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MULTIMODAL FUSION MODELS FOR EEG BIOMARKER RECOGNITION IN COGNITIVE NEUROSCIENCE APPLICATIONS

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Abstract:
The growing reliance on biometric authentication in security-critical applications has exposed limitations in conventional modalities such as fingerprints, facial recognition, and iris scans—particularly their vulnerability to spoofing and limited capacity for verifying user liveness. This has prompted the search for more secure and intrinsic biometric traits. EEG signals, generated by the brain's electrical activity, offer a novel and promising solution due to their uniqueness, difficulty to replicate, and dynamic nature under cognitive stimulation. The ability to use mental tasks to evoke person-specific electrophysiological patterns presents an opportunity to develop authentication systems that are both highly secure and resilient to impersonation attacks. This research is motivated by the potential of integrating EEG biometrics with advanced machine learning techniques to create a robust, spoof-resistant identity verification framework suitable for real-world, high-security environments.

Keywords: EEG-Based Biometric Authentication, Personal Identity Verification, Spoof-Resistant Authentication, Electrophysiological Patterns, Brainwave Biometrics, Feature Extraction, Deep Learning Classification, Secure Biometric Systems.

Introduction

Electroencephalography (EEG) captures the electrical activity of the brain non-invasively using scalp electrodes and extracts characteristic neural rhythms that are good signatures of subject neurophysiology suitable for recognition purposes. Placed against the drawbacks of traditional biometric such as fingerprints, face, and voice—whose public nature makes them vulnerable to presentation attacks—EEG provides a hidden alternative based on biological brain activity that makes it inherently more difficult to counterfeit and appealing to safe authentication applications.

EEG-based biometric systems are normally structured as a pipeline that includes signal acquisition, prepossessing, feature extraction, and classification, through which identity-discriminative information is extracted from spectral and spatio-temporal brain activity patterns. Current works increasingly utilize deep learning to enable automatic robust representation learning with diminished dependence on hand-crafted features and enhanced resistance to noise and session variation, thus enhancing both verification and identification performance in real-world implementations.

Beyond technological innovation, the appeal of EEG biometrics is complementing cybersecurity with protection by an internal and dynamic modality well suited to schemes today as part of multi-factor authentication. In contrast to static external features, EEG signals may also accommodate continuous or challenge-response authentication, further increasing the barrier for spoofing and identity theft. As the technology progresses further, researchers aim for end-to-end models combining preprocessing, feature learning, and decision-making all as one framework, thus simplifying user interaction and minimizing set-up time. This strategy pairs EEG's latent-based character with the modern need for frictionless but extremely secure authentication, thus positioning EEG as a promising cornerstone of future systems for identifying oneself that combine privacy, usability, and stringent defense against cyber attack.

Literature Review

A discovery of EEG by Richard Caton in 1875 had shown that there was fluctuating electrical activity on the surface of the mammalian cerebral cortex (rabbit). A few years later in 1929, Hans Berger, a German physiologist, recorded for the first-time electrical signals from the brain by placing electrodes on the brain [1, 2].

In 1937, Berger continues his work on the nature of alpha and beta waves in the human cortex. He also observed that signals from the brain were dependent on the general mental state of the subject (attention, relaxation or sleep) [2]. After that his work is marked and is used in many more applications like controlling a wheelchair, driving a drone, or moving car, smart home automation, neuroscience application like brain computer interface.

Sr no.	Paper name	Author name, publication & year	Summary of the paper	Research gap
1	Survey of EEG-based Biometric Authentication	Isuru Jayarathne & Michael Cohen, Senaka Amarakeerthi, 2017 IEEE 8th International Conference on Awareness Science and Technology	Comprehensively reviews EEG-based authentication methods including preprocessing, feature extraction, and classifier design. Highlights CNN, RNN, and hybrid deep models improving accuracy over handcrafted features.	Lack of standardized datasets and cross-day evaluation protocols limits real-world generalization.
2	Verifying a Person's Identity Using Brain Responses to Visual Stimuli	Denise Kerbaj1, Walid Hassan, Amine Nait-Ali1	Explores event-related potential (ERP)-based EEG verification using visual stimuli as a biometric trigger. Demonstrates high	Scalability to passive conditions and large populations remains unexplored.

