A Novel Biometric Based on ECG Signals and Images for Human Authentication

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Abstract: *This paper represents a complete system for using Electrocardiogram (ECG) images for human authentication. In this study, the proposed algorithm is divided into three main stages: Pre-processing stage, feature extraction stage and classification stage. A real database is used; it consists of 120 ECG images which are collected from 20 persons. The preprocessing stage is done on the ECG image. Preprocessing should remove all variations and details from an ECG image that are meaningless to the authentication method. In addition, this paper discusses briefly an extended version of work previously published on ECG feature extraction. In classification stage, neural network is used to make persons authentication. At the end, a system for real-time authentication is built. The proposed system achieves high sensitivity results for extracting ECG features and for human authentication.*

Keywords: *ECG image, human authentication and neural network.*

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1. Introduction

An Electrocardiogram (ECG) is a picture of the electrical conduction of the heart. By examining changes from normal on the ECG, clinicians can identify a myriad of cardiac disease processes. The main part of the ECG contains a P wave, QRS complex, and T wave. The P wave indicates atrial depolarization. The QRS complex consists of a Q wave, R wave and S wave. The QRS complex represents ventricular depolarization. The T wave comes after the QRS complex and indicates ventricular repolarization. Figure 1 shows a normal QRS complex with the individual parts labelled and a normal full 12-lead ECG [6]. The uniqueness of the electrocardiogram signal has encouraged its use in building different biometric identification systems. These particular elements of an ECG complex are shown in Figure 2.

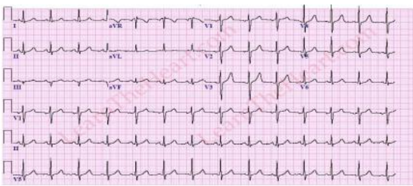


Figure 1. A normal-full 12 lead ECG.

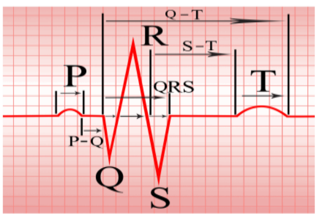


Figure 2. Particular elements of an ECG complex.

This paper introduces an algorithm for pre-processing ECG image. Pre-processing operations are usually specialised image processing operations that transform the input ECG image into another with reduced noise and variation. Those operations include binarisation, filtering, enhancing and baseline detection. Ideally, pre-processing should remove all variations and details from an ECG image that are meaningless to the extraction method. For feature extraction stage, previous researches have been worked on feature extraction stage including threshold dependent methods like filtering and threshold methods [12], wavelet based methods, [3, 4, 8, 9, 13], neural networks methods [10, 15, 16], and threshold free method was introduced by Algunaidi *et al.* [1].

Algunaidi's algorithm facilitated the detection of the maternal peaks without pre-determined thresholds, using fixed length RR moving interval to detect the R peaks, calculated based on the normal maximum and minimum heart rate. This algorithm is able to detect the QRS peaks at different levels of threshold, without respecting threshold value. Since the moving interval requires enough samples for its second edge, some peaks are left undetected towards the end. Nagarkoti *et al.* [11] used varying length moving interval instead of using fixed length RR interval to obtain all the maternal QRS peaks present in the Abdominal Electrocardiogram (AECG) data. Chen *et al.* [2] computed wavelet decomposition coefficients and calibrating the position of the R wave through the modulus maxima point detection of wavelet function by using Mallat algorithm for wavelet decomposition. Kadambe *et al.* [7] worked on Spline wavelet and adaptive threshold to detect QRS ECG waves. Shang *et al.* [14] applied Biorthogonal B-Spline wavelet to detect QRS in order to solve the problems of occasional occurrence algorithm of negative R waves and misdetection and false detection of irregular R waves. Hammad *et al.* [5] used scanning method and removing method to detect QRS ECG peaks.

This study develops an algorithm to detect types of ECG signals (normal and abnormal signals) and ECG images, and develops an algorithm to differentiate between persons in order to prepare a complete ECG system for human authentication. In this study neural network modelling methods are used. Feed forward neural network method is introduced in classification stage to detect and characterize different ECG waveforms from person to other.

This paper is organized as follows: section 1 provides introduction to the research topic. Section 2 describes the pre-processing stage on ECG image. Section 3 discusses briefly an extended version of work previously published on ECG feature extraction [5]. In section 4, the classification stage using neural network is described. In section 5, results are discussed and conclusion is drawn in section 6.

