Multichannel EEG-based Biometric Using Improved RBF Neural Networks

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***Abstract*—Electroencephalogram (EEG) brainwaves have recently emerged as a promising biometric that can be used for individual identification. In this study, we present a new visual stimuli-driven, non-volitional brain responses based methodological framework towards individual identification. The non-volitional mechanism provides an even more secure way in which the individuals are not aware of security credentials and thus can not manipulate their brain activities. Given the intercorrelated structure of brain functional areas, instead of making the identification decision relying on any single EEG channel, we propose a new identification approach based on the decision-level fusion of multichannel EEG signals, using the Radial Basis Function (RBF) neural network and its improved versions. Specifically, the identification decision is determined according to the identification patterns reflected from multiple EEG channels over the desired brain functional region. We evaluate the performance of our proposed methods based on four different visual stimuli and four independent EEG channels. Experimental results show that, the proposed fusion technique can significantly improve the identification accuracy, compared to the conventional single channel based solution. For RBF network, the accuracy of identifying 37 subjects could reach over 70%, which is better than the average accuracy of about 55% achieved through individual channels. For the improved RBF networks, the frequency-based decision making could reach the accuracy of 90%, while the probability-based method could reach over 91%. Our study lays a foundation for future investigation of more accurate and reliable brainwave-based biometrics.**

I. Introduction

Over the past few decades, biometric approaches have gained dramatically increasing interest for individual identification and authentication, since they are closely associated with an individual's physiological or behavioral features. Some of those features, such as fingerprint, face, iris and voice [1], have been extensively investigated and proved to be scientifically unique across the entire human population, which result in very promising biometrics in the cyber security domain. However, those existing biometric characteristics still suffer from various limitations and weaknesses, far from perfect. For example, the fingerprint is a popular biometric measurement with a high matching accuracy, however it can be faked [2] or obtained by force. It has been reported that a violent gang in Malaysia chopped off a car owner's finger to get round the vehicle's hi-tech security system [3] and a fingerprint of a Germany's federal minister of defense has been collected and cloned by a hacker group using pictures taken with a standard camera [4]. The "noncancellable" nature of fingerprints or iris make the breach of such identity information catastrophic and non-recoverable to the nation's security [5]. Therefore, it is highly desired to seek new biometric approaches that can possibly overcome those limitations.

Recently, electroencephalogram (EEG) based biometrics, representing the unique human brain activities, have emerged as a new and promising way for labeling each individual person [6], [7]. EEG records the brain's electrical activity which is inherently determined by the person's unique pattern of neural pathways and closely associated with each individual's unique memory and knowledge base and sensitive to mood, stress and mental state [8]. Thus EEG signals can be a more secure and reliable identification and authentication biometric because it is unique for each individual [9], [10], impossible to imitate others' brain activities [7], [11], very difficult to be obtained under force and threat and stable over time [12].

EEG signals collected over the entire scalp reflect a wide range of brain activities and the signals from the electrodes placed over the occipital lobe and a broad region of the medial scalp are believed to be able to show more distinguishable features (closely related to the individual's visual association and semantic memory), compared to the ones collected from other locations. Although a single EEG channel in the desired region could largely represent the brain activities, the signals are very sensitive to artifacts, e.g., the movement between the electrodes and the head, and contain useless information. It is very challenging to point out which specific channel (that is, which specific position point on the scalp) has better signal quality over the course of time. For example, occipital lobe region is the visual processing center of human brain containing most of visual cortex. Channel Oz has shown better performance than other channels, like O1, O2, and Pz [13]–[15]. However, it does not necessarily mean that the Oz channel can always make the right decision, while other channels always give incorrect decisions. It is important to note that, EEG signals from different channels are eventually reflecting the brain activities in response to the same visual stimulus, especially the channels which are close to each other can obtain similar brainwaves. Thus, in this study, we argue that a more accurate identification decision can be achieved by concurrently investigating EEG signals from multiple channels, which will help mitigate the influence of unexpected or random artifacts in certain channels, as well as reinforce the consistent identification results from one or more channels.

In this paper, we present a multichannel EEG-based user identification framework using an improved RBF neural network and fusing the identification results from various independent EEG channels at the decision level. We also seek to explore the potential impacts and performance of adopting different types of visual stimuli. Specifically, we analyzed four EEG electrode channels (over the occipital lobe region) under four types of visual stimuli from 37 human subjects. The rest of the paper is organized as follows: Section II gives a brief introduction to the related work. Section III introduces the RBF network and the improved versions we proposed for making the final identification decision. Section IV describes the experimental setting for EEG data collection and preliminary identification decision makings, and then discusses the experimental results. Section V concludes our research work and results.

