Multi-Component Based Neural Network Beat Detection in Electrocardiogram Analysis

T Last, CD Nugent, FJ Owens

Faculty of Engineering, University of Ulster at Jordanstown, Northern Ireland

Abstract

Electrocardiogram (ECG) classification systems have the potential to benefit from the inclusion of automated measurement capabilities. The first stage in the computerized processing of the ECG is Beat Detection. The accuracy of the beat detector is very important for the overall system performance hence there is benefit in improving its accuracy. In the present study we introduce the concept of a multi-component based approach to beat detection based on neural networks (NNs). A database containing in excess of approximately 3000 cardiac cycles was used to evaluate the techniques developed. Results showed the enhanced capability of the multi-component based approaches to detect up to 2988 beats in comparison to 2848 beats achieved by standard benchmarking techniques of non-syntactic and cross-correlation methods. These results have subsequently demonstrated the improvements which can be achieved through utilization of the proposed approach.

1. Introduction

Computerized classification of the electrocardiogram (ECG) has been an active area of research for over 4 decades. The purpose of such a complex process is to determine any cardiac abnormalities a patient may have. Prior to the actual classification process, important pre-processing stages of beat detection and feature extraction prepare and extract important and relevant information from the patient's ECG signal. Specifically, the purpose of beat detection is to detect each cardiac cycle and to insert beat markers for the P-wave onset and offset, the QRS onset and offset and the T-wave offset in addition to locating the peak of each of the aforementioned components.

Given that the overall classification process is dependent on the quality of the marker insertions during beat detection, this pre-processing stage is still a very important area of research. Several approaches have been adopted in the past. Most commonly, beat detection approaches are based on well-established, non-syntactic algorithms [1-3] and cross-correlation (CC) algorithms [1,4].

The present study introduces the general concept of multi-component based beat detection in ECG analysis. Two different approaches have been developed to demonstrate the new technology: a multi-component based CC method [5] and a multi-component approach based on Neural Networks (NN). In the remainder of this paper the concept of the multi-component based CC method is introduced along with a detailed description relating to the approach based on NNs. These descriptions are followed by the presentation of the results of the performance of each technique following exposure to a large set of ECG recordings. Comparisons of these results are made with the performance attained using a number of benchmarking methods based on non-syntactic and cross-correlation based algorithms.

2. Methods

In a multi-component based approach to beat detection the individual waveform components, P-wave, QRS-complex and T-wave, are sought in isolation as opposed to being sought in one complete process [5]. The benefit of such an approach is that each waveform can be detected independently from each other. The three detectors can be used in parallel operating on the same ECG record. Appropriate and sophisticated weighting schemes can then be provided to combine the results of the three classifiers to permit a consensus identification of a cardiac cycle and subsequently to identify the marker positions for the individual inter-wave components.

In the current study we present the details of a new approach to multi-component beat detection based on NNs. This is an extension to a previous realisation of the technique based on CC (full details can be found in [5]).

Within the NN based approach separate interwave components are used to generate appropriate training data for the individual NNs. Three different NNs are used; one for detecting the QRS-complex, one for detecting the P-wave and another for detecting the T-wave. The consensus decision is provided following processing by a final weighting stage (Figure 1).

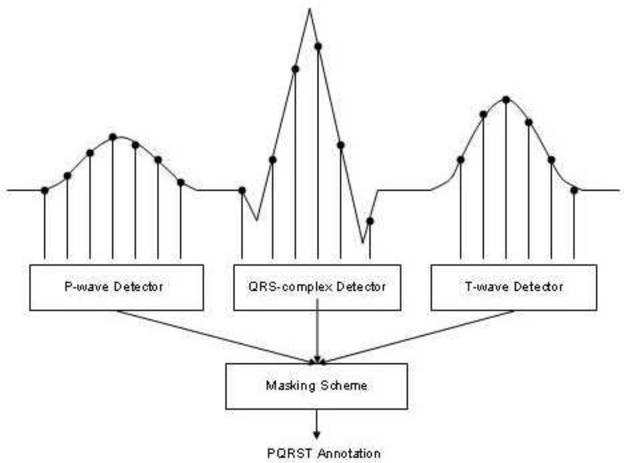

Figure 1 Multi-component based NN beat detection

Two-layer feed forward NNs were used for the development of each detector. The training process was patient specific i.e. based on a section of the patient's own ECG recording. It involved the extraction of the templates, the generation of the training vectors, the actual NN training as well as the identification of an appropriate threshold value for the detector. The number of input neurons in the NN was equal to the number of samples of each respective template. The number of neurons in the hidden layer was chosen to be approximately 1/10 of the number of neurons in the input layer. Prior to each detection run, a template vector of the inter-wave component was prepared and an appropriate training matrix was generated. Together with the matrix for training, a target vector was provided to train the actual NN in order to detect the selected waveform components. The training set for the network is generated from the patient's own record. The data for the training matrix is generated from sample values from less than one ECG beat. Following selection of an ECG cycle the samples of the QRS-complex template are stored as the first vector of the training matrix. Following this the window from which the previous selection was based is shifted to the left by one sample and the corresponding vector is added to the matrix.