2. Preprocessing Stage

This paper works on a database consists of 120 real images of lead II ECG which is collected from 20 persons. This database is taken from 15 men and 5 women, their ages are between 30 and 70 years old. Figure 3 shows an example of a record ECG from the database (16.mat record). ECG strips (printed on a thermal paper) in JPEG format are scanned. The scanned ECG strips are enhanced by using pre-processing stage. Figure 4 shows the general block diagram of the system. The proposed approach is implemented in MATLAB. Figure 5 shows block diagram of the pre-processing stage. The pre-processing stage consists of 4 steps as the following:

2.1. Convert ECG Image to Grayscale Image

The first step is to convert the input ECG image to grayscale image by eliminating the hue and saturation information while retaining the luminance.

2.2. Image Enhancement

This step enhances the ECG image by making the signal lines sharper. The image is enhanced by using image adjustment functions. Imadjust function is used with suitable threshold (0.3 for low intensities and 0.7 for high intensities).

2.3. Binarisation

The enhanced ECG image is converted to a binary ECG image. The output image replaces all pixels in the input image with luminance greater than gray threshold with the value 1 (white) and replaces all other pixels with the value 0 (black).

2.4. Median Filter

Finally, for reducing noise, median filter is used. Median filter is a nonlinear operation often used in image processing to reduce "salt and pepper" noise. This filter is more effective than convolution when the goal is to simultaneously reduce noise and preserve edges.

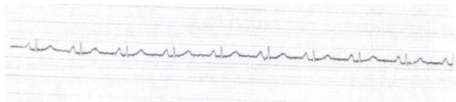


Figure 3. Example of ECG image record 16 mat according to database.

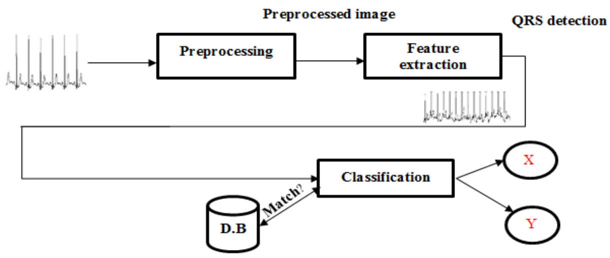


Figure 4. General block diagram of the system.

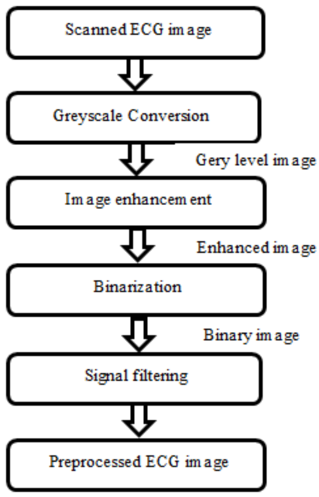


Figure 5. Block diagram for pre-processing stage.

3. Feature Extraction Stage

This section discusses briefly an extended version of work previously published on ECG feature extraction [5] then, applies this algorithm on the proposed database. The feature extraction algorithm is divided into two stages; the first stage is detecting R-waves above base line of ECG binary image. The second stage is detecting R-waves below the baseline of ECG binary image.

3.1. Detecting R-Waves Above Baseline

This stage is divided into three steps. First step is determining the baseline of the signal in the image by getting the sum of all pixels located in each row represents the signal. The baseline is the row which has the minimum values that result from the summation or is the row which has the maximum number of zero pixels. In second step, the scanning method is done to find the peaks by scanning each row from top row to reach the baseline. The first peak is detected by searching for first value of zero pixel while scanning is occurred. In third step, after detecting the first peak, its corresponding value on the baseline (fp) is calculated, then removing method is applied to all the pixels in the area between the row containing the first peak to the baseline and between column i to column (j) by setting them to one. Where column (i) is the column containing the first zero pixel before (fp) and column (j) is the column containing the first zero pixel after (fp). Then repeating the previous steps on the next peak to reach the baseline. After doing this stage on the ECG image, all peaks are detected above the baseline. Figure 6 shows the result of the first stage on record 7 in the proposed database.

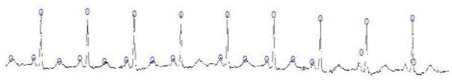


Figure 6. Result of first stage in the feature extraction algorithm on record 7 in database.

