Improving the Feature Stability and Classification Performance of Bimodal Brain and Heart Biometrics

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Abstract Electrical activities from brain (electroencephalogram, EEG) and heart (electrocardiogram, ECG) have been proposed as biometric modalities but the combined use of these signals appear not to have been studied thoroughly. Also, the feature stability of these signals has been a limiting factor for biometric usage. This paper presents results from a pilot study that reveal the combined use of brain and heart modalities provide improved classification performance and furthermore, an improvement in the stability of the features over time through the use of binaural brain entrainment. The classification rate was increased, for the case of the neural network classifier from 92.4% to 95.1% and for the case of LDA, from 98.6% to 99.8%. The average standard deviation with binaural brain entrainment using all the inter-session features (from all the subjects) was 1.09, as compared to 1.26 without entrainment. This result suggests the improved stability of both the EEG and ECG features over time and hence resulting in higher classification performance. Overall, the results indicate that combining ECG and EEG gives improved classification performance and that through the use of binaural brain entrainment, both the ECG and EEG features are more stable over time.

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1 Introduction

Identification and authentication of individuals using various biometric modalities is an active research area due to its importance in everyday activities such as banking transactions and computer logins. In addition, the worldwide interest in security has further raised the importance of this topic.

Some of the common modalities used in biometrics are fingerprint, palmprint, face and iris [1], but other less common biometric modalities such as keystroke dynamics [2], gait [3] and ear shape [4] have also been proposed. More recently, biometrics based on the electrical activity of the heart (electrocardiogram, ECG) [5-7] and brain (electroencephalogram, EEG) [7-9] have emerged. Traditionally, ECG and EEG are used for medical diagnosis but these have also found use in biometrics, since they have been shown to be less prone to counterfeit (in supervised conditions such as in research lab environments).

An overview of the use of non-fiducial features such as Hjorth parameters, fiducial features and hybrid combinations of both for ECG biometrics have been explored using various classifiers, such as nearest neighbour and neural networks in [6, 7]. When compared to EEG, ECG is easier to record since in practice most biometric studies use only a single lead signal (from two active electrodes) [5], whereas EEG can require up to 64 channels [8]. ECG signals vary with the physical conditions under which the readings are taken, and thus recording is normally restricted to resting conditions only. On the other hand, EEG recording must be conducted under specific mental conditions [10] to reduce their variability. Typical features derived from EEG signals for biometric applications include spectral [8] and autoregressive (AR) [10] features.

Most of the previous studies have investigated the use of ECG and EEG features separately rather than employing them in combination. However, given that neural responses (i.e. EEG) also influence the cardiac rhythms (i.e. ECG) it would seem the use of their combined use might lead to improved classification rates. However, whilst it is generally known that ECG and EEG biometric offer fraud resistance due to their uniqueness for each individual, the features obtained from such measures are not stable over time [6, 11], which is perhaps why most of the studies only report performance within sessions rather than inter-sessions. For example, in [12], the authors have studied using ECG and EEG for biometrics that gave perfect reliability but it is not clear whether the system's classification rate remained as high after a lapse of time. Another study [13] successfully utilised wavelet features from EEG recorded over a short period of two weeks but as the patterns were randomised for training and testing, stability of features would not possibly been established.

Therefore, this study has dual objectives. Firstly, to investigate the use of combined ECG and EEG features to improve the classification performance. Secondly, to investigate the use of a novel application of binaural brain entrainment to minimise the inter-session variability of the ECG and EEG features. It is first shown that combining AR and Hjorth features from ECG with EEG energies in the alpha and gamma bands, provides improved classification performance for both multilayer perceptron neural network (NN) and linear discriminant analysis (LDA) classifiers. Next, the variability of these features over time is shown to be less when the ECG and EEG signals are recorded under binaural brain entrainment, and this reduction in variability leads to even higher classification rates.

2 Methodology

Data from five subjects (one female and four males within the age range of 24-39) were recorded using a Biosemi Active Two device [14], over six sessions separated by monthly intervals. The study received ethical approval and the subjects signed consent forms after being briefed on the objective of the study. Subjects were paid a small honorarium for their time and agreed to attend six monthly sessions[1]. ECG data were recorded from left and right wrists whilst the EEG data were obtained from 19 locations (based on the standard 10-20 location [15]), as shown in Figure 1. In addition, two mastoid electrode locations were used as reference channels and used as described in another study [11]. Scalp and wrist preparation were not required due to the use of active electrodes, but water based gel was used to increase the contact between the scalp/skin and electrodes. The single lead ECG signal was obtained by subtracting the data from the two wrist electrodes, whilst the 19 channel EEG signals were derived by using the average of the mastoid channels as reference.

