Quality Filtering of EEG Signals for Enhanced Biometric Recognition

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Abstract: In this paper we present a biometric person recognition system based on EEG signals incorporating a novel strategy to find and utilize the most informative data segments using the concept of Sample Entropy. The users are presented with a stimulus that prompts a motor-imagery response. This is then measured using an array of EEG sensors. A sliding-window segmentation scheme and Wavelet Packet Decomposition are adopted for primary feature extraction before the quality measurement stage. The quality-filtered feature windows are then used to extract secondary features that are in turn classified using a linear discriminant classifier. The proposed system is tested using a publicly available EEG database and it shows that entropy filtering results in a significant improvement on performance. An average identification accuracy rate of more than 90% is achieved for 109 subjects using only eight electrodes, utilizing only the highest quality for each subject.

1 Introduction & Related work

Biometric person recognition technologies have been an active area of research in recent years driven by advances in machine learning techniques and availability of low-cost sensors. While this has resulted in significant deployments in a range of applications, important challenges still remain to their widespread adoption and acceptance [JSSLA04]. Because of this, the search for new biometric modalities continues. In this paper, we investigate a relatively new source of biometric information with the potential to overcome some of these challenges in some applications – Electroencephalogram (EEG) signals.

Using EEG signals as a biometric modality is a relatively new area of research. Palaniappan et al. reported that by measuring 40 Hz oscillations from 61 electrodes a classification rate of 95.25% can be achieved [PDa07]. Their experiment concentrated on investigating the Visual Evoke Potential (VEP) when 20 subjects were stimulated by viewing sets of picture, the stimulus duration of each picture was 300 ms with an inter-trial interval of 5.1s. Their later experiments showed that by processing VEP of the EEG gamma band signal, even when the number of subjects increased to more than 100, the accuracy rate achieved was 98.12%; and after the number of electrodes was optimized (35 out of 61 were kept) the median accuracy rate still reached 97.62% for 40 subjects [PDb07]. However, these performance levels were achieved at a cost: several electrodes (at least 35) were needed even after algorithm optimizations.

For practical use as a biometric modality the EEG sensor equipment must be easy to set up: ideally the number of electrodes should be as small as possible. Recently some researchers have tested the identification performance with only one electrode. Fei Su et al. [SLAYJ10, SLAJ10] reported a system that could achieve an average accuracy of 97.5% for 40 subjects acquiring the signal from a single electrode only (FP1 in the international 10-20 system [NF05]), subjects were not required to perform any mental or physical tasks. The features were based on combining the coefficients of an auto-regressive model and Power Spectrum Density (PSD), and these were classified using a kNN-FDA (k-Nearest Neighbour and Fisher's linear Discriminant Analysis) combined classifier. The recording of their experiment contains 480 records and each record lasts for 5 minutes, ten-fold cross validation was used for testing. Palaniappan et al. [PGRS11] claimed a 100% accuracy rate with three subjects using visual stimuli consisting of different numbers depicted on a screen. The signal was recorded using a single sensor at Cz position [Ch85] and was classified using a single hidden layer neural network. Despite these encouraging accuracy rates, the limitation of these experiments are either their relatively long signal recording duration needed for training and testing, or the small number of subjects involved.

In this paper we propose a new processing scheme that is designed to only utilize the most information-rich data, and hence achieve acceptable performance by using relatively small number of electrodes (up to eight electrodes) on 109 subjects. The paper has the following structure: the general scheme for EEG data acquisition will be presented in Section 2, along with the electrodes positioning and the block diagram of the system. The principal algorithms used in the proposed system will be introduced in Section 3. Section 4 outlines the novel entropy-based method for quality measurement followed by the experimental results as well as the tests for optimizing the system parameters. Section 5 provides a summary and suggestions for further work.

