EEG for Automatic Person Recognition

Patrizio Campisi and Daria La Rocca
Università degli Studi "Roma Tre"

Gaetano Scarano
Sapienza Università di Roma

Electroencephalography is potentially more secure and privacy-compliant than traditional biometric identifiers.

Recording human brain activity in the form of electrical signals dates back to 1924, when German physiologist and psychiatrist Hens Berger placed some electrodes on a patient's scalp and by means of a galvanometer recorded the first electroencephalogram.

Since then, research on electroencephalography (EEG) has progressed dramatically, providing a valuable instrument for use in the diagnosis and treatment of spinal cord injuries, strokes, and brain disorders including epilepsy, Alzheimer's disease, schizophrenia, and Parkinson's disease. EEG signals also form the basis of brain-computer and brain-machine interfaces, with both rehabilitative and entertainment applications.

In recent years, interest has grown in also using EEG for biometric recognition.

EEG BIOMETRICS: PROS AND CONS

EEG signals have several advantages over traditional biometric identifiers such as fingerprints and iris and face scans with respect to both security and privacy compliance.

Because EEG signals are produced by ionic current flows within the brain's neurons, they're inherently "secret." EEG-based recognition systems still require privacy-protection mechanisms—once the signals are acquired they can reveal personal health information—but the source of the data isn't exposed to external influences.

In addition, EEG-based biometric systems are robust against sensor spoofing. Unlike conventional biometrics, an attacker can't covertly acquire EEG signals in physical form or synthetically generate them at a later time and feed them to sensors. Also, there's no need for specially designed sensors to provide liveness detection.

Another advantage of EEG-based recognition systems is that they don't exclude people with certain physical disabilities or severe injuries—for example, missing hands, aniridia (absence of the iris), or burned fingers.

Furthermore, the ability to constantly and transparently monitor spontaneous brain activity or responses to cognitive stimuli provides a safeguard against person substitution, to which one-time login verification systems are susceptible.

At the same time, using EEG signals as a biometric identifier has some drawbacks.

First, investigators can't capture such signals at a distance, as they can with iris and face scans, which limits system usability.

Second, EEG acquisition devices are more expensive than the devices used for classical biometrics. Setting them up and operating them is also more intrusive and time-consuming, making them potentially less acceptable in many contexts.

Third, EEG activity is a genotypic characteristic, which limits its uniqueness. In fact, research indicates that there are no significant differences in EEG signals belonging to monozygotic twins.

EEG-BASED RECOGNITION SYSTEMS

A generic EEG-based automatic recognition system consists of an acquisition module that senses a subject's EEG signals, a preprocessing module that removes noise and artifacts from the signals, a feature extraction module that separates the signals' representative elements, and a matching module that generates a