The window is shifted sample by sample for approximately half of the R-R interval to the left, with each time the resulting vector being added to the training matrix. The same process is repeated by shifting the window sample by sample to the right. Assuming an R-R interval has an approximate average length of 360 samples, the resulting training matrix will consist of 361 training vectors. A target vector with the same size is provided consisting of values equated to "1" for the original template vector as well as for the two closest vectors to the left and to the right indicating a valid QRS-complex. This inclusion of five correct positions separated by one sample within the training data is used to compensate for temporal mis-alignment during the detection process. The remaining values of the target vector are equated to "0" indicating no valid QRS-complex. Figure 2 shows an example training matrix following the shifting of the window to the left and right. In order to improve the visibility, the figure only contains a sample of vectors of the generated matrix.

After preparing the training data the NN is trained. During the detection process of unseen recordings, the complete ECG record is shifted through the inputs of the network. The network provides an output between "0" and "1" each time. Values above a certain threshold are considered as a hit, i.e. detection of a QRS-complex. The threshold value is provided during the training process as described previously, and is generated individually for each record. Given that the extracted template also includes the relative marker positions for the peak, the onset and the offset the detected complex can be annotated automatically without the need for any additional gradient-based search methods. The detector calculates the peak location of the detected QRS-complex by adding the relative peak position of the original template to the position of the simulation peak.

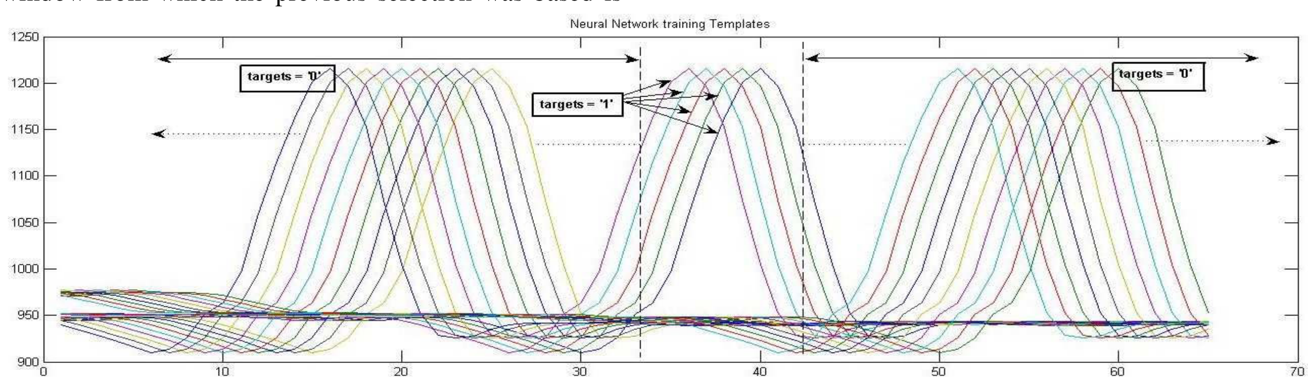

Figure 2 Training vectors for the QRS-complex detection network.

The method described above for the QRS-complex detection is subsequently adopted for detecting the P-wave and the T-wave. Although the three detection methods for the QRS-complex, the P-wave and the T-wave can be used independently, appropriate masking schemes are deployed to provide a consensus for the final detection result. These masking schemes help to decide which waveform detections are valid and which are not. This decision may depend, for example, on the relative location of the different waveforms to each other. In the current approach, windows for P-waves and T-waves are defined before and after detected QRS-complexes. P-waves and T-waves detected within these windows are considered to be correctly detected waveform components, whereas P-waves and T-waves detected outside of the window are considered to be false positives.

3. Results

To evaluate the performance of the different beat detection algorithms, ECG records from the standard and well established QT Database [6] were employed. The QT Database includes a large variety of normal and abnormal ECG signals. The records were primarily chosen from existing databases, including the MIT BIH Arrhythmia Database, the European Society of Cardiology ST-T Database, and several other ECG databases collected at Boston's Beth Israel Deaconess Medical Centre. The QT Database contains a total of 105 fifteen-minute excerpts of two-channel ECG recordings. Within each record more than 30 beats were manually annotated by cardiologists. The annotations included markers for the beginning, peak and end of the P-wave, the beginning and end of the QRS-complex, and the peak and end of the T-wave. In the present study, approximately 3000 beats from this database were used to validate the performance of the proposed algorithms.

To quantify the correctness and the precision of each algorithm the mean error (me) and the standard deviation of this error (SD) were used. Equations 1 and 2 are representative of these measures:

$$me = \frac{1}{N}\sum_{1}^{N}\left(x_{id} - x_{im}\right) \qquad (1)$$

$$SD = \frac{1}{N}\sum_{1}^{N}\sqrt{\left(x_{id} - x_{im}\right)^2} \qquad (2)$$

where x_{id} is the marker position as detected by the algorithm and x_{im} is the manually annotated marker position originally provided with the QT database. The mean error indicates how close the detector's result is from the expert's annotations. Information about the stability of the QRS detector is provided by the SD. A set of tolerances exist which are considered as minimum values that the automatic algorithms should achieve.

