal and find distinct points from the solstice points through, then the other step is the categorizing process those signals. Several algorithms have developed for the classification of signals, especially the ECG signal, such as the traditional neural network (ANN) which used for less accurate requirements and slow speeds. Therefore, the quantum neural network (QNN) was used to classify the ECG signals in this system in order to improve the performance of the network and address the defects of the ANN network. The overall block diagram of the system is depicted in figure 2.

![Figure 2. The standard architecture of feature extraction and quantum neural network](image)

4. Quantum Neural Network

(QNN) is an active and dynamic science based on a mixture of artificial neural network and quantum computing. Furthermore, it is distinguished by a gather attributes of the neurological modeling and fuzzy theoretical principles. In linear time, QNNs have solving of the non-linear problems, like classical neural networks. Its fuzzy nature enables to break down information of samples into separate levels, represented by certainty or uncertainty [5]. Instead of the ordinary sigmoid functions employed by conventional BP-NN, according to the idea of quanta state superposition, the transfer function of neurons in hidden layer is expressed as linear superposition of multi-sigmoid function, i.e. Multi-level transfer function [6]. Typically, the cell of hidden layer neural can deal more cases than traditional sigmoid functionality which can deal just two cases. The interval of quantum for every sigmoid function is different. A data map can be different and at a different level by controlling the intervals of quantum to make flexibility classification. Figure 3 shows the standard architecture of the QNN. The network is Consists of a three-layer BPNN, which are made up of a number of neurons.

![Figure 3. Structure of ECG classification system](image)
5. Algorithm of QNN Learning

The process of the training begins first with updated synaptic weights, for the sake of training QNN continually split the space of features for a certain dataset. After that, the parameters of the hidden layer neuron quantum intervals are updated for the sake of solving the uncertainty which is included in the data of the sample that based on algorithm of gradient descent. In every one of the epochs of the training, the algorithm of the training alters the two weights of connectivity amongst various quantum intervals and layers of hidden layers [7].

5.1 Updating QNN synaptic weights

At first synaptic weights must be altered, and that includes providing the entire training dataset to network and a forward passing, afterwards utilize the back propagation similar to a typical NN. Assume that $x^k = [x_k^1, x_k^2, x_k^3, ..., x_k^m]$ is $k = 1, ..., m$ is $k - \theta h$ of the input feature vectors and assume that $d^k = [d_k^1, d_k^2, d_k^3, ..., d_k^n]^T$ is the target vector of the output for $x^k$ while $d_i^k = 1$ in the case whereas $x_k^i \in C_i$ and $d_i^k = 0$ if $x_k^i \notin C_i$. Assume that $y^k_i = [y^k_1, y^k_2, y^k_3, ..., y^k_n]^T$ is the real output [7].

Weights of the QNN are altered in the direction of the minimization of QNN outputs’ squared error represented $E$ in eq10 in a sequential manner for every $k[8]$.

\[
E = \frac{1}{2} \sum_{i=1}^{m} (y^k_i - y_i)^2
\]

represents the entire number of training patterns. $E$ represents the MSE functions. Modification of the synaptic weight values may be accomplished by changing or adapting all synaptic weights by amount which is commensurate with gradient with regard to that specific value of the synaptic weight [9].

Through calculation the derivative of with regard to will get update as

\[
w_{ji}(r + 1) = w_{ji}(r) - \eta \frac{\partial E}{\partial w_{ji}}
\]

is the value of before the adaptation is the value after adapting for input and represents by a positive small number which is referred to as the rate of the learning.

\[
\eta
\]

Where

\[
w_{ji}(r + 1) = w_{ji}(r) - \eta \frac{\partial E}{\partial w_{ji}}
\]

After the substitution of the eq4.7 with eq4.4, the equation of the update becomes

\[
\frac{\partial E}{\partial w_{ji}} = \sum_{i=1}^{m} (y^k_i - y_i) x^k_i
\]

Since

\[
\frac{\partial E}{\partial w_{ji}} = \sum_{i=1}^{m} (y^k_i - y_i) x^k_i
\]

Whereas $v_{ji}$ is output of the hidden neuron.