			accuracy in small controlled groups under task-driven conditions.	
3	Hidden Biometrics: Using Biosignals and Biomedical Images for Security Applications	Amine Nait-Ali, 2011 7th International Workshop on Systems, Signal Processing and their Applications	Introduces hidden biometrics, positioning EEG as a secure, non-visible biometric resistant to spoofing and replay attacks.	Requires validation of multimodal and real-world implementations to confirm robustness.
4	Artifact Removal in Physiological Signals: Practices and Possibilities	Sweeney et al., 2011, IEEE Reviews in Biomedical Engineering	Reviews adaptive filters, ICA, and wavelet-based methods for EEG artifact removal. Compares effectiveness for motion, ocular, and muscle noise suppression.	Few approaches validated under real-time or low-cost device constraints.
5	Removal of Artifacts from EEG Signals Using Adaptive Filter Through Wavelet Transform	Kumar et al., ICSP2008 Proceedings	Proposes hybrid LMS and wavelet adaptive filtering for EEG artifact removal, improving signal-to-noise ratio with low computational cost.	Requires large-scale biometric evaluation and cross-session reproducibility tests.
6	Wavelet-Based Ocular Artifact Removal from EEG Signals Using ARMA and Adaptive Filtering	Kumar et al., 2009 IEEE	Combines ARMA and adaptive filters for blink and eye-movement artifact suppression without auxiliary sensors.	Limited validation on diverse datasets; generalization remains open.
7	Removal of Artifacts from EEG Signals using Adaptive Filter through Wavelet Transform	Daly et al.,ICSP2008 Proceedings	Employs ICA with accelerometer correction to mitigate head-motion artifacts in EEG recordings for improved	Dependent on additional hardware; scalability to consumer setups uncertain.

			biometric consistency.	
8	Challenges in EEG Data Collection for Biometric Systems	Puce & Hämäläinen, 2018, Brain Sciences	Discusses practical issues in EEG data acquisition—variability, noise, and environment—affecting biometric repeatability.	Lack of standardized acquisition protocols and environment normalization.
9	I Think, Therefore I Am: Usability and Security of Authentication Using Brainwaves	Chuang et al., 2013,	Examines user comfort, security trade-offs, and feasibility of EEG-based authentication systems for daily use.	Cross-day permanence and session variability not sufficiently addressed.
10	Analysing the Robust EEG Channel Set for Person Authentication	Altahat et al., 2015, Frontiers in Neuroscience	Identifies minimal channel subsets providing robust person identification, optimizing electrode placement for portable devices.	Needs validation across larger, multi-session datasets to ensure permanence.
11	BrainID: Development of an EEG-Based Biometric Authentication System	Jayarathne et al., 2016, IEEE Access	Develops BrainID, a full pipeline combining CSP and LDA for person authentication using cognitive tasks. Achieves reliable within-session accuracy.	Device and inter-session variability affect permanence; requires broader benchmarking.
12	Brainwaves as Authentication Method: Proving Feasibility Under Two Different Approaches	Blondet et al., 2024,IEEE	Evaluates two EEG authentication paradigms—task-based and resting-state—showing both feasible for user identification.	Cross-day reliability and scalability to real-world conditions remain underexplored.