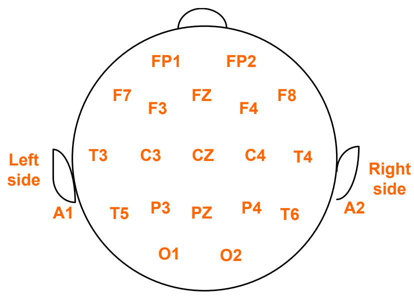

Fig.1 EEG electrode locations used in this study

[1] Many subjects dropped out in the initial stage as they could not commit for the six months period. Hence, the five subjects were the only available test population.

The sampling frequency was 256 Hz, which is sufficient to avoid aliasing in both the ECG and EEG signals. Subjects were asked to sit comfortably with their eyes closed and data obtained for two minutes each in the following conditions:

- Listening to relaxing music (i.e. waves hitting the beach); this is the control condition
- Listening to the same music but with masked binaural tones; this is the entrained condition

Two minutes recording was deemed sufficient to obtain responses based on a previous study [16]. Subjects were blind to the conditions (i.e. the subjects did not know which was the entrained and which was the control condition, as the music was the same in both cases) and the order of the conditions were alternated during the six monthly sessions. The music played was the same during each of the sessions, so as to reduce any effect the actual choice of music might have upon the classification performance. The binaural tones were generated by using two sinusoidal waves, one with frequency of 400 Hz (presented to the left ear) and another with frequency of 408 Hz (presented to the right ear). The tones were presented using Etymotic flat frequency response stereo ear phones (to avoid any spectral attenuation) with disposable ear plugs [17] and they were masked by the 'waves' music, hence they were not heard in the ordinary sense. It is known that such binaural tones can evoke a third pseudo-tone in the brain that differs in frequency of the evoking tones [18]. Hence, the brain will perceive also hearing a tone at 8 Hz, which is the difference of 400 Hz and 408 Hz. The 8 Hz was chosen as it falls within the alpha frequency region, commonly found in the EEG rhythm during eyes closed and relaxed situation [19].

2.1 ECG Signal Processing

The ECG signal was band-pass filtered in the range of 1-35 Hz using an Elliptic IIR filter (with forward-reverse filtering to avoid phase distortion) with a minimum stopband attenuation of 30 dB and maximum passband ripple of 0.1 dB. To reliably detect R peaks in the ECG signal, the signal was then high pass filtered with a cut-off at 10 Hz and then, in order to avoid spurious peaks [5], a R peak was detected to exist within the signal wherever the peak values exceeded the maximum amplitude multiplied by a threshold Th (for all subjects):

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

With the R peak locations identified, the average R-R interval length was computed and the 1-35 Hz band-pass filtered ECG signal was then further segmented into segments consisting of four R peaks plus half of an R-R interval on either side, as shown in Figure 2. Forty such segments were obtained for each session and each condition, for each subject.

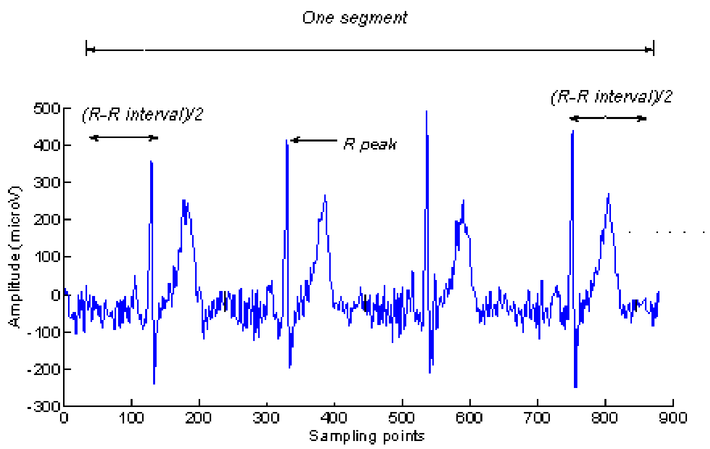

Fig. 2 Example of a segment from ECG signal

An autoregressive (AR) model was used [20] to extract features from each segment, according to equation:

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

where p is the model order, $x(n)$ is the segmented ECG signal at the sampled point n, a_k are the real valued AR coefficients and $e(n)$ represents the white noise error term which is assumed to be independent of past samples.