The synaptic weight linking the hidden unit to input by update equation derived

\[
v_{ji}(r + 1) = v_{ji}(r) - \eta \frac{\partial E}{\partial v_{ji}}
\]

Whereas and are the values of before and after the adaptation.

\[
\eta
\]

for as represented in eq13.,and

\[
\eta
\]

The substitution of the eq18 and eq20 in eq11, the (eq) of the update will be represented by:

\[
\frac{\partial E}{\partial w_{ji}} = \sum_{i=1}^{m} (y^k_i - y_i) x^k_i
\]

Results

\[
\frac{\partial E}{\partial v_{ji}} = \sum_{i=1}^{m} (y^k_i - y_i) x^k_i
\]

Since

\[
\frac{\partial E}{\partial v_{ji}} = \sum_{i=1}^{m} (y^k_i - y_i) x^k_i
\]

Whereas

\[
\eta
\]

5.2 Quantum Interval Updates

The parameters of the quantum hidden layer neuron intervals are altered for the sake of solving the uncertainty which exists in the sample data. In every one of the training stages, through the reduction of uncertainty...
class-conditional variances in quantum intervals of the outputs of the hidden layer will be trained. Then, training is going to get synaptic weights, after that, the hidden neurons’ quantum intervals may be trained prior to updating for the jump-positions, the training dataset is given to network[10]. One more time for the sake of calculating \( \langle \cdot \rangle \) which will appear as a forward pass kind, after an update of \( s \) is performed. The i-th hidden unit’s output variance for class is

\[
\sigma^2_i = \frac{1}{m} \sum_{c=1}^{C} \sum_{n=1}^{N_c} [y_{i,n} - \mu_i] [y_{i,n} - \mu_i] \tag{25}
\]

represents the neuron’s input in the hidden layer, \( y_{i,n} \) represents the vector of the input, and average values are taken for every one of the classes. \( C \) represents cardinal number, \( i \) represents the pattern class amount. Adapting parameters has been based on minimizing the objective function \( G \) which is created via the summation of \( (\cdot) \) over each class and each hidden unit, in other words

\[
\frac{dG}{ds} = \frac{1}{2} \sum_{c=1}^{C} \sum_{n=1}^{N_c} \sum_{i=1}^{I} \sigma^2_i \tag{26}
\]

Throughout setting changes in \( G \), The equation of the update for the \( s \) may be obtained, due to the fact that \( s \) is proportionate to \( G \) gradient with respect to the \( s \) as

\[
\frac{dG}{ds} = \sum_{i=1}^{I} \sigma^2_i \tag{27}
\]

represents the ratio of the learning for the \( s \). Based on eq27and eq28, is:

\[
\Delta s = \frac{\sum_{i=1}^{I} \sigma^2_i}{\sum_{i=1}^{I} \sigma^2_i} \tag{31}
\]

Based on eq4.21 and eq4.22, the equation of the adjustment for \( \Delta s \) will be:

\[
\Delta s = \frac{\sum_{i=1}^{I} \sigma^2_i}{\sum_{i=1}^{I} \sigma^2_i} \tag{32}
\]

The interval of the quantum may be found as:

\[
\langle \cdot \rangle \tag{33}
\]

represents the rate of learning for \( \Delta s \), the summation of the hidden neuron outputs for each input which belongs to \( c_i \) class divided by number of the samples in this class.

6. Data Selection
In the system that has been presented, 6 ECG signal classes have been chosen, which have been produced from physio-net [10]. There are 42 heart beats of all categories.