13	Low-Cost EEG-Based Authentication	Ashby et al., IEEE EMBS Conference on Neural Engineering Cancun, Mexico, 2011	Implements authentication using inexpensive consumer-grade EEG with AR and PSD features, achieving competitive accuracy.	Noise sensitivity and lack of standard datasets limit deployment consistency.
14	In-Ear EEG Biometrics for Feasible Real-World Authentication	Nakamura et al., 2018, IEEE Transactions on Information Forensics and Security	Presents in-ear EEG setup enabling discreet and continuous biometric verification with high user comfort.	Requires longitudinal testing and hardware miniaturization studies for scalability.
15	A survey of emerging biometric modalities	Sushil Chauhana, A.S. Arorab, Amit Kaul,ICEBT ,2010	Studies show ECG and lip prints can aid in human identification. ECG is secure but needs wider testing; lip prints need more validation. Combining them with other biometrics can improve accuracy and usability.	Research Gap: ECG and lip print biometrics lack large-scale validation and consistency studies across different conditions. Further research is needed to confirm their reliability and integration into multimodal systems.
16	A Novel Approach to Brain Biometric User Recognition	Reshmi K.C.1, Ihsana Muhammed P., Priya V.V., Akhila V.A,RAEREST 2016	Brain biometrics use brain signals for user recognition and offer high reliability due to their uniqueness, resistance to spoofing, and continuous identification. They are also applied in lie detection, crime analysis, and detecting memories	Brain biometrics need more studies on signal stability, large-scale testing, and practical implementation to ensure accuracy and usability in real-world security systems.

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			of specific events, making them more secure than traditional biometrics.	

Problem Statement:
To demonstrate a secure and spoof-resistant alternative to traditional biometrics, through EEG-based personal identity verification using brainwave patterns evoked during mental tasks. Design and test an effective EEG- coupled individual authentication measure biometric performance indices (FAR, FRR, EER) on controllable but repeatable protocols.
Objectives:

- To Design a standard acquisition protocol on Emotiv-class equipment in compliance with the 10-20 system and task design adequate to deliberate EEG biometrics.

- Apply strong artefact mitigation (band/notch filters, eye blinks) to accommodate near real- time application.

- To Benchmark feature sets using light-weight classifiers (SVM) and present FAR, FRR and EER.

- To Evaluate cross-session performance through repeatable train/test splits and track documentation.

Project Requirement
Human resources: Sample Size: 10-15 participants. Inclusion Criteria: Healthy individuals aged 18–50.
Exclusion Criteria: Neurological disorders or use of medication affecting brain activity.
Software requirement
software: Python (with MNE, SciPy, scikit-learn, TensorFlow)

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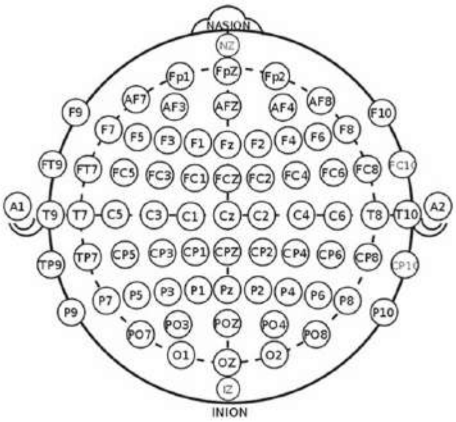
Hardware requirement

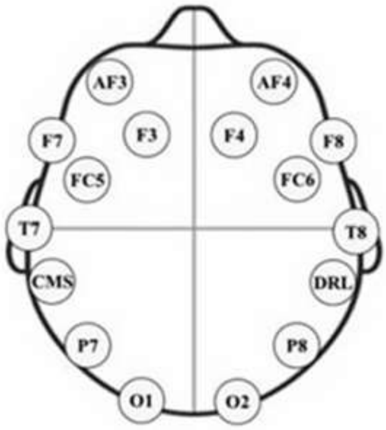
The Emotiv EPOC^{X} uses 14 active EEG channels positioned according to the electrode placement system. These positions correspond to specific regions of the brain, allowing the headset to capture electrophysiological activity from different functional areas.
Additionally, it includes two reference electrodes (CMS/DRL) that help improve signal quality.
CMS / DRL (Reference System)

- **CMS (Common Mode Sense):** Acts like a reference electrode, measuring the common voltage of all active electrodes.
- **DRL (Driven Right Leg):** Works together with CMS to cancel out electrical noise (especially 50/60 Hz power-line interference).
- In the EPOC^{X}, these are located at P3/P4 (behind the ears, M1/M2 mastoid locations).

