



Human Identification by ECG Signals through Neural Network

Vichitra Dubey, Vineet Richaria

Student of M.Tech 4th semester, Software Engineering, LaxmiNarayan College of Technology

Head of the department Computer Science, LaxmiNarayan College of Technology

Abstract

A cardiogram (ECG) may be a bioelectrical signal that records the heart's electrical activity versus time. It's a vital diagnostic tool for assessing heart functions. The interpretation of graphical record signal is an application of pattern recognition. The techniques utilized in this pattern recognition comprise: signal pre-processing, QRS detection, feature extraction and neural network for signal classification. Totally different graphical record feature inputs were utilized in the experiments to check and notice a fascinating options input for graphical record classification. Among totally different structures, it had been found that a 3 layer network structure with twenty five inputs, five neurons within the output layer and five neurons in its hidden layers possessed the most effective performance with highest recognition rate of ninety one.8% for 5 viscus conditions

Keyword: graphical record; QRS



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I. INTRODUCTION

The graphical record may be a bioelectric signal that records the heart's electrical activity versus time; thus it's a vital diagnostic tool for assessing heart performs. The electrical current due to the depolarization of the Sinus Atria (SA) node stimulates the close cardiac muscle and spreads into the center tissues. A little proportion of the electrical current flow to the body surface. By applying electrodes on the skin at the chosen points, the electrical potential generated by this current are often recorded as AN graphical record signal. The interpretation of the graphical record signal is AN application of pattern recognition. The purpose of pattern recognition is to mechanically classes a system into one in every of variety of various categories. AN fully fledged heart specialist will simply diagnose numerous heart diseases simply by observing the graphical record waveforms output signal. In some specific cases, subtle graphical record analysers win a better degree of accuracy than that of heart specialist, however at the moment there remains a gaggle of graphical record waveforms that ar too tough to spot by computers. However, the utilization of computerised analysis of simply getable graphical record waveforms will significantly scale back the doctor's employment. Some analyzers assist the doctor by manufacturing a designation; others give a restricted range of parameters by that the doctor will build his diagnosis

As illustrated in Figure one.1 there ar four major steps to the graphical record signal pattern recognition, namely, pre-processing of the signal, QRS detection, graphical record feature extraction and graphical record signal classification

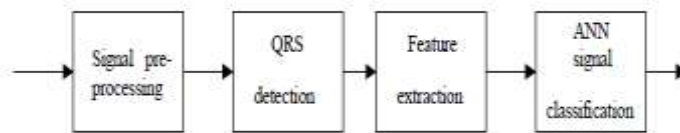


Figure 1.1 Pattern Recognition

The first step is that the mensuration of acquisition amount, which needs a good vary of the graphical record signal assortment together with totally different abnormalities. the information may be collected from real subjects within the future, however it's presently on the market from the info. The second step is QRS detection that to corresponds to the amount of chamber contraction or depolarisation. The third step is to search out the littlest set of options that maximize the classification performance of following step. graphical record feature extraction is especially utilized in this step. the selection of options depends on the techniques utilized in the forth step. Consequently the set of options that ar best for one technique don't seem to be essentially best for an additional. as a result of the unknown interactions of various sets of options, it's not possible to predict the optimum options for a selected classification technique. totally different techniques like applied math classifiers, artificial neural network and computer science are often used for graphical record classification. the factitious neural network are utilized in this project to try and do the graphical record classification. Neural networks ar particularly helpful for classification perform, that ar tolerant of some impreciseness if many coaching knowledge is obtainable. If there ar enough coaching knowledge and spare computing resources for a neural network, it's attainable to coach a feed-forward neural network to perform virtually any signal classification resolution. Generally, the graphical record is one in every of the oldest and also the most well liked instrument-bound measurements in medical applications. it's followed the progress of instrumentation technology. Its most up-to-date biological process step, to the computer-based system, has allowed patients to wear their pc monitor or has provided AN increased, high