7. Technique Implementation for the Extraction of ECG Signal Attributes
The results which were implemented have shown the excellent results for the ECG signal’s features extraction through the extract of solstice points, which can be considered as the basic points of change in the ECG signal form.

i. The Results of the Normalization
This process makes all the variables of the inputs in the same range, in order to ensure the impact of the variables. Figure 4 shows examples of normalization results for time normalization and amplitude normalization for short, showing four categories as a sample of all categories.
ii. Results of the solstice points Extraction
The solstice points extraction process is heavily dependent upon the form of a single beat of ECG signal. The technique of extraction of solstice points then decreasing these solstice points are similar. solstice points number will be equally for each beats of six classes. The coefficients are then extracted from the solstice points selected and distinctive. Extraction solstice points of ECG signal for six classes illustrates in figure 5.(a).

iii. The Results of the Attributes Extraction
Signal attributes are the characteristics which make discrepancy between signals (abnormal as well as normal) of the signals of ECG is possible and the process of attributes extractions means extract of important information and beneficial of signal. The number of the characteristics which have been obtained from every one of the beats was compared to achieve the best results that is capable of clearly distinguishing amongst them. Fig5.(b). show the coefficients (attributes) extracted using S-Interpolation. All coefficient show a clear distinction from the other category, where coefficients are taken randomly for each attribute and from each category. An experiment was changed to change the number of categories used in the proposed system. First, five categories were used, and secondly six categories were used. The result was excellent in terms of accuracy in distinguishing between categories.

8. Results of the Classification of the ECG Signals
The QNN specifications used in the proposed system are with: Layers number (L)=3, ni=24, nh=24, no=6, ns=6, learning rate( )=0.07, Learning Rate of Jump Positions( )=0.01, slope factor in the hidden layer =1.5, Slope factor in the output layer =1, Maximum no. of iterations=100 which represents the initial state, and later the parameters of this network are changed to know the effect of the change in it. The number of the characteristics of every one of the beats was split to 2 parts: The first one has been utilized to train the Quantum NN which is referred to as the training samples. Those samples have been arbitrarily taken as 75% ,50% of data. Those samples are transmitted for the training via network, after that, the error value is calculated. The second part is utilized to test the Quantum NN and it is referred to as the samples of testing, which have been arbitrarily taken as 25% ,50%. The samples of the testing undergo testing on QNN’s feed forward and, after that error and
accuracy values of the testing data are computed. As can be seen in table (1), as well as figure6. The specifications of quantum neural network (QNN) in the proposed work (Initial State )

Table (1). (QNN) Classification for five classes (a). Normal. (b). STElevMLIII. (c). AMLII2 (d). LBB. (e (RBBI). according to data sent to the network selection randomly

<table>
<thead>
<tr>
<th>Training of (QNN)</th>
<th>Test of (QNN)</th>
<th>MSE for Training</th>
<th>MSE for testing</th>
<th>Training Set Accuracy (%)</th>
<th>Test Set Accuracy (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>75%</td>
<td>25%</td>
<td>0.0759</td>
<td>0.2794</td>
<td>96.8</td>
<td>92.4</td>
</tr>
<tr>
<td>50%</td>
<td>50%</td>
<td>0.1107</td>
<td>0.3357</td>
<td>85.236095</td>
<td>86.592381</td>
</tr>
</tbody>
</table>

Classification of (QNN) for five classes (a). Normal. (b). STElevMLIII. (c). AMLII2 (d). LBB. (e). (RBBI). according to data sent to the network selection randomly

<table>
<thead>
<tr>
<th>Training of (QNN)</th>
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<th>MSE for Training</th>
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<th>Test Set Accuracy (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>75%</td>
<td>25%</td>
<td>0.0795</td>
<td>0.2499</td>
<td>96</td>
<td>90</td>
</tr>
<tr>
<td>50%</td>
<td>50%</td>
<td>0.1214</td>
<td>0.3988</td>
<td>88.8</td>
<td>88.2</td>
</tr>
</tbody>
</table>

Figure (6). (QNN) Classification for five classes by 75%, 50% and Classification for six classes by 75%, 50%

For the sake of assessing the network efficiency which is performed with the use of the program, the precision of the classification has been assessed for every one of the cases with the use of the relation below:

\[
\text{Accuracy(34)}
\]