Determining the appropriate order of the AR model is an important step in such an approach since if the model is too small it will not represent the signal in sufficient detail and if order is too large the representation will include the original signal noise. The model order was selected using the Akaike Information Citerion (AIC) which selects the model order to minimise the following function [21]:

$$AIC(p) = N \ln \sigma_e^2(p) + 2p\,, \tag{3}$$

where p is the model order, N is the length of the signal, $\sigma_e^2(p)$ is the estimated error variance for the model. The term $2p$ represents the penalty for selecting higher order models.

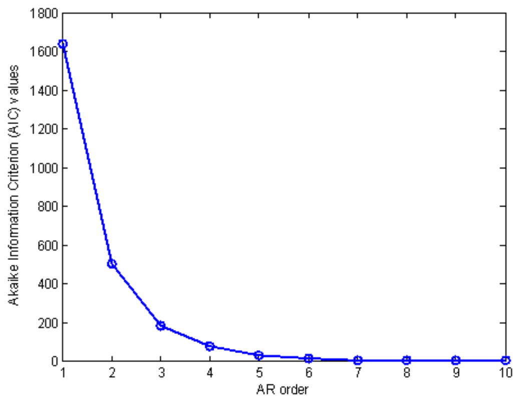

Fig. 3 Averaged AIC values vs AR order

AIC was computed from order one to ten for all the ECG data segments and the average values of these were plotted for analysis, as shown in Figure 3. It can be seen that the gradient does not change significantly after order six. Hence, a sixth order model was selected. The six AR features for each ECG segment were obtained using Burg's method, which is more accurate than the Levinson-Durbin method because it uses the data points directly, unlike the Levinson-Durbin method, which relies upon the estimation of the autocorrelation function of the data, which is generally erroneous for small data segments [20]. Burg's method also uses more data points simultaneously by minimising not only a forward error (as in the Levinson-Durbin case) but also a backward error [20].

In addition to the AR features, two Hjorth features namely mobility and complexity [22] were also used in the feature set:

$$MOB = \sqrt{\mathrm{var}(x')/\mathrm{var}(x)} \tag{4}$$

$$Complexity = \sqrt{(\mathrm{var}(x'')/\mathrm{var}(x'))/(\mathrm{var}(x')/\mathrm{var}(x))} \tag{5}$$

where *var* denotes variance, x is the ECG segment, x' is the first derivative of the ECG segment, while x'' is the second derivative of the ECG segment. These particular Hjorth features were chosen based upon their reported performance in another ECG biometric study [5].

2.2 EEG Signal Processing

The EEG signals were segmented into intervals corresponding to those derived in the ECG processing. Thus forty segments for each of the 19 channels were obtained, for each condition and for each subject in each session. Next, these EEG signals were band-pass filtered in the alpha and gamma frequency ranges of 8-12 Hz and 30-50 Hz, respectively using a forward-reverse Elliptic IIR filter with a minimum stopband attenuation of 30 dB and a maximum passband ripple of 0.1 dB. The energy in each channel was obtained by computing the variance of the signal giving 19 energy features for both the alpha band and also for the gamma band. Both the gamma band [8] and the alpha band [23] have been previously employed successfully for biometrics applications and hence used here.

2.3 Classification

Two classifiers were used to classify the combined ECG and EEG feature vectors: NN with a single hidden layer (with architecture as shown in Figure 4) and LDA. These classifiers were used to classify the features into five categories representing each subject. The size for the NN hidden layer was varied from 5 to 150 in steps of 5 while the number of units in the input layer changed according to the number of utilized features. The number of output units was set to five as there were five classes. The activation functions were sigmoid and the learning method was resilient backpropagation [24] due to its quick speed and the training was conducted until the error limit fell below 0.0001 or reached epoch limit of 1000.

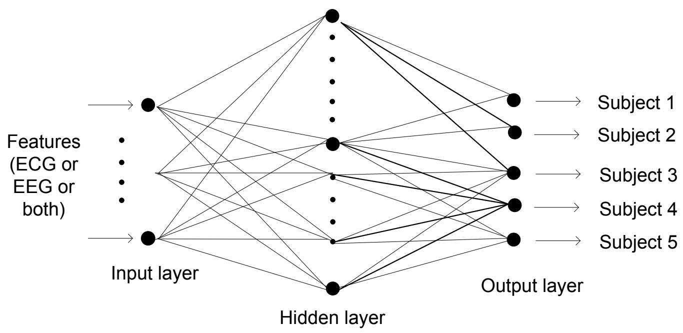

Fig. 4 MLP NN architecture as used here

Despite its simplicity, LDA has been shown to give comparable or even better results than NN for EEG classification [25]. It is also advantageous due to its low computational resource consumption and simplicity of design and hence it was used to compare with the NN results. As there were five classes, the LDA was used with one-against-the-rest approach, where different discriminant functions classified the features (one function per class).