3.2. Detecting R-Waves Below Baseline

In this stage all bottoms (negative peaks) below the baseline are detected. This stage is divided into two steps. First step is scanning method. The scanning method is done to find the negative peaks by scanning each row from the lowest row to reach the baseline. The first negative peak is detected by finding the first zero pixel while doing the scan. In second step, after detecting the first peak, its corresponding value on the baseline (fp) is calculated, and then the same removing method is done such as the third step in the first stage. After doing this stage on the ECG image, all peaks are detected in whole ECG image. Figure 7 shows the result of the second stage on record 8 in the proposed database. This algorithm is applied to the proposed database to detect the peaks from all ECG images in the database. The algorithm shows a good result for detecting peaks from ECG images in the database. In feature extraction stage all peaks are detected in whole ECG images. K-means clustering algorithm is used to group all peaks into five groups (P, Q, R, S and T) to separate the peaks from each other and get all features from ECG image.

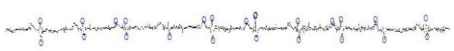
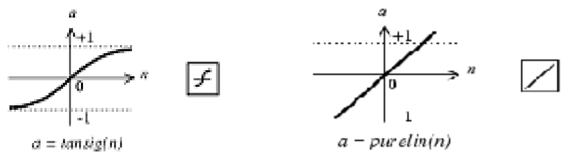


Figure 7. Result of second stage in feature extraction algorithm on record 8 in database.

4. Classification Stag

In this stage, Feed-Forward Neural Network (FFNN) is used to verify the persons. In this proposed system, the tansig transfer function is applied for hidden layers. This function is a good trade-off for neural networks, where speed is important and the exact shape of the transfer function is not. The purelin transfer function is applied for output layer. It calculates the output layer from its net input. Figures 8-a and b shows the tansig and purelin symbol. The network training function is the trainlm function. This function updates weight and bias values according to Levenberg-Marquardt optimization. Trainlm supports training with validation and test vectors if the network's NET.divideFcn property is set to a data division function. Validation vectors are used to stop training early if the network performance on the validation vectors fails to improve or remains the same for maximum fail epochs in a row. Test vectors are used as a further check that the network is generalizing well, but do not have any effect on training. Trainlm function can train any network as long as its weight, net input, and transfer functions. Training stops when any of these conditions occurs:

- The maximum number of epochs (repetitions) is reached.
- The maximum amount of time is exceeded.
- Performance is minimized to the goal.
- The performance gradient falls below minimum grade.
- Validation performance has increased more than maximum failure times since the last time it decreased (when using validation).



a) Tan-sigmoid transfer function. b) Linear transfer function.

Figure 8. Graphs and symbols of tansig function and purelin function.

In this study, training and testing sets are formed by 120 ECG images. 20 images are used for training and 100 images are used for testing. The inputs for this network are the ECG features that extracted from the feature extraction algorithm. The features for each person are: The first R-peak, the first P-R interval and the first R-R interval. A network is created with 3 features input, one hidden layer of 150 nodes and one output layer with five nodes. The network is simulated and trained for 105 epochs. This feed-forward network consists of two layers using the dotprod weight function, netsum net input function, and the specified transfer function. The first layer has weights coming from the inputs and has default bias. The last layer is the network output. Adaption is done with training for 20 persons, which updates weights with the specified training function. Performance is measured according to the specified performance function. Figure 9 shows a multilayer perceptron network with one hidden layer. Here the activation function g is used in hidden layer and the activation function p is used in output layers. The superscript of n, θ, or w refers to the first layer (hidden layer) or the second layer (output layer). The output, y_i, i = (1, 2, 3, 4 and 5) of the network becomes as 1:

$$y_i = P\left(\sum_{j=1}^{150} w_{ij}^2 g\left(n_j^1\right) + \theta_i^2\right) = P\left(\sum_{j=1}^{150} w_{ij}^2 g\left(\sum_{k=1}^{3} w_{kj}^1 x_k + \theta_j^1\right) + \theta_i^2\right) \quad (1)$$

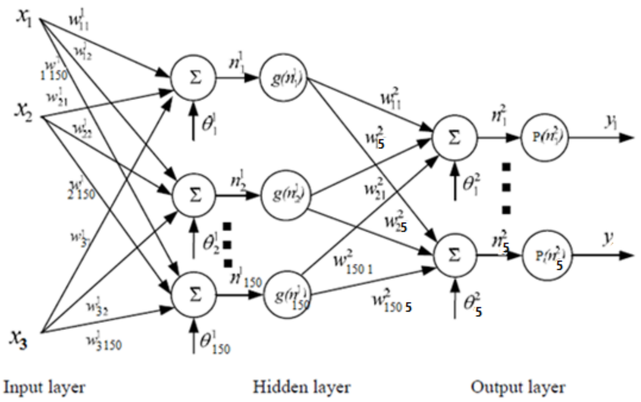


Figure 9. Multilayer perceptron network with one hidden layer.