II. Summary of graphical record SYSTEM

The standard twelve graphical record systems encompass four limb electrodes and 6 chest electrodes. conjointly, the electrodes (or leads) read the electrical activity of the center from 12 different ositions, six normal limb-leads and six serosa chest-leads showed in Table1.1 Each lead: (1) Views the electrical activity of the center from a unique angle,

(2) encompasses a positive and negative part, and

(3) monitors specific parts of the center from the purpose of read of the positive conductor therein lead

Table 1.1 ECG lead system. Source:(Jardins T. D., 2002)

Standard Leads	Limb Leads	Chest Leads
Bipolar Leads	Unipolar Leads	Unipolar Leads
Lead I	AVR	V1
Lead II	AVL	V2
Lead III	AVF	V3
		V4
		V5
		V6

The ECG, over one cycle, encompasses a characteristic morphology as shown in Figure one.3 comprising a P wave, a QRS complicated and a T wave. the conventional graphical record configurations ar composed of waves, complexes, segments, and intervals recorded as voltage (on a vertical axis) against the clock (on a horizontal axis). one wave shape begins and ends at the baseline. once the wave shape continues past the baseline, it changes into another wave shape. 2 or additional waveforms along ar referred to as a fancy. A flat, straight, or isoelectric line is named a phase. A waveform, or complex, connected to a phase is named AN interval. All graphical record tracings on top of the baseline are

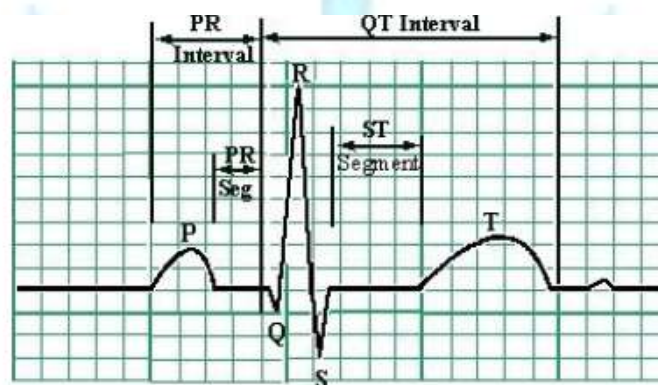


Figure 1.3 The Human graphical record signal over one cycle

A: The P waveThe propagation of the SA nerve impulse through the atria leads to contraction of the atria (depolarisation), manufacturing the P wave. The magnitude of the P wave is often low (50-100uV) and one hundred millisecond in period.

B: The PR intervalThe PR interval begins with the onset of the P wave (Pi) and ends at the onset of the Q wave (Qi). It represents the period of the conductivity through the atria to the ventricles. traditional mensuration for PR interval is 120ms-200ms. it's shown in Figure one.4.

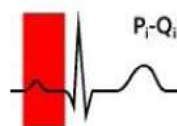


Figure 1.4 PR Interval

The PR phase begins with the end point of the P wave (Pt) and ends at the onset of the Q wave (Qi). It represents the period of the conductivity from the heart muscle, down the bundle of its finish through the bundle branches to the muscle. it's shown in Figure one.5.



Figure 1.5 PR phase

C: The QRS complicated The QRS complicated corresponds to the amount of chamber contraction or depolarisation. The chamber repolarisation signal is swamped by the a lot of larger chamber signal. it's the results of chamber depolarisation through the Bundle Branches and Parkinje fibre. The QRS complicated is way larger signal than the P wave owing to the quantity of chamber tissue concerned, though some signal cancellation happens because the waves of depolarisation within the left and right sides of the center move in opposite directions. If either aspect of the center isn't functioning properly, the scale of the QRS complicated could increase. As shown in Figure one.6. QRS are often measured from the start of the primary wave within the QRS to wherever the last wave within the QRS returns to the baseline. traditional mensuration for QRS is 60ms-100ms.