Electrode	Brain Region	Function
AF3, AF4	Frontal (anterior)	Attention, working memory
F7, F8	Lateral frontal	Language (F7), emotion/behavior (F8)
F3, F4	Frontal cortex	Motor planning, cognition
FC5, FC6	Fronto-central	Problem-solving, motor imagery
T7, T8	Temporal lobes	Auditory, speech, memory
P7, P8	Parietal lobes	Spatial awareness, sensory integration
O1, O2	Occipital lobe	Visual processing
CMS/DRL	Reference (P3/P4/M1/M2)	Noise reduction & signal stabilization

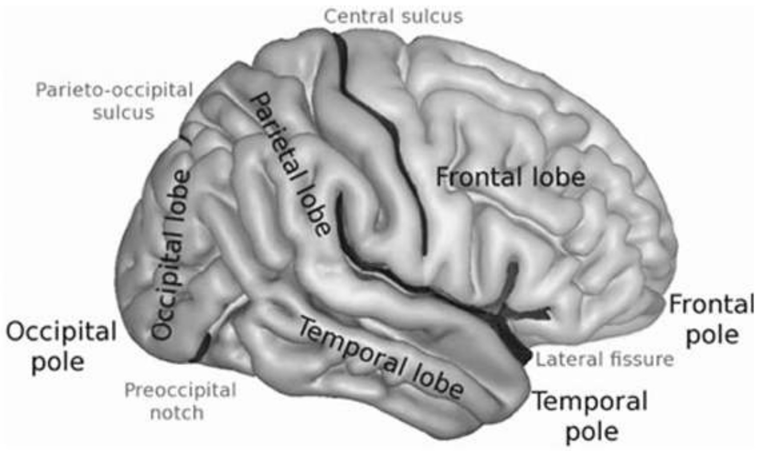
F-frontal, T-temporal, C-Central, P-parietal, O-occipital





The brain is composed of two parts called cerebral hemispheres. Each hemisphere is divided into four parts (see Fig.) called lobes. Each lobe has a role to play.

1. The frontal lobe, which occupies an important place in the brain, is responsible for resonance, problem solving, movement control, planning, and control of voluntary movements
2. The temporal lobe is involved in the processing of language, memory and the auditory system functions
3. The parietal lobe is intervening in the treatment of sensory information
4. The occipital lobe which allows the recognition of shapes, colors and visual in for mation.



Methodology

EEG Aquisation

Electroencephalography (EEG) recording is the most important initial step in obtaining brain activity for biometric identification. EEG signals are captured non-invasively by electrodes applied to the scalp in accordance with the international 10–20 system, which provides for consistent electrode placement between and among subjects and experiments. For this research, a commercial, portable, user-friendly EEG device, the Emotiv EPOC, was utilized. This headset consists of 14 channels (AF3, F7, F3, FC5, T7, P7, O1, O2, P8, T8, FC6, F4, F8, AF4) and two reference electrodes (CMS and DRL), which provide for the stable recording of brain activity related to cognition and motor activities.

The Emotiv EPOC samples at 128 Hz, adequate for capturing brain rhythms through the principal frequency bands (delta, theta, alpha, beta, and low gamma). Subjects were engaged in a battery of cognitive and motor imagery tasks intended to create discrete neural responses during data acquisition. For instance, the protocol contained basic tasks like opening and closing the eyes for 15 seconds in three repetitions and more complex cognitive actions like imagery of hand movements, object manipulation, or calculating numbers. The tasks were given with brief inter-trial intervals and were cued by visual images to maintain consistency between subjects.

The subjects in this experiment were 10 healthy volunteers between the ages of 18 and 50, without neurological disorders or medication that would influence brain activity. Subject artifacts were minimized by having subjects sit in a quiet room, being told to be still, and not to speak when recordings were being made. EEG signals collected usually spanned 0.5 to 50 Hz, which corresponded to the effective frequency range of human brain rhythms.