5. Results

This section shows the result for the pre-processing stage on selected ECG image from the database after each step. This section also shows comparisons between the Hammad's algorithm [5] and the previous algorithms for detecting R-peaks from ECG signals, and the results for applying the Hammad's algorithm [5] on selected ECG image from our database. Finally, the results from classification stage are shown. To assess the performance of all algorithms, two parameters are used [11]:

1. The Sensitivity (Se) is the fraction of real events that are correctly detected and defined as 2:

$$Se = TP / (TP + FN) \quad (2)$$

2. The Positive Predictivity (+P) is the fraction of detections that are real events and defined as 3:

$$+P = TP / \left(TP + FP\right) \quad (3)$$

Where False Negative (FN) denotes the number of missed detections, False Positive (FP) represents number of extra detections and True Positive (TP) is the number of correctly detected QRS complexes.

Figures 10, 11, 12, 13 and 14 show the result for all steps in the pre-processing stage on ECG image from the database.

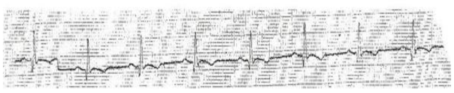


Figure 10. Input ECG image.

Figure 11. Grayscale ECG image.

Figure 12. Enhanced ECG image.

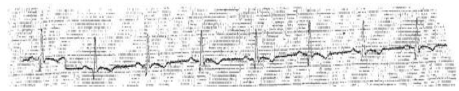


Figure 13. Binary ECG image.

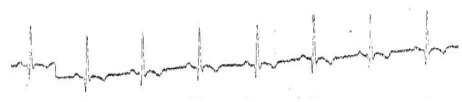


Figure 14. Final result of ECG image after pre-processing stage.

Table 1 shows a comparison of performance for fetal R-peaks detection between Hammad's algorithm and other two algorithms [1, 11] on 25 records FECG database. In this case, as shown in the table, the average Se of the Nagarkoti's algorithm [11] is 86.68% and its +P is 81.88%. The average sensitivity and +P, according to Algunaidi's algorithm [1] are 72.80% and 79.25% respectively. The average Se of Hammad's algorithm is 100% and its +P is 96.78%. The result shows big different in detecting FECG between Hammad's algorithm and the other two algorithms.

Table 1. Comparison of performance for fetal R peak.

Record	Performance For Fetal R - Peak Detection								
	According to Algunaidi's algorithm			According to Nagarkoti's algorithm			According to Hammad's algorithm		
	TP	Se(%)	Pe(%)	TP	Se(%)	Pe(%)	TP	Se(%)	Pe(%)
102	17	89.47	80.95	29	90.62	90.62	29	100	100
115	19	79.16	100	33	100	100	33	100	97
127	20	74.07	68.96	34	75.56	69.38	32	100	100
154	16	69.56	69.56	36	85.71	73.46	29	100	96.6
192	17	94.44	100	38	86.36	73.07	29	100	96.6
244	15	65.21	75	29	69.04	69.04	28	100	100
252	19	59.37	59.37	36	92.30	85.71	32	100	96.9
274	20	66.67	80	25	83.34	100	31	100	100
300	17	56.67	56.67	31	70.45	70.45	31	100	96.8
308	18	72	85.71	29	69.04	69.04	29	100	93.5
323	18	100	100	33	100	100	31	100	96.8
368	17	94.44	80.95	31	70.45	67.39	30	100	93.7
384	18	78.26	72	33	75	70.21	30	100	96.7
392	16	55.17	61.53	33	89.18	86.84	33	100	97
410	18	64.28	69.23	31	72.09	70.45	31	100	93.9
416	18	60	60	33	100	100	34	100	94.4
436	20	76.92	58.82	34	97.14	91.89	32	100	100
444	17	89.47	89.47	31	86.11	88.57	32	100	91.4
445	16	64	94.11	36	80.00	70.58	29	100	96.6
515	16	94.11	100	31	88.57	83.78	31	100	100
571	17	100	100	41	95.34	87.23	31	100	96.8
585	17	85	100	44	100	81.48	30	100	100
595	18	90	78.26	43	97.72	82.69	31	100	91.7
597	17	77.27	89.47	41	95.34	83.67	31	100	96.8
621	16	51.61	51.61	44	97.78	81.48	32	100	96.9
Total/Average	437	72.80	79.25	823	86.68	81.88	771	100	96.78

The results of the performance for R-peaks detection using Hammad's algorithm on 20 ECG images from the proposed database show that the average Se is 92.44 % and the +P is 96.38%. The feature extraction algorithm shows a good result for detecting the ECG images from the proposed database.