Figure 1.6 QRS period

D: The ST phase The ST phase represents the time between the chamber depolarization and also the repolarisation. The ST phase begins at the top of the QRS complicated (called J point) and ends at the start of the T wave. Normally, the ST phase measures zero.12 second or less. The precise finish of depolarization (S) is tough to see as a number of the chamber cells are setting out to repolarise. it's shown in Figure one.7

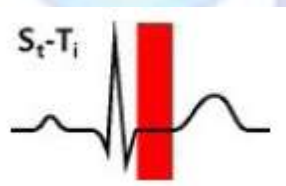


Figure 1.7 ST phase

E: The T wave The T wave results from the repolarisation of the ventricles and is of a extended duration than the QRS complicated as a result of the chamber repolarisation happens additional slowly than depolarization. Normally, the T wave encompasses a positive deflection of regarding zero.5mv, though it should have a negative deflection. It may, however, be of such low amplitude that it's tough to scan. The period of the T wave ordinarily measures zero.20 second or less.

F: The QT interval The QT interval begins at the onset of the Q wave (Q_i) and ends at the end point of the T wave (T_t), representing the period of the chamber depolarisation/repolarisation.

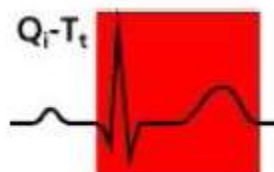


Figure 1.8 QT Interval



The normal QT interval measures regarding zero.38 second, and varies in males and females and with age. As a general rule, the QT interval ought to be regarding forty p.c of the measured R-R INTERVAL. THE QT INTERVAL IS SHOWN IN FIGURE one.8.

III. QRS DETECTION algorithmic rule

The QRS complicated is that the most putting wave shape inside the cardiogram (ECG). Since it reflects the electrical activity inside the center throughout the chamber contraction, the time of its prevalence additionally as its form give a lot of data regarding this state of the center. owing to its characteristic form, it is the premise for the automatic determination of the center rate, as AN entry purpose for classification theme of the cycle, and it's usually utilized in graphical record knowledge compression algorithms. thereinsense, QRS detection provides the basics for pretty much all automatic graphical record analysis algorithms (Kohler B.U. et al., 2002). The QT interval is one parameter that's required to receive the most attention traditional QTc length is 420ms, however {it could|it's going to|it should}be potential concern if QTc> 450 ms and it may increase the chance of tachyarrhythmia if QTc> five hundred ms. the form of ST phase within the graphical record is another vital indication within the designation of heart downside. So, the measurements taken on the ST phase forms another predominant think about the interpretation section of the graphical record. So, four basic sorts of algorithms were enclosed during this analysis. the primary 3 varieties ar named by a 2 letters prefix "AF" for algorithms supported each amplitude and reckoning, "FD" for algorithms supported 1st derivate solely, "FS" algorithmic rule utilises each 1st and second derivate. The last one is "median" algorithmic rule.

1) Algorithms supported each amplitude and reckoning (AF1, AF2, and AF3) AF1 conception for this QRS detector was derived kind the algorithmic rule developed by Moriet-Mahoudeaux. If $X(n)$ represents a one-dimensional array of n sample points of the synthesized digitized graphical record, AN amplitude threshold is calculated as a fraction of the most important positive valued component of that array.

A QRS candidate happens once 3 consecutive points within the reckoning array exceed a positive slope threshold and followed inside following one hundred ms by 2 consecutive points that exceed the negative threshold. AF2 algorithmic rule is AN adaptation of the analog QRS detection theme developed by

Fraden and Neuman AF3 conception was taken from Gustafson the primary by-product is calculated at every purpose of the graphical record. the primary by-product array is then sought for points that exceed a continuing threshold, then following 3 by-product values should conjointly exceed the brink. If these conditions ar meet, purpose i are often classified as a QRS candidate if following 2 sample points have positive slope amplitude merchandise.

2) Algorithms supported 1st derivate solely (FD1 and FD2) FD1 algorithmic rule was custom-made from the one developed by Menard .FD2 algorithmic rule may be a modification of AN early digital QRS detection theme developed by Holsinger. The by-product is calculated for the graphical record. This array is searched till some extent is found that exceeds the slope threshold. A QRS candidate happens if another purpose within the next 3 sample points exceeds the brink.