Numerous tests have been carried out on network through altering the parameter values. The number of the quantum intervals (ns) are altered for the sake of revealing degree of their influence network classification. Table.4 illustrates the various (ns) values of the hidden node in hidden layer and the precision of the QNN classification. QNN Classification into different values of (ns) as well as figures.7.
Table 2: Various quantum interval (n_s) values and network classification

<table>
<thead>
<tr>
<th>No. of quantum interval (n_s)</th>
<th>MSE for Training</th>
<th>MSE for Testing</th>
<th>Training Accuracy (%)</th>
<th>Accuracy (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>n_s=1</td>
<td>0.2447</td>
<td>0.3911</td>
<td>86</td>
<td>60</td>
</tr>
<tr>
<td>n_s=2</td>
<td>0.0770</td>
<td>0.4986</td>
<td>96</td>
<td>61.5</td>
</tr>
<tr>
<td>n_s=3</td>
<td>0.1175</td>
<td>0.4386</td>
<td>89</td>
<td>76.6</td>
</tr>
<tr>
<td>n_s=5</td>
<td>0.0759</td>
<td>0.2794</td>
<td>96.9</td>
<td>92.4</td>
</tr>
<tr>
<td>n_s=6</td>
<td>0.1333</td>
<td>0.4957</td>
<td>93.5</td>
<td>70</td>
</tr>
</tbody>
</table>

Fig 7. QNN Classification to (n_s=1), (n_s=2), (n_s=3), (n_s=5), (n_s=6)

(QNN) classification precision into the various (n_h) values of for nodes in the hidden layer. The results illustrate in table 3. It illustrates QNN classification into different values of the number of the nodes in hidden layer (n_h).

Table 3: Number of the nodes in the hidden (n_h) and network classification precision

<table>
<thead>
<tr>
<th>No. of nodes in hidden layer (n_h)</th>
<th>MSE for training</th>
<th>MSE for testing</th>
<th>Training Accuracy (%)</th>
<th>Accuracy (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>n_h=1ni</td>
<td>0.0759</td>
<td>0.2794</td>
<td>96.8</td>
<td>92.4</td>
</tr>
<tr>
<td>n_h=2ni</td>
<td>0.2723</td>
<td>0.5408</td>
<td>58.62</td>
<td>61.53</td>
</tr>
<tr>
<td>n_h= 1ni/2</td>
<td>0.3717</td>
<td>0.5481</td>
<td>65.52</td>
<td>77.14</td>
</tr>
</tbody>
</table>

9. Discussion

In this work, the data of the 6 ECG classes is utilized for testing the suggested system performance (SI-QNN). Each one of the Programs is carried out with the use of MATLAB programming language (V7.12, R-2011-a). The number of vectors are 42 vectors for every class. Accuracy of the extracted features based completely on the extraction accuracy of solstice points sites. It was clear the great accuracy for S-Interpolation technique through convergence between the features each class and the clear contrast between the features for the Six classes. Making the process of the classification higher in speed and simplicity. The precision of the classification n_s is equal to 1, meaning that it utilizes NN, provided an exceptional rating which is equal to 100% and an adequate error rate. Which means that in the case where the characteristics have been of high precision, they require a simple method for the classification.
10. Conclusions

The suggested system of the (SI-QNN) is distinguished with great effectiveness for the classification of the signals of the ECG. The precision of the classification which has been implemented considerably relies on the characteristics which have been obtained by a S-Interpolation method, which is dependent on the shape of the signal, which is why, it has been important accurately normalizing signal. The benefit of the extraction and selection of the solstice points with the use of the same method, this means that there is no need for new techniques to reduce features. Also, it differs from previous research, where an increase in the number of categories was made and the number of features decreased, which leads to ease of design in practice, and the feature extraction technique also differs.[11]. The interpolation method used has proven to be effective and accurate for extracting features for each type of signal. The features obtained can be considered the lowest number of features that give the most efficiency, while the efficiency has reached $96.5\%, 0.0759\text{MSE}$ in the case where the number of features obtained is 24.

11. References

[10] PhysioBank, MIT-BIH, Database”.
http://www.physionet.org/physiobank/database