2 Experiment scheme

The proposed biometric system is based on measuring the evoked response of users when they are confronted with a stimulus and asked to perform a task. The EEG signals from the user are obtained by a sensor system attached to their scalp. The user is presented with a stimulus (e.g. visual target on the screen) which requests them to perform or imagine motor tasks. The EEG signals thus generated are then gathered, and processed to provide identity information for the particular user. The "EEG Motor Movement/Imagery Dataset", supplied by the developers of the BCI2000 instrumentation system [SJHBR04, GAG+00] was used for evaluating the proposed algorithm and the performance of the system in an identification (one-to-many recognition) scenario. The sampling rate of the sensor was 160 Hz, and EEG data from

109 subjects were recorded. The database includes a number of recordings for each individual recorded in a single session and separated by short intervals. These include two-minute baseline recordings, one with the eyes open and one with the eyes closed. Three two-minute recording runs (separated by a “a couple of minutes”) are also made (Runs 1 to 3) for each of four different motor/imagery tasks (Tasks 1 to 4) [EMD09].

The proposed system is trained and evaluated using data obtained from Task 4 which was a motor imagery task for both hands and feet. The reason for adopting Task 4 is that the motor imagery task might better avoid the contamination of the EEG signal by other bioelectrical signals such as electromyography (EMG). Due to the need for ease of deployment as a biometric modality, no more than eight electrodes are used and their positions are clustered around the centre of the motor cortex: FC_1, FC_2, C_3, Cz, C_4, CP_3, CP_z, and CP_4 [Ch85]. The electrode positions are depicted in Figure 1.

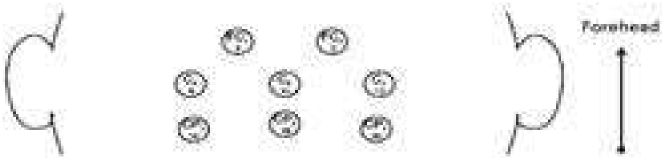

Fig. 1 Tested electrode positions, modified from the figure in [EMD09] (10-10 system [Ch85])

The block diagram of the proposed system is shown in Figure 2. The Wavelet Packet Decomposition [Da92] is used to generate the primary features. An entropy-based measurement method is designed to select optimal primary feature windows for generating secondary features which are then passed to a classifier. *M*, *K* and *L* are three parameters for controlling the system performance and are described in the following section.

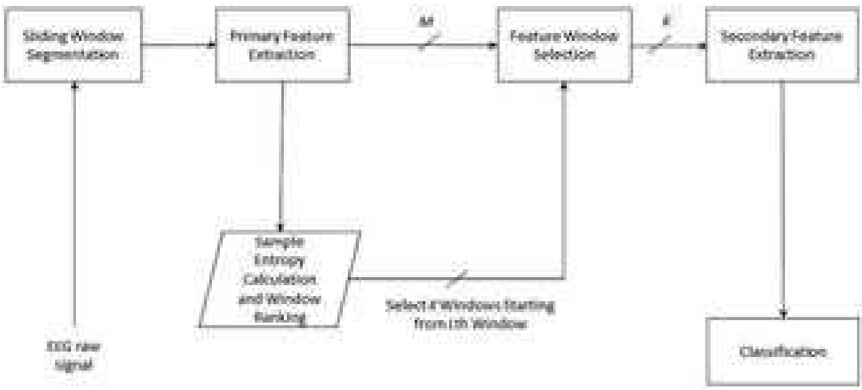

Fig. 2 Block diagram of the system

3 Pre-processing and Feature Extraction

One goal of pre-processing and feature extraction, especially when EEG signals are used for biometric recognition, is to remove the unwanted signal components (such as signals generated by eye blinks and heartbeats) and only include the essential identity-bearing information for classification. For the proposed system, Wavelet Packet Decomposition (WPD) is utilized for the first stage of feature generation. This is followed by a novel method for quality measurement, designed to select and use only a small amount of data segments which are most likely to provide a correct recognition before feature extraction.

3.1 Sample Entropy for Quality Measurement

This section is devoted to the novel entropy-based filtering method. The motivation of adopting Sample Entropy for quality measurement is presented first, followed by a description of the scheme for using it in EEG filtering in the proposed system.