The results of the comparison of performance for R peaks detection between Hammad's algorithm and other two algorithms [2, 14] on 18 records of the MIT-BIH arrhythmia database show that the average accuracy rate of Hammad's algorithm is the highest one and shows high accuracy detection for the signals that have positive and negative R peaks.

The result and performance of classification are trained with the back propagation method. The result of testing 100 data samples is 98%. The errors are found in records 6 and 16 in the database. Record 6 has abnormal ECG image of the person 6 and record 16 has an unclear image.

6. Conclusions

A complete ECG system is implemented with high accuracy and high performance for human authentication. This system discusses briefly an extended version of work previously published on ECG feature extraction algorithm for detecting peaks which works on ECG image and can also work on ECG signal after converting it to ECG image. This system is applied on a real data. This system can also detect all ECG signals (normal ECG and abnormal ECG). Finally, this system achieves very good results for human authentication in the classification stage.

References

[1] Algunaidi M., Ali M., and Islam M., "Evaluation of an Improved Algorithm for Fetal QRS Detection," *International Journal of the Physical Sciences*, vol. 6, no. 2, pp. 213-220, 2011.

[2] Chen Q., Liu J., and Li G., "QRS Wave Group Detection Based on B-Spline Wavelet and Adaptive Threshold," *in Proceeding of International Conference on Computer, Mechatronics, Control and Electronic Engineering*, China, pp. 272-275, 2010.

[3] Doh Z., Olmez T., and Yazgan E., "ECG Waveform Classification Using the Neural Network and Wavelet Transform," *in Proceeding of The 1st Joint BMEW/EMBS Conference Serving Humanity Advancing Technology OD*, Atlanta, pp. 273-279, 1999.

[4] Faezipour M., Saeed T., Nourani A., and Tamil A., "Wavelet Based Denoising and Beat Detection of ECG Signal," *in Proceeding of Life Science Systems and Applications Workshop*, pp. 100-103, 2009.

[5] Hammad M., Ibrahim M., and Hadhoud M., "A Novel Approach for Maternal and Fetal R- Peaks Detection," *International Organization of Sientific Research*, vol. 4, no. 1, pp. 84-90, 2014.

[6] Heallio Learn The Heart, http://www.learntheheart.com/ecg-review/ecg-interpretation-tutorial/introduction-to-theecg, Last Visited 2015.

[7] Kadambe S., Murray R., and FBartels G. "Wavelet Transform-Based QRS Complex Detector." *IEEE Transactions on Biomedical Engineering*, vol. 46, no. 7, pp. 838-848, 1999.

[8] Karvounis E., Papaloukas C., Fotiadis D., and Michalis L., "Fetal Heart Rate Extraction From Composite Maternal ECG Using Complex Continuous Wavelet Transform," *in Procedding of IEEE Computer in Cardiology*, Chicago, pp. 737-740, 1996.

[9] Li C., Zheng C., and Tai C., "Detection of ECG Characteristic Points Using Wavelet Transforms," *IEEE Transactions on Biomedical Engineering*, vol. 42, no. 1, pp. 22-28, 1995.

[10] AL-Azzo M. and Badri L., "Multilayer Neural Network-Burg Combination for Acoustical Detection of Buried Objects," *The International Arab Journal for Information Technology*, vol. 7, no. 4, pp. 373-379, 2010.

[11] Nagarkoti S., Singh B., and Kaushik B., "An Improved Threshold Free Algorithm for Maternal and Fetal Heart Rate Detection," *International Journal of Computer Application*, pp. 33-38, 2012.

[12] Pan W. and Tompkins I., "A Real-Time QRS Detection Algorithm," *IEEE Transactions on Biomedical Engineering*, vol. 32, no. 3, pp. 230-236, 1985.

[13] Sahambi J., Tandon S., and Bhatt R., "Using Wavelet Transforms for ECG characterization," *IEEE Engineering in Medicine and Biology Magazine*, vol. 16, no. 1, pp. 77-83, 1997.

[14] Shang Y., Lei S., and Liu B., "QRS Characteristic Waveform Extraction Based On Biorthogonal B-Spline Wavelet," *International Journal of Control and Automation*, vol. 7, no. 1, pp. 95-106, 2014.

[15] Szilagyi S. "Wavelet Transform and Neural-Network-Based Adaptive Filtering for QRS Detection," *in Proceeding of the 22nd Annual International Conference of the IEEE*, Chicago, pp. 1267-1270, 2000.

[16] Xue Q., Hu Y., and Tompkins W., "Neural-Network-based Adaptive Filtering for QRS Detection," *IEEE Transactions on Biomedical Engineering*, vol. 39, no. 4, pp. 317-329, 1992.

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