II. Related Work

Existing research has demonstrated that EEG brainwave signals can be used as a viable biometric for individual identification and authentication. Those prior research efforts represent different emphasis. For instance, some researchers focus on the work to find out the more effective stimuli or mental tasks, while some others investigate a variety of noise removal methods, feature extraction methods and classifiers to improve the identification accuracy. Electrode locations and which channels can best capture the brain activities are also concerned. One way is to choose the channel which reflects the brain activities most. Poulos *et al.* [16], [17] proposed a linear rational model of ARMA type to fit the alpha band EEG signals. Using the learning vector quantization (LVQ) neural network (NN) on the voltage difference between leads O2 and Cz, for the 75 people being tested, to distinguish a specific person from others, correct classification scores of LVQ classifier in the range of 72% to 84% were obtained. Gui *et al.* [18] used Oz channel which is located in the occipital region to analyze the identification performance on 32 subjects using neural network to classify features after wavelet packet decomposition (WPD). The accuracy of authentication (i.e., recognizing the authorized individuals) was around 90%, but the accuracy of identifying all the 32 subjects individually is only from about 10% to 50%. Euclidean distance (ED) and dynamic time warping (DTW) approaches were proposed to analyze four EEG channels separately [19]. The results showed that the Oz channel performed better than the other three channels and it can reach an accuracy of over 80% for ED method and about 68% for DTW method.

Since any single channel itself can hardly reflect the entire picture of highly complicated brain activities, not to mention the influence of noises and artifacts, it is thus desirable to investigate multiple interrelated EEG channels around the target brain functional region which can elicit the most distinguishable brain activities. On the other side, the potentially increasing computational overhead caused by more EEG signal channels requires us to pick up a small set of EEG channels in our framework. Researchers have been trying to make decisions using two or more EEG channels. The most common way is to combine the feature vectors of each channel together to form a new feature vector and then use these combined feature vectors for classification. For instance, Ashby *et al.* [20] extracted 5 features, the autoregressive (AR) coefficients, power spectral density (PSD), spectral power (SP), interhemispheric power difference (IHPD) and interhemispheric channel linear complexity (IHLC) from 14 channels. After combining them all together, the final dimension of the feature vector is 1358. Then they used the linear SVM classifier for authentication on 5 individuals and got the false rejection rate (FRR) of 2.4% to 5.1%, and the false acceptance rate (FAR) of 0.7% to 1.1%. Nguyen *et al.* [21] extracted 21 AR coefficients and 12 PSD components from channel C3, C4 and Cz and resulted a feature set of 99 features. They reached the best average equal error rate of 4.09% for support vector data description (SVDD) with RBF kernel and 4.41% for Gaussian mixture model (GMM) on 9 subjects. In [22], the authors extracted the same features but from 6 channels and formed a feature vector of 198 attributes. Shedeed [23] extracted 92 and 40 features for Discrete Fourier Transform (DFT) and 72 and 96 features for WPD from 6 channels. Using artificial neural network (ANN) as the classifier, the accuracy reached over 87% to verify 3 subjects. Other studies also form the feature vector in a similar way, e.g., Hema [24] extracted 129 PSD features from 2 channels and Liang [25] extracted 36 AR features from 6 channels. Although multiple channels could bring more useful information, the dimension is quite large. Thus, methods, like principle component analysis [26] and one-way-analysis-of-variance (ANOVA) [27], [28] were adopted to lower the dimension and keep the most relevant features.

III. Methods

A. Radial Basis Function (RBF) Network

RBF network [29] is a particular type of artificial neural network that uses radial basis functions as activation functions. The general architecture of RBF network is shown in Figure 1. It typically has three layers: an input layer, a hidden layer with non-linear RBF activation functions and a linear output layer. Given an input vector of real numbers $x \in \Re^n$, the output of the network is a linear combination of radial basis functions of the input vector, $f : \Re^n \rightarrow \Re$, and is given by Equation 1.

$$f(x) = \sum_{i=1}^{N} w_i \phi(\|x - c_i\|) \tag{1}$$

where N is the number of neurons in the hidden layer, c_i is the center vector for neuron i, w_i is the weight of neuron i

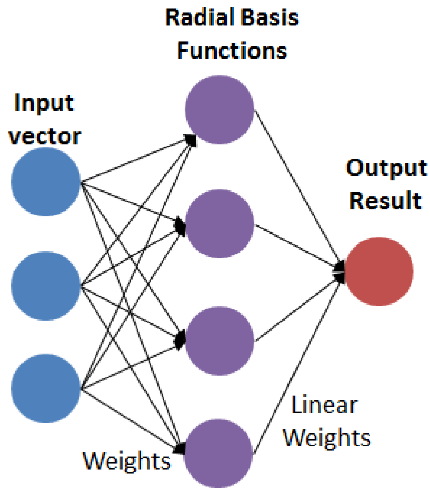

Fig. 1. Architecture of a RBF network

in the linear output neuron, and ϕ is the radial basis function depends only on the distance from the input vector to a center vector.