Table 1 provides an overview of the performance achieved by each algorithm following exposure to 2999 beats from the QT database. The results of the algorithms were compared with the original annotations. The performance of the multi-component based approaches was compared with two benchmarking techniques based on a non-syntactic approach and a conventional CC based approach. The results presented in Table 1 show performance rates of 97,7 % and 99,6 % for the multi-component approaches in comparison to approximately 95% achieved by the benchmarking techniques.

In Table 2 the differences of the SD measurements for the various approaches are listed. The SD values presented in Table 2 indicate that the multi-component based approach also outperformed the two benchmarking techniques with respect to stability. As an indicator for the stability of the multi-component methods the SD values for the three QRS-complex markers were calculated for all methods. The multi-component based approaches achieved better results for the two boundary marker insertions. The values for SD attained by the multi-component based methods are very close (+/- 5 %) to the values defined as acceptable tolerances for the onset of the QRS-complex. The SD for the QRS-offset position is about 60% less than the corresponding performance value for the two benchmarking approaches and about 55% less than the accepted tolerances. The results measured for the QRS-peak markers show the greatest accuracy for the two CC based methods. The results here are about eight times better than for the non-syntactic approach and about two times better than for the multi-component based NN approach

The results presented in this section show that the multi-component based approaches perform better than the two chosen benchmarking techniques with regard to both the accuracy of beat detection and stability.

	Non-syntactic	CC	Multi-component based CC	Multi-component based NN
Number of detected QRS-complexes (out of 2999)	2848 (95 %)	2798 (93,3 %)	2929 (97,7 %)	2988 (99,6 %)

Table 1 Results of performance following evaluation with 2999 complexes.

Marker	Accepted Tolerances for SD [ms]	Non-syntactic SD [ms]	CC SD [ms]	Multi-component based CC SD [ms]	Multi-component based NN SD [ms]
QRS-onset	**6,50**	10,40	10,10	6,60	4,93
QRS-peak		14,30	1,80	1,80	3,74
QRS-offset	**11,60**	12,80	13,10	6,90	5,06

Table 2 Accepted tolerances for SD and results for each approach.

4. Discussion and conclusions

The overall performance is significantly influenced by the performance of the beat detection pre-processing stage. Different approaches were discussed. The technique of multi-component based beat detection was introduced in detail and two algorithms based on this method have been developed. The first approach, the multi-component based CC method, was already introduced in [5] in detail. A variant of this approach, the multi-component based NN method, was presented in this study. Evaluating the results summarized in the previous section, the latest approach which is based on NNs has confirmed the results achieved with the CC based method. Both methods benefit from the advantages of such a multi-component based approach. Hence, the two multi-component based approaches can detect the individual waveform components independently. Nevertheless, there is a wide range of fine tuning opportunities for each of the inter-waveform detectors. During a training period, in both approaches, the three waveform detectors are trained independently. This training phase is of course very important for the overall detection result. Appropriate weighting schemes can be implemented to improve the detection results. Depending on the relative locations of the different waveforms, these weighting schemes can help to decide which waveform detections are valid and which are not valid.

Another advantage of the multi-component technique is that annotated templates for each waveform component are provided to the algorithms during the learning phase. These templates also contain the relative locations of the inter-waveform onset and offset markers. Compared to the non-syntactic approaches, no further heuristic gradient searching technique is required for the marker insertion. This advantage can be seen in Table 2, which shows the calculated SD values for each method.

The two multi-component based approaches outperformed the two benchmarking techniques in beat detection. However, the results achieved with both multi-component methods are very close to each other. Currently there are further studies under investigation to demonstrate the advantages and disadvantages of the NN based method compared to the CC based method. It is assumed that the multi-component based NN approach can achieve better performances in certain cases, however, more sophisticated and also more complicated training is required for this technique.

References

[1] Nugent CD, Webb JAC, Wright GTH, Black ND: Electrocardiogram I: Pre-processing prior to classification. Automedica 1998, 16:263-288.

[2] Ligtenberg A, Kunt M: A robust-digital QRS detection algorithm for arrhythmia monitoring. Computers and Biomedical Research 1993, 16:273-286.

[3] Pan J, Tompkins WJ: A real-time QRS detection algorithm. IEEE Transactions on Biomedical Engineering 1985, 32:230-236.

[4] Abboud S, Sadeh D: The use of cross-correlation function for the alignment of ECG waveforms and rejection of extrasystoles. Computers and Biomedical Research 1984, 17:258-266.

[5] Thorsten Last, Chris D Nugent, Frank J Owens: Multi-component based cross correlation beat detection in electrocardiogram analysis. BioMedical Engineering OnLine 2004, 3:26

[6] Laguna P, Mark RG, Goldberger A, Moody GB: A database for the evaluation of algorithms for measurement the QT and other waveform intervals in the ECG. Computers in Cardiology 1997, 24:673-676.

Address for correspondence
Thorsten Last
Hussenstrasse 31
78462 Konstanz
Germany
E-mail: tote_last@yahoo.de