To analyse the results of the classifiers, a six fold cross validation test for inter-session classification was used, where features from five sessions were used for training and the remaining 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). To further reduce the bias caused by the stochastic nature of NN, the training and testing was repeated ten times for each case, giving a total of 60 classifications for each hidden unit (HU) and the mean classification performance computed. The classifications were repeated for different combinations of ECG (six AR and two Hjorth) and EEG features (19 alpha and 19 gamma energies) and the results are reported in the next section.

3 Results and Discussion

Table 1 show the results of the ten runs of six-fold cross validation NN for different hidden unit (HU) sizes, for various feature combinations (ECG - AR, Hjorth and combined, EEG - alpha, gamma and combined, all - ECG combined with EEG) for the control and binaural conditions, respectively. To save space, only the mean ± standard deviation of these classification performance values are shown.

In general, it can be seen that using a combination of both AR and Hjorth features improved the classification performance for majority of the HU sizes. An ANOVA test (using MATLAB's anova1 function) gave a statistically significance difference in this case with $F(2,87)=535.8$, $p<0.00001$. The use of AR features from ECG performed better than the Hjorth features (paired t-test, $t(29)=19.6$, $p<0.00001$, using MATLAB's *ttest* function).

Similarly to the ECG results, the combination of the EEG features significantly improved the classification performance ($F(2,87)=190.9$, $p<0.00001$) and when comparing the performance of the individual bands, the alpha band performed better than the gamma band ($t(29)=19.3$, $p<0.00001$). This is likely to be due to the fact that alpha band is more prominent during eyes closed and relaxed conditions but nevertheless, the classification results indicate that there is complementary biometric information contained in both the chosen EEG spectral bands.

Comparing ECG and EEG features, the ECG features (AR and Hjorth) performed better than EEG (alpha and gamma bands) with a statistical significance of $t(29)=37.8$, $p<0.00001$. Combining all the available features from ECG and EEG gave significantly improved performance ($F(6,203)=391.8$, $p<0.00001$), which illustrates that the combined features have complementary individual-specific information which is useful for biometric purposes.

Considering the binaural conditions, once again the results indicate that the combined use of both the AR and Hjorth features improved classification performance ($F(2,87)=534.4$, $p<0.00001$), and that AR gave better performance than

Hjorth features ($t(29)=21.9$, $p<0.00001$) when they were used in isolation. More importantly, comparing the NN classification performance of ECG features under control and binaural conditions illustrates that a statistically significant higher classification rate was obtained under binaural conditions ($t(29)=27.6$, $p<0.00001$). It is speculated that under entrained conditions, the sympathetic and parasympathetic systems are more controlled, therefore leading to less variability in the heart rhythms.

Using both the alpha and gamma features from EEG improved classification performance (($F(2,87)=288.6$, $p<0.00001$) and similarly to the previous control condition case, the alpha band EEG used alone provided a better classification rate than using gamma band features alone ($t(29)=16.4$, $p<0.00001$). Comparing EEG features under both sets of experimental conditions indicates, that once again, a higher classification performance was achieved when the measurements were taken under binaural conditions ($t(29)=34.5$, $p<0.00001$).

With combination of ECG and EEG features, the classification performance was improved for the binaural condition (($F(6,203)=532.1$, $p<0.00001$) and similar to the previous control condition results, the ECG features, rather than the EEG features, provided the higher classification performance ($t(29)=30.6$, $p<0.00001$).

In the control condition, using both AR and Hjorth ECG features gave an average classification performance of 91.5%, whilst using both alpha and gamma bands of EEG give 87.5%, however, when used in combination an improved classification of 92.4% was achieved. Under binaural brain entrainment conditions and when all features were used, a further improvement in the classification rate was achieved (95.1%). Using the final column results from Table 1 reveal that NN performances (when using all the available features) are superior under binaural conditions as compared to control ($t(29)=31.7$, $p<0.00001$).