RBF network is more intuitive than the multi-layer perceptron neural network. According to [30], the RBF network could be simplified without the radial basis function but keeping the norm calculation. Such simplification has enabled the possibility of developing a dedicated, ultra-low-power silicon chip which has been proven to be very effective in supporting RBF classification tasks [31], [32], including the potential brain-based biometric authentication applications. In this architecture, each neuron is designed to save the pattern and influence field of which the area means the similarity domain. To build a model of the network, the information of the training data is learned and stored in the neurons in the training phase. Figure 2 shows a decision space mapping results of the neurons using Manhattan distance after training. The influence fields reflected by the diamond areas, the patterns which are the centers of the diamonds, and the categories which are shown by different colors are stored in the neurons. In the training process, when an input vector and its category is presented to the network, the neurons in the hidden layer will check whether one of them can recognize this input pattern with the same category. If this is the case, the neurons will keep the same. As the black point at (7, 10) is in the same domain belonging to the point at (6, 10), no new neuron will be activated to save this input. On the contrary, if the input is not recognized by any neuron, a new one will be created to store the pattern and its category, and also its similarity range. It can happen that a vector in category B falls in the similarity domain of different category A. In this case, a new neuron is created to store the input of B and also the influence field of category A shrinks so that it no longer recognizes the vector of category B. Based on these actions, the neurons will learn the information of the training data, which lead to the different areas and colors of the diamonds in the figure.

When the training process is finished, the recognition process simply check the corresponding category of the influence field which the testing pattern falls in. Since the influence fields of different categories may overlap to each other, it is possible that a pattern falls in a region covering by multiple influence fields which can cause an *uncertainty*. And also a pattern can fall out of any influence field and causes *unknown* status. So we propose to adopt a simple way using the smallest distance to make a decision.

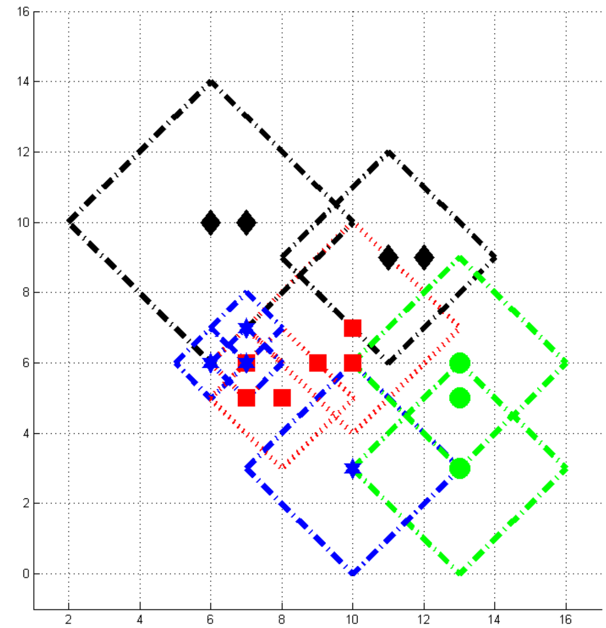

Fig. 2. Decision space mapping

B. Improved RBF Neural Network

The RBF network uses the regular distance, such as Euclidean distance or Manhattan distance, between the input vector and center vectors to make classification decisions. But this is only reasonable when the processed data are numeric. In the case of brain biometric, we use the RBF network at the decision level, after the preliminary identification results have been obtained based on the four EEG channels respectively. Although we could numerically label the subjects, the labeled data could still introduce errors when we try to find out the similarity between two patterns. For example, it could happen that the input vector and one pattern stored in the neurons are very similar to each other except that the decisions from each channel are quite different. If the labeled values of different samples are very far from each other, the RBF network would give a larger distance value. There may be another chance that, a stored pattern, whose preliminary results are different from the input vector with the labeled values, is closer to the input vector. In this case, although the distance is small, the pattern is quite different from the input pattern. Therefore, we propose a more reasonable distance evaluation method and decision making scheme according to the specific characteristics of the input vectors.