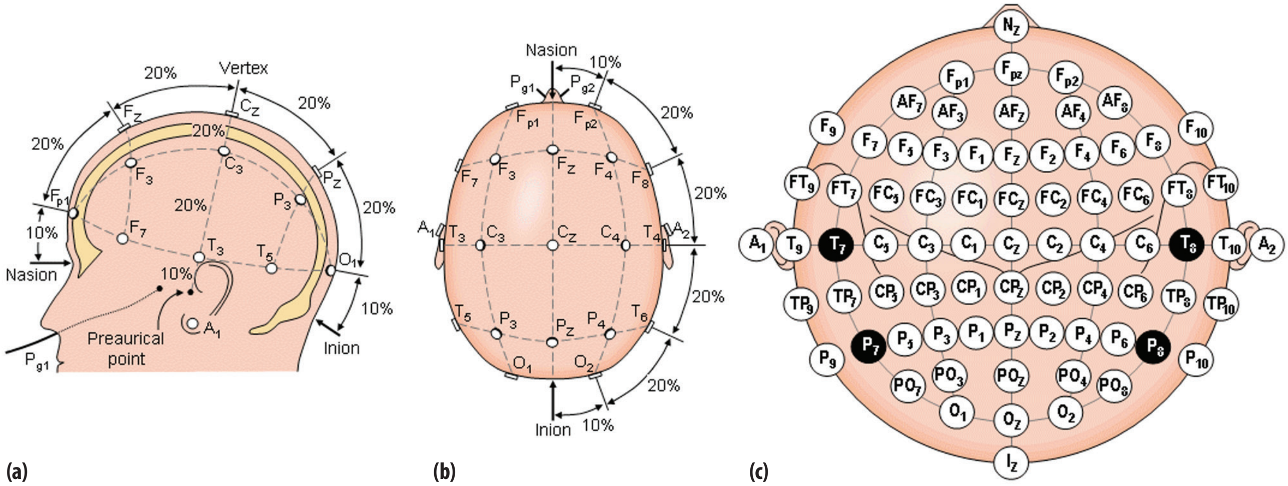

Figure 1. EEG electrode positioning. Arrangement of 21 electrodes, as seen from (a) the left of and (b) above the head, according to the international 10-20 system. (c) A 75-electrode extension of the 10-20 standard that provides higher spatial resolution. The letters F, T, C, P, and O stand for frontal, temporal, central, parietal, and occipital lobes. Even and odd numbers identify electrodes on the right and left hemispheres, respectively, and "z" (zero) refers to electrodes placed on the midline. (Source: J. Malmivuo and R. Plonsey, *Bioelectromagnetism: Principles and Applications of Bioelectric and Biomagnetic Fields,* Oxford Univ. Press, 1995.)

score. The system uses the score to rank the most probable subjects or to make a decision about the subject's claimed identity.

The system can acquire EEG signals during spontaneous brain activity—for example, while the subject is at rest with open or closed eyes. It can also collect the signals in the presence of visual, auditory, or tactile stimuli (including real-world stimuli such as music, speech, or video) or during the execution of real or imagined tasks such as body movements or speech. The signals induced by such stimuli originate in different parts of the brain and vary significantly in bandwidth and amplitude.

An EEG acquisition device consists of a set of amplifiers, a multichannel analogue-to-digital converter, and a set of electrodes, placed on the scalp, that sense the brain's electrical activity. Traditional passive electrodes require the use of conductive gel to reduce the electrode-skin impedance, which can be uncomfortable to the user and takes time to apply, but newer active electrodes with built-in circuitry don't require gel.

Electrode positioning traditionally follows the 10-20 system recommended by the International Federation of Societies for Electroencephalography and Clinical Neurophysiology. The "10" and "20" indicate that interelectrode distance is 10 or 20 percent of the distance between select longitudinal line segments connecting two reference points, the nasion (point between forehead and nose) and the inion (bump at back of skull).

Figures 1a and 1b show a standard 21-electrode arrangement, while Figure 1c shows a 75-electrode extension of the standard that provides higher spatial resolution.

The most relevant cerebral activities fall in the range of [0.5, 40] Hz. There are five main rhythms that can be distinguished within EEG signals: delta (δ), theta (θ), alpha (α), beta (β), and gamma (γ). Table 1 lists the bandwidth range and characteristics of these rhythms, while Figure 2 provides an example of each. EEG signal amplitude is about 100 μV when measured on the scalp and about 1-2 mV when measured on the brain's surface.

Background noise caused by continuous and spontaneous cerebral activity usually contaminates EEG signals and can obscure the electrical effects a cognitive stimulus produces. Signals also contain biological artifacts related to eye movements, the heart beat, muscle activity, and so on. Several techniques can remove such noise and artifacts, including adaptive filtering, principal component analysis, and blind source separation.

STATE OF THE ART

Marios Poulos and colleagues were among the first to experiment with EEG biometrics when in 1999 they presented an automatic person identification system that was based on EEG signals acquired from four subjects in a resting state with closed eyes ("Person Identification Based on Parametric Processing of the EEG," *Proc. 6th IEEE Int'l Conf. Electronics, Circuits and Systems* [ICECS 99], IEEE, 1999, pp. 283-286). The researchers employed the O_2 channel, extracted the rhythm α from the signals, and used autoregressive (AR) modeling and Kohonen's linear vector quantization to model the signals and classify their characteristics.

We recently applied the same protocol to acquire EEG signals from

48 subjects using several electrode configurations (P. Campisi et al., "Brain Waves-Based User Recognition Using the 'Eyes Closed Resting Conditions' Protocol," *Proc. IEEE Int'l Workshop Information Forensics and Security* [WIFS 11], IEEE, 2011; doi:10.1109/WIFS.2011.6123138). We employed AR modeling and polynomial-regression-based classification.

Ramaswamy Palaniappan and Danilo Mandic used visual stimuli consisting of black-and-white drawings of common objects and 61 channels to acquire EEG signals from 102 subjects ("Biometrics from Brain Electrical Activity: A Machine Learning Approach," *IEEE Trans. Pattern Analysis and Machine Intelligence,* Apr. 2007, pp. 738-742). They used a neural network to classify the signals' spectral characteristics.