The classification performance of the LDA classifier is given in Table 2. Similar to the NN classifier results, it can be seen that the use of both AR and Hjorth ECG features provides improved classification when compared to the use of either of the ECG features separately. Table 2 also illustrates that combining the EEG features from both alpha and gamma bands gave better performance, than using the spectral bands separately. This is the case for both the control and binaural entrained conditions. More importantly, a combination of all the available features led to a further improvement in classification performance. Finally, as hypothesised, the classification performances were higher for the binaural condition as compared to the control case for any feature combination. Statistical testing (ANOVA and paired t-test) that was done for NN results was not possible for LDA results as only six-fold cross validation results were available. The case was different with NN, where the use of several HU sizes led to availability of a higher number of classification performance values sufficient for statistical testing.

Comparing the classifiers, it is evident that LDA provides the better classification performance for most of the feature combinations. When all the features were used, LDA performed better than NN.

The results of analysing the standard deviation of the features across all the sessions from both sets of conditions are shown in Table 3, where it can be seen that for all the subjects, the average standard deviation of all the features across sessions is lower by 13.2% for the binaural condition as compared to the control condition. The lower standard deviation denotes that the feature values were more stable for the binaural condition even after a significant period of time (as the six sessions were conducted across monthly intervals).

Table 1. NN classification performance (%, mean±std) for the control and binaural conditions

	Features						
HU size	AR	Hjorth	AR+Hjorth	Alpha	Gamma	Alpha+ Gamma	All (ECG +EEG)
Control	88.6±2.5	78.7±0.5	91.5±1.1	85.9±0.7	80.6±2.2	87.5±1.0	92.4±0.8
Binaural	93.2±2.1	84.0±0.4	94.5±0.9	86.9±0.6	83.6±1.6	90.0±0.7	95.1±0.7

4 Conclusion

This study has attempted to combine features from ECG and EEG to obtain improved individual identification performance. In addition, a novel approach based on binaural brain entrainment was applied during ECG and EEG recording to analyse the stability of the extracted features. The results show that combining the features from both ECG and EEG modalities gave significantly improved classification performance as compared to using either of the modality alone. It can also be concluded from the results that the use of brain entrainment significantly improved the classification performance as compared to without entrainment. It is speculated that brain entrainment allows the subjects to be more relaxed and hence minimise the feature variability over the monthly recording sessions.

When using all the available features, the LDA classifier provided the better classification performance; therefore, the use of the LDA is suggested since it has the added advantage of being simpler to design and quicker to use.

It should be noted here that a comparative analysis of all the various features utilised in ECG and EEG is beyond the scope of this paper, and therefore it is possible that the use of other features and classifiers could result in further improved performance. There are practicalities such as requiring the subject to be still and also on the cumbersomeness for data enrollment that need to be overcome before such approaches can be compared to conventional biometrics. But nevertheless, this study has shown that combining features from ECG and EEG is useful for biometrics, and the binaural brain entrainment reduces the variability of these features over time, thereby increasing the potential for use in biometric applications.

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Table 2. Mean and standard deviation of LDA classification (%) results for the different feature combinations

	Features						
	AR	Hjorth	ECG (AR, Hjorth)	Alpha	Gamma	EEG (Alpha, Gamma)	All (ECG and EEG)
Control	94.1±0.02	80.3±0.08	96.6±0.01	87.5±0.02	76.9±0.06	92.9±0.02	98.6±0.02
Binaural	97.4±0.01	81.1±0.06	98.1±0.008	89.8±0.08	80.8±0.02	93.5±0.03	99.8±0.002

Table 3. Standard deviation of features for each subject for both conditions

	Control					**Binaural**				
Feature	AR	Hjorth	Alpha energy	Gamma energy	All	AR	Hjorth	Alpha energy	Gamma energy	All
Subject										
1	0.4014	0.0831	0.1720	0.1217	0.4918	0.2895	0.0400	0.1520	0.1269	0.3959
2	1.5813	0.0714	0.1709	0.1575	1.6154	1.3620	0.0400	0.1463	0.1463	1.3936
3	1.3251	0.0608	0.1661	0.1497	1.3618	1.1257	0.0332	0.1517	0.1421	1.1628
4	1.1546	0.0529	0.2117	0.1490	1.2030	0.9836	0.0346	0.2133	0.1435	1.0374
5	1.2841	0.0510	0.2105	0.1597	1.3312	1.1518	0.0361	0.2117	0.1549	1.2020
Overall average	1.2165	0.0648	0.1873	0.1480	1.2590	1.0488	0.0374	0.1778	0.1432	1.0928

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