3.1.1 Motivation for using entropy as a measure of quality

Like human speech, the EEG signal produced by the brain is non-stationary [CBEV95]. As a stochastic time series, the frequencies of the typical EEG signal vary over time depending on what brain functions are being performed. Also similar to speaker recognition, it is unlikely the whole time series is equally informative for the purpose of identity recognition. In order to reduce the amount of the data used for processing and improve its quality, it is necessary to find a strategy to extract the most useful segments of the data and discard the relatively less-informative portions of it. Entropy of the EEG signal has been used as a feature to identify the seizures in epileptic patients. It has been reported that during seizure patients' brains generate lower entropy EEG signals than for healthy people. This implies that the healthy brain signal possess less regularity than a brain during seizure [AMK09]. In that experiment they tested three different kinds of entropies calculated from EEG segments (Shannon entropy, Sample entropy and Log entropy) and all of them showed such a trend. Liang et al. later investigated whether the entropy of the EEG signal could also identify sleeping stages. They measured the EEG signal on an epoch-by-epoch basis, using multi-scale entropy analysis (MSE) and noticed that the "entropy values monotonically decrease from awake to deep sleep" [SCY+12]. These results suggest that entropy may be used to measure the level of brain activity from EEG signals in healthy human brain functions. The more active the brain is with cognitive/motor functions the more unpredictable the EEG signal is likely to be, hence the higher the entropy value. Based on this hypothesis, we propose to use the Sample Entropy as a measure of EEG signal quality for biometric applications as described below.

3.1.2 Using sample entropy to filter EEG data

After calculating the WPD for each window of the time series, the sample entropy of each wavelet coefficients window is computed. In the experiments reported in the next section, each recording run of approximately 2 minutes is segmented into windows of

960 samples (6 seconds duration) using a sliding window approach with a shift of 24 samples between windows, thus producing 760 windows for every EEG band per electrode. More generally, the number of windows generated per band per electrode can be defined as a system parameter, M, as shown in Figure 2. These coefficient windows are then fed to the SampEn calculation module which ranks the windows in order of their entropy values listing them from the highest entropy window to the lowest. For each band, K out of M windows, starting from the L-th value in the entropy-sorted list of entropy values, are preserved in order to reduce the quantity of data needed for further processing and remove the information-poor windows. In the experiments that follow, only about 1/10 of the data (80 windows) is used for secondary feature extraction and classification. The standard deviation of the wavelet coefficients from the selected windows are then calculated to serve as the secondary features for classification. It has been suggested that the choice of the tolerance threshold r is important in the calculation of SampEn: if it is set at too high a value, detailed system information may be lost and if it is set at too small a value, poor conditional probability estimates might result [RR00]. In the experiments reported below r is set to 1 and run length m is set to 2.

4 Experiment Results and Evaluations

During the training phase, for every electrode per subject M=760 windows are fed to the WPD stage. Each window is decomposed into nine bands of wavelet coefficients. Since eight electrodes are used in the experiments, before the entropy screening stage a total of $8 \times 760 \times 9 = 54720$ coefficient windows are generated for each subject. Next, the Sample Entropy is calculated for each window and the windows are sorted in descending order of SampEn. Out of the M windows for each electrode and band, K (=80) windows (hereby referred to as "observations") are retained, starting from the L-th ranked window (L = 1, ... , M-K), as a contiguous range from the SampEn-sorted list of windows to preserve the most information-bearing part of the data. This amounts to roughly 10% of the whole data. After this quality measurement and screening stage, for every subject only 5760 out of 54720 windows are kept and the standard deviation (σ) of each coefficient window is calculated and used as features for classification using a normalised Linear Discriminant Classifier (LDC, [DJD+04]). This choice of classifier was based on tests and comparisons with several other classifiers (Support Vector Machines with different kernels, k-Nearest Neighbour classifiers, kernel-LDC and kernel-k-NN) using the database described above.

4.1 Entropy filtering optimization (optimising *L*)

Different contiguous ranges of windows from the entropy-sorted list of coefficient windows are extracted and used to filter the training data and only those windows within the selected range are used for classifier training. The first range tested is for the windows with the highest entropy values (rank 1 to 80). The system is trained and tested with the same range of entropy value ranks. Data from Run 2 is used for testing the identification accuracy. A range of high-entropy ranks (130th to 360th range) is identified which provides high biometric performance. It could be that the highest ranking windows correspond to activities that do not carry identity information. As each window lasts 6 seconds, it could include 5 to 6 cycles of motor actions (e.g. opening and closing of hands). This could be considered as a relatively regular function with moderate SampEn values. Tests with different parameter L, suggests that the windows corresponding to approximately the highest 15% rankings (L = 1 to 180) Sample Entropy values should be discarded to improve performance.

