Identity Verification using Resting State Brain Signals

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INTRODUCTION

In the last several decades, computers or automated technologies have been utilized to verify the identity of humans using biometrics (i.e., physical and behavioral characteristics) (Wayman, Jain, Maltoni, & Maio, 2004), as it often surpasses the conventional automatic identity verification measures like passwords and personal identification numbers (PINs) by offering positive human identification. For example, the use of a PIN actually denotes the automatic identification of the PIN, not necessarily identification of the person who has provided it. The same applies with cards and tokens, which could be presented by anyone who successfully steals the card or token. PINs and passwords also have the problem of being compromised by 'shoulder surfing' and people picking the obvious choices. Even the recently proposed graphical passwords share similar problems.

The fingerprint-based biometrics has seen the most extensive deployment (Maltoni, Maio, Jain, & Prabhakar, 2003). Nevertheless, the field of biometrics remains exciting and actively researched after the continuing threats of transaction forgery and security breaches in e-commerce and electronic banking. Further, it is also very useful in other areas such as access to restricted places (control gates) or resources (computer log-in, automated teller machines, digital multimedia data access). As such, other biometrics like signatures (Jonghyon, Chulhan, & Jaihie, 2005), face (Chellappa, Wilson, & Sirohey, 1995), palmprint (Duta, Jain, & Mardia, 2002), hand geometry (Sanchez-Reillo, Sanchez-Avila, & Gonzalez-Marcos, 2000), iris (Wildes, 1997), and voice (Roberts, Ephraim, & Sabrin, 2005) have been proposed as an alternative or to augment the fingerprint technology. More recently, the field of biometrics has seen the emergence of newer biometrics techniques like keyboard dynamics (Bechtel, Serpen, & Brown, 2001), ear force fields (Hurley, Nixon, & Carter, 2005), heart signals (Biel, Pettersson, Philipson, & Wide, 2001), odor (Korotkaya, 2003), and brain signals (Paranjape, Mahovsky, Benedicenti, & Koles, 2001; Poulos, Rangoussi, Chrissikopoulos, & Evangelou, 1999a, 1999b; Palaniappan, 2004).

There are only a small number of reported studies on using brain signals as biometrics, which can further be classified as electroencephalogram (EEG) based or Visual Evoked Potential (VEP) based. The advantage of using EEG- or VEP-based biometrics compared to other biometrics is its distinctiveness—that is, it is difficult to be duplicated by someone else, therefore not easily forged or stolen. The storage is not a problem as the feature vector is of a small size compared to other image-based biometrics.

BACKGROUND

A brief description on some of the previous studies on brain signal biometrics follows. Paranjape et al. (2001) examined the use of autoregressive (AR) coefficients with discriminant analysis that gave classification of about 80% for 349 EEG patterns from 40 subjects. Poulos et al. (1999a) used Learning Vector Quantizer[1] network to classify AR parameters of alpha rhythm EEG, where classification performance of 72-84% were obtained from four subjects with 255 EEG patterns. In another study, Poulos et al. (1999b) utilized this same EEG data and feature extraction method but used computational geometry to classify the unknown EEGs, which gave an average classification of 95%.

In another previous study (Palaniappan, 2004), VEP-based biometrics were proposed. This method was based on using energy of gamma band VEP potentials recorded from 61 channels while the subjects perceived common pictures. Perception of the picture stimulus

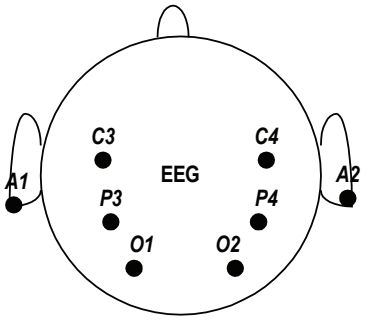
evokes recognition and memory, which involves gamma oscillations, which were distinct between the subjects, thereby being suitable for biometrics.

All these previous studies that used brain signals as biometrics concentrated on identification of a user from a pool of users. In this study, the focus is on verification of a user's claimed identity rather than identification. Further novelty of the proposed methods lies in the use of a two-stage verification procedure that gives good accuracy. It is also easier for the user as it requires only brain signals recorded during resting state, which do not require any degree of mental effort as compared to the requirement of focusing on the recognition of a picture stimulus as in the study in Palaniappan (2004). In addition, the proposed method requires only six channels, as compared to 61 channels as in Palaniappan (2004).

A system to verify the identity will either accept the user claiming a given identity or reject his or her claim. The user is called a client in the former case and an impostor in the latter case. There are two types of errors in this system: false match error (FME) or false non-match error (FNME). The former is the error made by the system when wrongly accepting an impostor, while the latter is the error made when wrongly rejecting the client.

A realistic application scenario for this sort of biometrics would be targeted at small groups of people, where the security would be an utmost important issue—for example, access to classified confidential documents or entry to restricted areas. Fingerprints could be easily forged, and most of the other biometrics like palmprint, face, and iris share the same problem of easy forgery. But it is not easy to duplicate the thought processes in the brain. However, it should be noted that this discussion applies to fraud in the samples, not fraud in the other parts of the system (extracted features, decision, etc.), which has the possibility of fraud for any biometrics.

Figure 1. Electrode placement



EXPERIMENTAL STUDY

Data

EEG data from five subjects were used in this study. The subjects were seated in an industrial acoustics company sound-controlled booth with dim lighting and a noiseless fan (for ventilation). An Electro-Cap elastic electrode cap was used to record EEG signals from positions C3, C4, P3, P4, O1, and O2 (shown in Figure 1), defined by the 10-20 system of electrode placement. The impedances of all electrodes were kept below 5 KΩ. Measurements were made with reference to electrically linked mastoids, A1 and A2. The electrodes were connected through a bank of amplifiers (Grass7P511), whose band-pass analogue filters were set at 0.1 to 100 Hz. The data were sampled at 250 Hz with a Lab Master 12-bit A/D converter mounted on a computer. Before each recording session, the system was calibrated with a known voltage.

In this study, EEG signals were recorded from subjects while performing four different mental activities (shown illustratively in Figure 2), without vocalizing or making any other physical movements. These mental activities were:

a. **Mathematical multiplication activity:** The subjects were given nontrivial multiplication problems. The activities were non-repeating and designed so that an immediate answer was not apparent.
b. **Geometric figure rotation activity:** The subjects were given 30 seconds to study a particular three-dimensional block object, after which the drawing was removed and the subjects were asked to visualize the object being rotated about an axis.
c. **Mental letter composing activity:** The subjects were asked to mentally compose a letter to a friend or a relative without vocalizing. Since the activity was repeated several times, the subjects were told to continue with the letter from where they left off.
d. **Visual counting activity:** The subjects were asked to imagine a blackboard and to visualize