In the preliminary results from four channels, it is frequent that incorrectly predicted channels are more likely to give the same incorrect results. The channels making correct predictions are not the same at all the times. Therefore, instead of using distances like Euclidean distance or Manhattan distance, we propose to use the total number of correctly identified channels, ignoring the order of the results from four channels, as the distance to present the similarity between two patterns. We use the similarity score to represent the distance. Two vectors are more similar if the similarity score is higher. So the category that has the largest similarity score is more likely to be the output.

Before the classification, we first use a set of preliminary results to finish the training process by storing patterns and categories which are distinct from each other. Based on those stored information, we could start the testing process. When there is a new input vector, first the similarity scores to all the stored patterns are calculated. Let $S = \{s_1, s_2, \cdots, s_L\}$ represent the similarity scores between the input vector and the stored patterns, $Y = \{y_1, y_2, \cdots, y_L\}$ represent the corresponding categories, $D = \{D_1, D_2, \cdots, D_L\}$ denote the corresponding different samples between the input vector and stored vectors, where L is the number of activated neurons with stored patterns. The maximum similarity score is $s_{max} = max\{S\}$. The most possible results are the categories that have the maximum similarity score as Equation 2.

$$\hat{y} = y_i, \hat{D} = D_i \quad for \quad \forall i, s_i = s_{max} \tag{2}$$

where $y_i \in Y$, $D_i \in D$, and $s_i \in S$.

Since only four channels are considered in this study, it is possible that the similarity scores between the input pattern and several stored patterns in different categories are same. Let $SBJ = \{sbj_1, sbj_2, \cdots, sbj_M\}$ denote all the possible outputs in $\hat{y}$, $n_{SBJ} = \{n_1, n_2, \cdots, n_M\}$ are the corresponding frequencies, where M is the total number of different subjects that are being predicted. One method to make the final decision is based on the frequencies, called *frequency-based RBF network*, shown as Equation 3.

$$\hat{y}_{freq} = sbj_i, \quad i \text{ satisfies } n_i = max\{n_{SBJ}\} \tag{3}$$

Another method for final decision making is *probability-based RBF network*. Based on the training data, we can not only obtain the training model of RBF network, but also the probability matrix of correct and incorrect predictions between any two subjects. The matrix is denoted by A_N in Equation 4.

$$A_N = \begin{pmatrix} a_{1,1} & a_{1,2} & \cdots & a_{1,j} & \cdots & a_{1,N} \\ a_{2,1} & a_{2,2} & \cdots & a_{2,j} & \cdots & a_{2,N} \\ \vdots & \vdots & \ddots & \vdots & \ddots & \vdots \\ a_{i,1} & a_{i,2} & \cdots & a_{i,j} & \cdots & a_{i,N} \\ \vdots & \vdots & \ddots & \vdots & \ddots & \vdots \\ a_{N,1} & a_{N,2} & \cdots & a_{N,j} & \cdots & a_{N,N} \end{pmatrix} \tag{4}$$

where $a_{i,j}$ is the probability that subject i is recognized as subject j, and the sum of each row $\sum_{j=1}^{N} a_{i,j}$ is 1.

Based on the probability matrix A_N, the probability based method is to find the category in which the samples between any two patterns had the highest probability as shown in Equation 5.

$$\hat{y}_{prob} = \underset{\hat{y}_i \in \hat{y}, \hat{D}_i \in \hat{D}}{\operatorname{argmax}} \; p(\hat{y}_i | \hat{D}_i) \tag{5}$$

IV. Experiments and Results

A. EEG Data Collection

The raw EEG signals were collected from 37 adult participants (19 females, age range 18-25, mean age 19.53) using "EASY CAP" device (Ammersee, Germany) [33] from four electrode sites (Pz, O1, O2, Oz) around the area of the occipital lobe region, which is the visual processing center of the mammalian brain and is believed to better reflect each individual's visual cognitive behaviors [34]. The data was sampled at 500 Hz. 1.1 seconds of raw EEG signals were recorded, which made 550 samples for each channel. In this experiment, the participants were asked to silently read an unconnected list of texts which included 75 *words* (e.g., BAG, FISH), 75 *pseudowords* (e.g., MOG, TRAT), 75 *acronyms* (e.g., MTV, TNT), 75 *illegal strings* (e.g., BPW, PPS), and 150 instances of their own names [14]. By showing the subjects with the stimuli, the non-volitional ("involuntary" or "intuitive") brain activities were recorded. Each human subject was tested twice.