3) algorithmic rule utilizes each 1st and second derivate (FS1 and FS2) FS1 algorithmic rule may be a simplification of the QRS detection theme bestowed by Balda. absolutely the values of the primary and second derivate ar calculated from the graphical record. 2 arrays ar scaled then summed. one in every of the array is scanned till a threshold is met or exceeded. Once this happens, following eight points ar compared to the brink. If six or additional of those eight points meet or exceed the brink, the standards for identification of a QRS ar met. FS2 algorithmic rule was custom-made from the QRS detection theme developed by Ahlstrom and Tompkins. The corrected reckoning is calculated from the graphical record. Then this 1st corrected by-product is ironed. The corrected second by-product is calculated. the primary ironed by-product is another to the corrected second by-product. the most price of this array is set and scaled to function the first and secondary thresholds. The array of summed by-product is scanned till some extent exceeds the first threshold. so as to search out a QRS candidate, following six consecutive points should all meet or exceed the secondary threshold.

4) algorithmic rule supported median filter A median filter may be a non-linear filter for process digital signal. it's conjointly an honest choice for QRS detection (Chazal D. P., 1998).

IV. Graphical record FEATURE EXTRACTION

After pre-processing, the second stage towards classification is to extract options from the signals. The options, that represent the classification data contained within the signals,

are used as inputs to the classifier utilized in the classification stage.

The goal of the feature extraction stage is to search out the smallest set of options that allows acceptable classification rates to be achieved. In general, the developer cannot estimate the performance of a group of options while not coaching and testing the arrangement. Therefore, a feature choice is an unvaried method that involves trailing totally different feature sets till acceptable classification performance is achieved.

Feature extraction may be a key step in most pattern analysis tasks; the procedure is usually administered intuitively and heuristically. The final pointers are:

- Discrimination: options of pattern {in totally different|in several|in numerous} categories ought to have considerably different values.
- Reliability: options ought to have similar values for pattern of an equivalent category.
- Independence: options shouldn't be powerfully corrected to every alternative.
- Optimality: some redundant options ought to be deleted. A little range of options are most popular for reducing the quality of the classifier. Among variety of approaches for the task, the principal part analysis has, by far, been the foremost wide used approach.

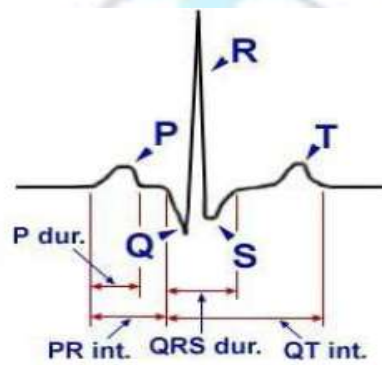


Figure 2.2 graphical record feature extraction

In one work by Chazal, 178 options were abstracted from a QRS complicated for a representative graphical record beat. When applying the transforms to the options there have been a complete of 229 reworked options. Strategies for deriving these options were determined from several existing graphical record literatures. In another work thirty options were extracted for a neural network employing a back propagation coaching algorithmic rule (Pretorius L.C. et al., 1992). These options are the input of following stage. With the preceding options, the additional the input the additional complicated are the network structure of the classification. The classification speed can become thus slow within the traditional notebook computer that it can't be accepted in analysis. To unravel this downside, vital and basic options from graphical record wave shape are introduced from the introduced literature. Moreover, the compressed style of the signal is another to the extracted options to examine the development of the classification performance in classification stage. The chosen options during this analysis are supported the prevailing feature extraction algorithmic rule. The graphical record options are often divided into 2 main categories: morphological and applied math options. Figure 2.2 illustrates a general indication of the P wave, QRS complicated, T wave, and U wave additionally because the ST phase, P-R and Q-T intervals during a traditional graphical record cycle. A gaggle of vital morphological parameters such as: the QRS complicated period, R-R interval, P-R interval, Q-T interval, ST segment, and R wave amplitude are often detected by applying totally different signal process techniques like QRS detection, QT interval and ST phase analysis. The graphical record options are often extracted from the QRS complicated, the ST phase, the applied math, and power spectral density (PSD) of the signal.