4.2 Performance as a function of training data volume (optimising *K*)

The amount of data used for training was varied to assess how a reduced training data volume affects the accuracy of the system. The number K of observations used for classification is reduced in a number of steps from 80 to 1 and the identification test results are noted. The results are relatively stable up to K=10. Still more than 70% accuracy rate can be achieved while only 2 observations are kept. However, the performance significantly degrades when only 1 observation is preserved. A compromise setting may be K=10 roughly using 1.3% of the data is utilized, and still achieving more than 90% identification rate for 109 subjects.

4.3 Performance as a function of test duration

Figure 3 depicts the degradation of the accuracy rate for identification when the testing duration t is reduced. These tests are all based on number of observations K=10 and starting value L=200, utilizing Run 2 (or part of it) for testing and the other two Runs for training. Hence, 4 minutes of recording is used for training the classifier and each point on the horizontal axis refers to testing with test durations of different length. Dropping the test duration by a factor of four from 120 seconds to 30 seconds results in a loss of mean accuracy of only 3.48%; dropping the test duration all the way to just 6 seconds, results in a drop in accuracy of less than 9% compared with using the whole two minutes of data for testing.

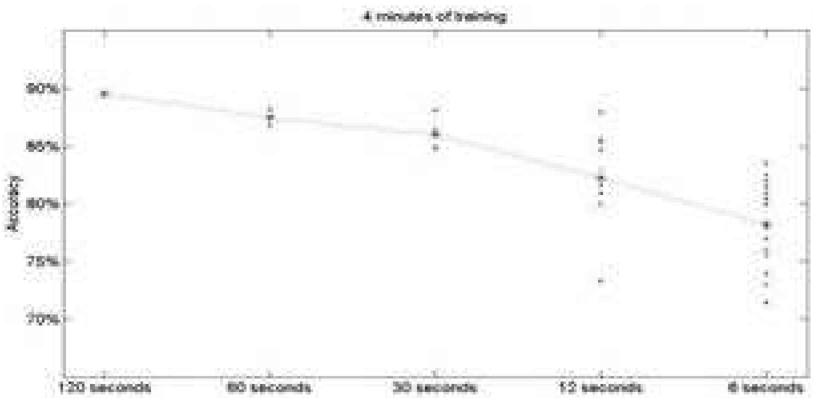

Fig. 3 Impact of the testing duration on average identification accuracy with K=10 and L=131

5 Conclusions and Future work

In this section to illustrate the impact of the proposed entropy filtering method a number of different schemes are compared as shown in Table 1. The schemes I to III employ entropy filtering while schemes IV and V are methods only unilizing wavelet decomposition. The results presented in Table 1 indicate that, given the chosen system paramters, the entropy filtering method improves the reconition performance by around 5% compared to using no entropy filtering at all. The results for Scheme III suggests that the low entropy-windows contain significantly less biometric imformation.

Table 1. Comparison of different schemes with and without entropy filtering

Schemes	*L*: Rank staring value	*K*: Preserved observations	Accuracy
I. Highest entropy	1	80	87.0%
II. Highest performance	131	80	90.4%
III. Lowest entropy	681	80	74.8%
IV. No entropy filtering	1	760	86.5%
V. No entropy filtering	1	80	85.6%

This paper explored the notion of quality for EEG signals used for biometric person identification. A novel system was presented where a measure of signal quality, the Sample Entropy, was used to filter the data available for biometric recognition. For a 109 subject database an identification rate of more than 90% was achieved. The results indicate comparative performance with other published methods while promising the possibility of being able to handle large number of subjects using data from fewer electrodes. Further work will focus on optimizing the system parameters separately for different frequency bands and increasing the amount of data used for system evaluation.

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