Sebastien Marcel and José del R. Millán used stimuli consisting of imagined left- and right-hand movements and the channels C_3, C_z, C_4, CP_1, CP_2, P_3, P_z, and P_4 to acquire EEG signals from nine subjects ("Person Authentication Using Brainwaves [EEG] and Maximum a Posteriori Model Adaptation," *IEEE Trans. Pattern Analysis and Machine Intelligence*, Apr. 2007, pp. 743-748). The researchers extracted the rhythms α and β from the signals, modeled them by means of a Gaussian mixture model, and used maximum a posteriori adaptation to classify the signal characteristics.

Katharine Brigham and B.V.K. Vijaya Kumar used 128 channels to record the EEG signals of six people who imagined speaking two syllables, and 64 channels to record the signals of 120 people shown black-and-white images ("Subject Identification from Electroencephalogram [EEG] Signals During Imagined Speech," *Proc. IEEE 4th Int'l Conf. Biometrics: Theory, Applications and Systems* [BTAS 10], IEEE, 2010; doi:10.1109/BTAS.2010.5634515). They employed AR signal modeling and a support vector machine as classifier.

Table 1. EEG signal rhythms.

Rhythm	Bandwidth	Description
Gamma (γ)	[30, 40] Hz	Low in amplitude; can indicate event brain synchronization and be used to confirm some brain disorders.
Beta (β)	[13, 30] Hz	Indicates an alert state, with active thinking and attention.
Alpha (α)	[8, 13] Hz	Indicates a relaxed state, with little or no attention or concentration.
Theta (θ)	[4, 8] Hz	Indicates creative inspiration or deep meditation; can also appear in dreaming sleep (REM stage).
Delta (δ)	[0.5, 4] Hz	Primarily associated with deep sleep or loss of body awareness, but can be present in the waking state.

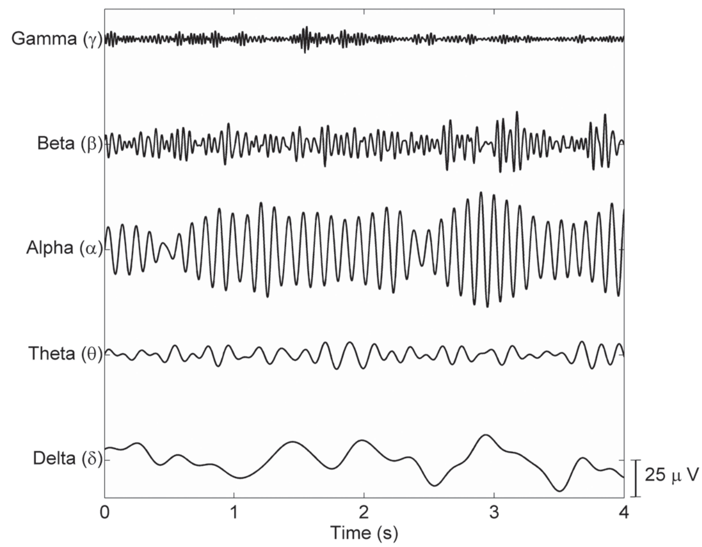

Figure 2. Example EEG signals acquired during a rest state with closed eyes.

Current user recognition systems rely on a subject's physical attributes or behavior. Preliminary studies have demonstrated that using EEG signals as a biometric identifier is potentially more secure and privacy compliant.

Researchers must overcome several challenges before a practical EEG-based person recognition system can be deployed. These include identifying the stimuli that produce the most discriminant mental signatures in EEG signals, optimizing the electrode configuration to minimize subject inconvenience while guaranteeing superior performance, and assessing signal stability over time for the same subject and signal discriminability for different subjects. ■

Patrizio Campisi *is a professor in the Department of Applied Electronics at Università degli Studi "Roma Tre." Contact him at campisi@uniroma3.it.*

Daria La Rocca *is a PhD student in the Department of Applied Electronics at Università degli Studi "Roma Tre." Contact her at dlarocca@uniroma3.it.*

Gaetano Scarano *is a professor in the Dipartimento di Ingegneria dell' Informazione, Elettronica e Telecomunicazioni at Sapienza Università di Roma. Contact him at gaetano.scarano@uniroma1.it.*

Editor: Karl Ricanek Jr., director of the Face Aging Group at the University of North Carolina Wilmington; ricanekk@uncw.edu