Signal quality is very noise-sensitive, especially from eye blinks, muscle activity, and electrode motion. To combat this, a band-pass filter (0.5–50 Hz) was used to eliminate unwanted low-frequency drifts and high-frequency noise. In addition, Independent Component Analysis (ICA) was utilized to separate and eliminate ocular and muscular artifacts. After which, the data were normalized using Z-score or min-max normalization between channels and time to maintain consistency prior to feature extraction.

The preprocessed EEG signals were subsequently available for downstream processing, i.e., feature extraction and classification. The acquisition protocol, involving controlled experimental conditions, standardized electrode placement, and meticulous preprocessing, provided high-quality EEG data appropriate for biometric authentication experiments

Data Pre-processing

Raw EEG signals acquired from the scalp are normally contaminated with a range of noise and artifacts from various sources and therefore obscure meaningful neural activity. Adequate preprocessing is therefore a necessary first step in optimizing signal quality and conditioning the data for reliable feature extraction and classification. For this work, preprocessing was especially designed to counteract the special problems of EEG data, such as its low amplitude, susceptibility to external artifacts, and sensitivity to confounds of a biological nature.

All preprocessing began with band-pass filtering. A 0.5–50 Hz band was used to eliminate slow drifts caused by movement of the baseline and high-frequency noise unrelated to brain function. This preprocessing step did not eliminate the major EEG rhythms of interest, such as delta, theta, alpha, and beta, for cognitive and motor tasks.

Afterward, data was put through an artifact removal process to remove non-neural contributions that might compromise analysis. Eye blinks, eye movements (electrooculographic), and muscle movements (electromyographic) are the most prevalent artifacts. To reduce these interferences, Independent Component Analysis was utilized. It decomposes the compounded EEG signals into statistically independent components so as to be able to identify and reject those for the ocular and muscular artifacts and keep real brain activity.

After removal of artifacts, the signals underwent normalization to ensure within participant and within-recording-session consistency. Both min-max scaling and Z-score normalization were utilized to standardize the range of amplitudes of the signals across all trials and all channels. It not only decreased inter-subject variability but also enhanced the accuracy of subsequent machine learning models by having all of the features contribute equally both during training and classification. In addition, preprocessing procedures of the EEG data also took place under a controlled condition to minimize external interferences. Recording procedures also occurred in a quiet room and participants sat comfortably to minimize head and body movements. These procedures eliminated any chance of shifts of electrodes or extraneous environmental noise affecting EEG recording quality.

The resultant final preprocessed dataset thus included clean, normalized EEG signals, void of prominent noise and associated artifacts, and conditionally optimized for subsequent feature extraction. Through an integration of filtering, correction of artifacts, and normalization procedures, the preprocessing pipeline provided a solid groundwork for efficient biometric verification using EEG signals.

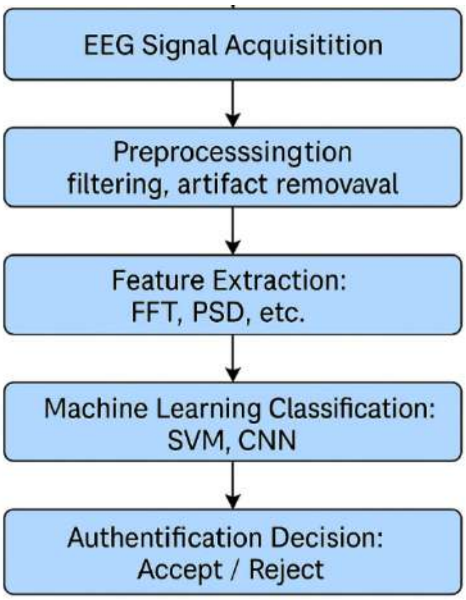
Feature Extraction

Once preprocessing of EEG data to remove noise and artifacts is performed, feature extraction follows, including transforming raw data to a concise and discriminative representation to be classified further. Because EEG signals are complex, non stationary, and varying from person to person, feature selection becomes essential to achieve accurate biometric verification.

