Achieving stability of ECG biometric features through binaural brain entrainment

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***Abstract* — In this paper, it is shown that classification of features from heart (electrocardiogram, ECG) signals for biometric purposes (i.e. for individual identification) degrades over a period of time and a method based on binaural brain entrainment is proposed to minimise the variations in the heart signals over time to improve the classification performance. The results indicate that variability of the heart features is reduced by 15.57% using the proposed method and this results in improving the classification accuracy from 90.35% to 95.77% when tested with five subjects with ECG data recorded over a period of six months. This pilot study indicates that binaural brain entrainment can be used to improve the stability of ECG features over time thereby increasing its potential to be used in biometric applications.**

Keywords—binaural; biometric; brain entrainment; electrocardiogram

I. INTRODUCTION

The last decade has seen emerging biometric technology based on brain (electroencephalogram, EEG) [1] and heart (electrocardiogram, ECG) [2-4] signals that can replace or augment existing biometric technologies such as fingerprints. ECG based biometric technology is more advantageous than EEG in the sense that it requires only three electrodes (for single lead systems: two bipolar and one ground/reference) as compared to multiple electrodes for EEG (such as 32 or 64) that can be cumbersome to set-up. The electrode placement is also simpler with the bipolar electrodes that can be easily placed on the hands and furthermore, the signal to noise ratio is higher for ECG as compared to EEG. However, it is known that both EEG and ECG suffer from stability issues over a period of time [5, 6] but feature stability is an important aspect of any biometric. Here, it is first shown that classification performance of ECG features drop when train and test data are from different sessions as compared to intra-session train and test data. Next, a novel method based on binaural brain entrainment is proposed to reduce the inter-session variations in the ECG and to obtain more stable features resulting in improved performance.

II. METHODOLOGY AND RESULTS

ECG data was recorded from five subjects (one female, four males, age range from 24 to 39) from three electrodes - one reference and two active electrodes in bipolar montage: one on left wrist and one on right wrist. This configuration gave one lead ECG. The sampling frequency was set as 256 Hz. Ethical approval for the study was obtained and the subjects signed consent form after being briefed on the objective of the study. Subjects were paid a small honorarium for their time.

Data was recorded from six sessions with monthly intervals. Subjects were instructed to close their eyes and relax while listening to the audio using Etymotic insert earphones (that have flat frequency responses). Two different conditions (each lasting two minutes) were designed with MATLAB:

- Relaxed - where the subjects listened to waves hitting the beach (i.e. relaxing music). The relaxed mode is the usual conventional method used in most studies related to ECG biometric;
- Entrained condition – where the subjects were listening to binaural tones. The binaural tones were generated using two sinusoidal (tone) waves, one with frequency of 400 Hz to the left ear and another with frequency of 408 Hz to the right ear and both tones were masked by the same relaxed music as in the other condition to avoid annoying effect of listening to the tones.

The order of the two conditions was alternated in the different sessions even though the subjects were not aware of whether the conditions were relaxed or entrained as in both conditions, they listened to the same music (the binaural tones were masked). The entrained condition evokes an effect where the brain rhythms oscillate around the spectral difference of the two tones of 8 Hz [7]. The frequency difference of 8 Hz between the two tones was selected as this frequency falls in alpha rhythm, which appears during relaxed and eyes closed conditions. However, EEG was not recorded here as the aim of the work was not on studying entrainment itself or EEG features for biometric purposes.

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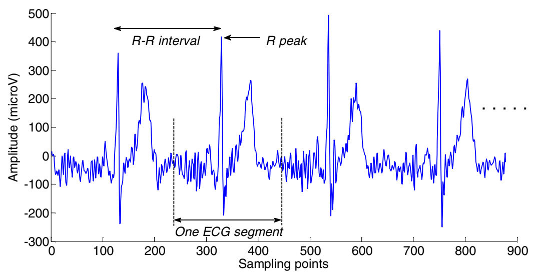

Fig. 1. Example of a segment (beat) extracted from ECG signal

The ECG signal was first band pass filtered from 1 to 35 Hz using an Elliptic IIR filter (forward-reverse filtering to avoid phase distortion). To amplify R peak for easier detection, a high pass filter was applied with cut-off at 10 Hz and R peaks were detected using a threshold, *Th* (for all the subjects):

$$Th > 0.3 * max\_amplitude\_ECG \tag{1}$$

Autoregressive (AR) model was used to extract features representative of each segment using:

$$x(n) = -\sum_{k=1}^{p} a_k x(n-k) + e(n), \tag{2}$$

where p is the model order, $x(n)$ is the segmented ECG signal at sampled point n, a_k are the real valued AR coefficients and $e(n)$ represents the white noise error term independent of past samples. Preliminary analysis using a small subset of the data with Akaike Information Criterion (AIC) gave order three to be suitable and hence, three AR features were obtained using Burg's method for each ECG segment.