V. NEURAL NETWORK CLASSIFICATION

Artificial neural networks (ANN) are trained to perform complicated perform in numerous fields of application together with pattern recognition, identification, classification, speech, vision and system. A neural network may be a massively parallel-distributed processor that encompasses a natural propensity for storing experiential information and creating it on the market to be used. It resembles the brain in 2 respects.

- 1) information is noninheritable by the network through a learning method,
- 2) Inter-neuron affiliation strengths called junction weights are wont to store the information.

In theory, neural networks will do something a traditional computer will do. we are able to train a neural network to perform a selected input ends up in a selected target output. Such a state of affairs is shown in Figure two.3 (Demuth H. and Beale M., 2001). There, the network is adjusted, supported a comparison of the output and also the target, till the network output matches the target. generally several such input/target pairs are used, during this supervised learning, to coach a network.

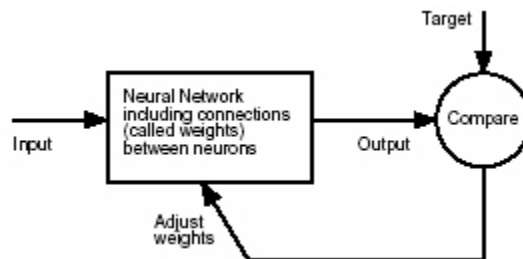


Figure 2.3 Neural Network change system

Pattern recognition may be a analysis space whose goal is that the classification of objects into variety of classes or categories [1]. Depending on the applying, these objects, or patterns, are often any cluster of measurements or observations that require to be classified (e.g. pictures or signals) [2]. The progress of classification may be supervised (when a desired output is understood and wont to reckon a blunder signal) or unsupervised (when no such error signal is used) [3]. From the angle of pattern recognition (PR), artificial neural networks (ANNs) are often thought to be AN extension of the many typical or not, techniques (e.g. applied math PR, knowledge bunch, application of fuzzy sets, structural PR, syntactical PR etc. [5]) that are

developed over many decades [4]. Neural networks are adaptive machines that have 'a natural propensity for storing experiential information and creating it on the market for use' [6]. In alternative words, a synthetic neural network is AN adaptive mathematical model or a machine structure that's designed to simulate a system of biological neurons to transfer data from its input to output during a desired manner [7]. they're referred to as adaptive as a result of they'll be trained so as to be told to estimate the parameters of some pattern employing a little range of exemplars at a time [3]. Neural network consists of easy separate interconnected units referred to as neurons. These neural nodes are connected by a group of weighted connections or synapses (Fig.1). Learning is accomplished by adjustment of those weights so AN association between AN input and an output pattern is discovered or analyzed. The design of those networks is organized into layers of neural units and is strictly

bounded to the coaching technique adopted. The dataset to be analyzed is fed to the alleged input layer and also the data, when being distributed to any or all of the input neurons, flows towards the output layer, passing through some intermediate or hidden layers.

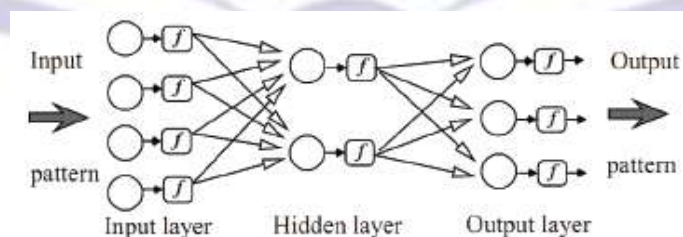


Fig.1 A multi-layer neural network.

Each nerve cell may be a easy mathematical model that transforms its input to AN output response. This transformation involves 2 steps: 1st, the activation of the nerve cell is computed because the weighted total of its inputs, and second this activation is reworked into a response by employing a transfer perform



VI.CONCLUSION

Artificial neural networks will expeditiously be used for the identification and classification of graphical record signals. many preparation trials indicated that achieving optimum performance, throughout processing, needs the non-linear neural network model to encompass 2 hidden layers of twenty neurons every. A additional complicated model will cause a dramatic increase of latent period.

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