The feature extraction for this project was concerned with the spectral and spatial structure of the EEG time series. There was a time series for each Emotiv EPOC headset channel from which useful patterns were extracted continuously. To first capture information within the prominent EEG bands of delta (0.5–4 Hz), theta (4–7 Hz), alpha (8–13 Hz), beta (14–30 Hz), and low gamma (>30 Hz), the frequency components of the time series were extracted. These are well-recognized rhythms for conveying cognitive states of motor imagery, relaxation, and alertness, and are strongly distinctive for varying subjects.

Aside from spectral measures, statistical parameters such as mean, variance, and standard deviation of the signal intensity and time variability were computed for every channel to define the signal intensity and time variability. Such simple and powerful measures help to characterize inter-individual variations in brain function. To further enhance spatial resolution, localized areas of electrodes had quantities extracted for them, with some of the techniques grouping electrodes in localized geodesic disks of various radii around electrode centers. This allowed for study of both localized and extended function of the brain. These extracted features were then summed to form feature vectors of every trial or task performed by participants. Each feature vector included the participant's neural response pattern, in essence a unique biometric "signature." To facilitate consistent comparison, the participant's feature vectors and across-session feature vectors were normalized so as to mitigate variability due to recording condition or electrode placement.

The last feature set was a combination of channel-wise frequency power, statistics, and spatial patterns, and it provided an enriched description of brain activity. These features acted as inputs for machine learning classifiers such as Support Vector Machines (SVM) to discriminate between people. Making use of both time- and frequency-based information, the step of feature extraction permitted us to construct a discriminative and dependable model for EEG biometric verification.



Machine Learning Classification and Matching

The next step after extracting the features was to utilize machine learning algorithms for biometric comparison and classification of EEG signals. This converts the extracted features to a decision-making process in such a manner to separate a person from somebody else with a high degree of accuracy.

For this work, Support Vector Machines (SVM) served as the underlying classification scheme. SVM is a good choice for EEG-based biometrics because it deals well with high dimensional information and is capable of discriminating complex, non-linear structures. Using kernel functions, SVM forms an optimal decision boundary between feature vectors of various subjects with a maximum margin and increasing generalizability across participants.

At training time, EEG feature vectors from a participant were utilized to create individualized models. Features of each participant were saved as a reference template of an individual's own unique neural signature. Cross-validation procedures for robustness were also utilized, wherein data from a single session were training and different sessions were being held for test purposes. This was to avoid overfitting and to ensure the classifier was capable of clearly identifying unseen data.

For matching, two measures were simultaneously applied on the classification model: cosine similarity and Euclidean distance. These similarity measures examine to what degree a new feature vector is similar to the participant's template stored. Cosine similarity determines the angle between feature vectors, focusing on similarity of pattern irrespective of amplitude, whereas Euclidean distance determines the absolute magnitude difference of vectors. Both provide each other mutually complementing insights on how to evaluate similarity of EEG pattern. Authentication process adopted a two-step protocol. In the first step, at enrollment time, EEG of each participant was captured, cleaned, and saved as feature templates. In the second step, at verification time, a participant's fresh EEG was fed to the same pipeline and its feature vector was matched against the template. A decision was taken on classification output and similarity values, wherein a high match verified the participant's identity.

This classification and matching scheme using machine learning enabled the system to reliably distinguish real users from imposters. Through a balance of efficient classifiers and similarity-based matching, the method provided a reliable and accurate EEG-based biometric verification method.

Conclusion

In the state of the art, we have seen that different approaches have been used to address the authentication. Using EEG signals is the approaches can be different on the choice of number of electrodes used, on the pre-processing, on the feature extraction method and/or on the model used for the classification. EEG provides an answer to many applications. We can also observe that the work that has been conducted to date gives very high accuracy. However, the observation that we must take into consideration is the lack of enough dataset available on this modality. It could allow a real comparison of the different approaches on the authentication based on the EEG.

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