A three layer perceptron neural network (as shown in Figure 2) was used as a classifier to classify the features into five categories representing each subject. The single hidden layer unit size was varied from 10 to 100 in steps of 10. The learning method used was resilient backpropagation due to its quick speed and the training was conducted until error limit fell below 0.0001.

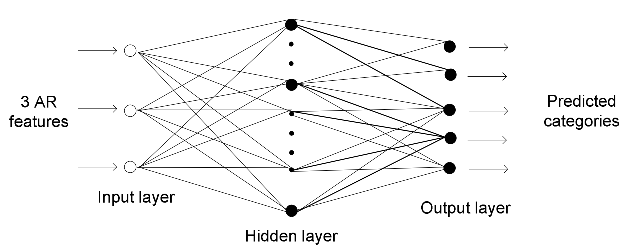

Fig. 2. Used neural network architecture

In the first stage, intra-session classification protocol was used to train and test the classifier using features from 20 segments for training and the rest 20 segments for testing from each subject (i.e. 100 segments for training in total from all the subjects and similar number for testing). To improve the reliability of the classification results, the classifier was trained and tested five times using different segments for training and testing from each subject, where the selection of segments was done randomly and the average classification accuracy calculated. Perfect classification accuracy was obtained for all hidden unit sizes for both the conditions in this intra-session classification protocol. This was as expected due to the fact that both training and testing data were obtained in the same session.

Next, inter-session classification protocol was conducted by five-fold cross validation each with features from ECG segments from five sessions for training and remaining one session for testing (i.e. 200 segments for training and 40 segments for testing from each subject, giving total of 1000 segments for training and 200 segments for testing). Table 1 shows the average of the five-fold cross validation results for the different hidden unit sizes.

TABLE I. CLASSIFICATION RESULTS FOR THE RELAXED AND PROPOSED (ENTRAINED) CONDITIONS FOR VARIOUS NEURAL NETWORK HIDDEN UNIT SIZES

Hidden unit size	Relaxed (%)	Entrained (%)
10	90.58	95.58
20	90.33	94.75
30	90.00	94.33
40	90.75	96.67
50	90.67	95.00
60	91.00	94.75
70	90.25	98.00
80	90.33	95.83
90	90.33	94.92
100	89.25	97.83
Average	90.35	95.77

TABLE II. CUMULATIVE VARIANCE OF THE AR FEATURES FOR ALL SESSIONS FOR EACH SUBJECT FOR BOTH CONDITIONS

Subject	**Relaxed (variance)**	**Entrained (variance)**
1	0.009	0.005
2	0.110	0.089
3	0.076	0.060
4	0.063	0.055
5	0.076	0.073
Average	0.0668	0.0564

III. DISCUSSION

As anticipated, perfect classification accuracies were obtained for both conditions during intra-session training and testing for all the hidden unit sizes. However, from Table 1, it can be seen that the classification performance dropped more for the relaxed condition as compared to the entrained condition for the inter-session classification protocol. The results of analysing the cumulative variance from the three AR features across all the sessions from both conditions are shown in Table 2, where it can be seen that for all the subjects, the variance of the AR features across sessions is lower by 15.57% for the entrained condition as compared to the relaxed condition. The lower variance denotes that the feature values were more stable for the entrained condition even after a period of time (as the six sessions were conducted across monthly intervals).

IV. CONCLUSION

ECG signal is a useful biometric to identify the individuality due to its uniqueness but suffers from the fact that the ECG patterns change over time even for the same person. A method based on binaural brain entrainment has been proposed here to reduce the variability in ECG signals over time. It is not exactly clear on how brain entrainment minimises variations in ECG but it is speculated that the sympathetic and parasympathetic responses of the autonomous nervous system is more controlled during entrainment and this affects the heart rhythms to be more consistent, thereby reducing the variations.

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