B. Preprocessing

Since the raw EEG signals are noisy, it is common to average many trials together which can get rid of the random brain activities but keep the event-related potentials (ERPs). Thus the EEG signals were first ensemble averaged for 50 individual measurements. Based on the ERPs, we can find that the morphology of the patterns from the same individual were very similar. Furthermore, the patterns were persistent during different tests which was an important indicator that the similar EEG patterns (i.e., non-volitional brain responses) could be captured in any later tests. Moreover, it can be observed that the patterns were quite different among different human subjects. Such observations testify the psychological rationale about the uniqueness of people's non-volitional brain responses, even to the exactly same stimuli, and also imply the feasibility of recognizing an individual through identifying the similarity between the unknown EEG brainwave segment and the reference pattern.

C. Decision Making

We used a simple but effective pattern matching approach, named Euclidean Distance (ED), to assess the similarity level among the unknown EEG brainwave segment and the reference pattern set, for each EEG electrode channel [19]. 10 trails for each subject and each channel from the first test were randomly chosen as the references. 10 trails for each subject

TABLE I
IDENTIFICATION PERFORMANCE OF DIFFERENT APPROACHES BASED ON SINGLE CHANNEL AND FOUR CHANNELS

Stimuli \ Channel	Single Channel				4 Channels		
	Pz	O1	O2	Oz	RBF network	Frequency based	Probability based
Acronyms	47.30%	55.68%	48.38%	53.24%	74.86%	88.65%	90.27%
Illegal Strings	58.92%	58.92%	59.46%	67.57%	78.92%	90.00%	91.62%
Pseudowords	54.32%	55.41%	52.16%	62.70%	71.08%	82.70%	84.05%
Words	47.84%	59.46%	52.43%	67.03%	70.27%	83.24%	86.49%

and each channel from the second test were also chosen. Then the ED method was adopted to make a preliminary decision between the trails and the references. These decisions were fed into the RBF network to build the training model. Another 10 different trails for each subject and each channel from the second test were also chosen to compare against the references, where the preliminary decision results were used as the testing dataset. When the training data and testing data were ready, we used the methods described in section III to evaluate the performance.

D. Experimental Results

Table I presents the accuracy of ED method based on single channels, and RBF network and improved RBF network based on four channels. The multi-channel-fused results are more accurate than the single-channel-based schemes. For example, for the single channel solutions, to identify all the 37 human subjects, the worst accuracy is 47.30% using acronyms and the Pz channel and the best accuracy is 67.57% using illegal strings and the Oz channel. In contrast, using the classic RBF network-based multi-channel fusion method, the worst accuracy is 70.27% using words and the best accuracy is 78.92% using illegal strings. More impressively, based on the proposed improved RBF networks, the best accuracy can reach 90.00% (frequency-based) and 91.62% (probability-based), both using illegal strings. According to the table, identification results based on four channels are much better than the ones based on any single channel, and the improved RBF network shows superior performance advantage, over the classic RBF network. Also, all the results indicate that the accuracy using illegal strings are higher than other visual stimuli.

E. Discussion

In this study, we proposed a new user identification methodological framework using improved RBF neural network approaches, leveraging the non-volitional brain activities which are associated with and reflect people's unique memory and knowledge. In the data collection stage, acronyms, illegal strings, words and pseudowords were presented to the human subjects. The involuntary responses of each individual when reading those stimuli were captured. Although the Oz channel showed stronger distinguishing capability compared with other channels around this region, it is still possible that other channels could make a correct decision while Oz channel was incorrect due to the noises or artifacts introduced during the EEG data collection process. The RBF network saved the possible patterns which have some errors that could happen to be one subject. Next time, when the same pattern is observed, the correct decision could be made. Thus, the RBF network can improve the performance compared with the single-channel scheme. Since the input data in the network were numerically labeled subjects, the regular distance could not represent the differences so well. The proposed methods used the pairs of the same numbers to avoid the problem and thus demonstrated better performance. Among different visual stimuli, illegal strings which were not familiar by people seem to be able to evoke more distinguishable human brain responses, than acronyms, pseudowords and words.

V. CONCLUSION

In this paper we focus on a preliminary study using non-volitional EEG brainwaves as a biometric, based on improved RBF neural networks, to identify 37 human subjects. For the classic RBF network, the accuracy can only reach 78.92%. The frequency-based and the probability-based RBF methods can reach an accuracy of 90.00% and 91.62% respectively. It is observed that illegal strings can evoke more distinguishable brain activity patterns among different individuals and thus lead to better identification accuracy. In general, the multi-channel EEG-based approach using improved RBF networks can achieve a significantly higher identification accuracy than the classic single-channel EEG-based identification method. This study represents an early stage research effort to strategically integrate the results from multiple sources together, which still suffers many limitations and drawbacks. In the future, we will explore more data and other types of visual stimuli and investigate more robust classification approaches.

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