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A Review of EEG-Based Face Recognition: Methodologies, Feature Extraction Techniques, and Classification Methods

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This review explores EEG-based face recognition, focusing on methodologies, feature extraction techniques, and classification methods. Recognizing familiar and unfamiliar faces is crucial for social interaction, with EEG capturing brain activity to provide objective insights. Critical neural responses like N170, P300, and P600 are discussed in terms of their role in face recognition. The review highlights traditional machine learning approaches, alongside advanced deep learning techniques. Despite advancements, challenges such as signal noise, individual variability, and limited dataset sizes persist. Future research directions include improved noise reduction, personalized models, and data augmentation, aiming to enhance the accuracy and applicability of EEG-based face recognition systems.

Keywords: *Familiar Face, EEG, Face Recognition*

1. Introduction

One of the most basic components of human communication and social interaction is the ability to recognize familiar and unfamiliar faces. The ability to recognize familiar individuals based on their facial features is crucial for social interactions, influencing how individuals greet, convey emotions, and engage with others. On the other hand, the failure to identify faces or the intentional act of pretending to not recognize someone might have important consequences in many situations, such as criminal inquiries and social exchanges. Objective classification of both familiar and unfamiliar faces can be beneficial in various areas such as crime detection, lie detection, and the diagnosis and treatment of mental disorders like Autism Spectrum Disorder (ASD) [1-3].

Electroencephalography (EEG) is a powerful tool that directly measures the electrical activity of the brain during face processing and recognition. This technique offers a potential means of discriminating an individual's familiarity with specific faces, providing objective and less easily countered results compared to self-report methods. EEG-based face recognition research has identified several neural responses associated with familiar and unfamiliar faces, such as event-related potentials (ERPs) like N170, P300, and P600 [4]. The N170 component, peaking around 170 milliseconds after the onset of a face stimulus, is particularly sensitive to the presence of faces and is thought to reflect the early stages of face perception. The P300 component, peaking around 300 milliseconds post-stimulus, is associated with the cognitive processes involved in recognizing familiar faces and is more pronounced in response to familiar faces compared to unfamiliar ones. The P600 component, with a peak latency of 600 milliseconds or later, is linked to higher-order cognitive processes and has been observed in tasks requiring complex facial recognition.These components reflect different stages of cognitive processing during face recognition and can be used to distinguish between familiar and unfamiliar faces. In other words, the ERP method measures the electrical energy of the brain that is recorded through electrodes that are embedded in a fabric cap that fits snugly on the head. Among various sensory modalities, such as auditory and visual modalities, the visual modality is the most commonly used sensory modality for person identity processing with what is known as the visual ERP, which is associated with the steady-state VEP (SSVEP) recorded at checkerboard flicker frequencies [5]. There have been review articles on the visual ERP in face perception tasks and facial identity processing, but the review of the visual ERP in person identity processing has not been integrated. The present review aims to rectify this and places major emphasis on understanding person identity processing, especially with respect to previous knowledge.

Identification of a person with whom one has prior experience and acquaintance, i.e., familiar face recognition, has long been known to be better than that of a randomly selected person from the same age, race, and gender category, i.e., unfamiliar face recognition. This is true whether the stimulus is visual or auditory, and is true of old faces as well as young ones. This is likely to be due to the fact that, in a majority of cases, both familiar voice and face will co-occur when we see a known person. The other reason could be that being able to identify visual and auditory attributes specific to a person's identity, e.g., facial identity and voice, respectively, is of paramount importance for an individual's survival, e.g., recognizing known faces, kin, friends, family, and enemies as well as known voices such as called personal contacts, spouse, offspring, parents, and siblings, etc. Thus, an understanding of the processing of known or familiar faces is not only of interest in its own right, but also serves as a model for understanding the processes that make this important function possible [6-9].

Recent advancements in machine learning and neural network technologies have significantly enhanced the analysis and classification of EEG signals. Traditional machine learning methods have achieved varying degrees of success in classifying EEG data related to face recognition tasks. For example, wavelet features and Fisher's linear classifier, as well as differential entropy features and support vector machines (SVMs), have been employed to classify familiar and unfamiliar faces with moderate accuracy [10]. However, these methods often lack generalizability across subjects and rely on limited datasets. Deep learning approaches, particularly convolutional neural networks (CNNs), have shown great promise in improving the classification performance of EEG-based face recognition systems [11].

The development of robust EEG-based face recognition systems involves addressing several challenges. One major challenge is the class imbalance in training data, which can affect the performance of the model and various artifacts, which can arise from spontaneous electrical signals, environmental factors, or activities generated by the subject. Techniques such as weighted loss functions and appropriate sampling strategies can help mitigate this issue. Another challenge is the limited size of training datasets, which can hinder the generalizability of the models. Collecting large and diverse EEG datasets is essential for training models that can perform well across different subjects and conditions [8-10]. Cross-subject validation is another critical aspect of EEG-based face recognition research. Many studies have reported high classification accuracies within a single subject but have struggled to achieve similar performance across different subjects. Cross-subject validation ensures that the models are not overfitting to the specific characteristics of individual subjects' EEG signals and can generalize to new, unseen subjects. This is crucial for practical applications where the system needs to perform reliably across a wide range of individuals [10].

This review aims to provide a comprehensive overview of the current state of EEG-based familiar and unfamiliar face recognition, focusing on the methodologies, feature extraction techniques, and classification methods reported in recent studies. By synthesizing findings from various research efforts, this paper seeks to highlight the progress made in this field and identify areas for future research and development. The review will cover different experimental paradigms used in EEG-based face recognition, the types of features extracted from EEG signals, the machine learning and deep learning methods employed for classification, and the challenges and future directions in this area of research.

The primary motivation to review EEG studies is that, despite less spatial and temporal resolutions compared to fMRI and MEG, EEG has many potential advantages, which could make it a more favorable technique for pattern recognition, brain-computer interface, and cognitive models of face processing studies. These potential advantages include (1) a more favorable temporal resolution (less than a millisecond), (2) a less costly technique, and (3) portable. Furthermore, the contributions of this study are the development of a face stimuli classification benchmark for a conventional pre-trained base model and the demonstration of application-specific recommendations to improve the deep learning model's adoption process for different models and classification strategies.

The remainder of this paper is organized as follows. In Section 2, we present the experimental paradigms in EEG-based face recognition. Section 3 gives a review of general feature extraction techniques from EEG signals and face recognition challenges. The comprehensive analysis of the deep learning model performance is provided in Section 4. In Section 5, the observation of the findings, model comparisons, and guidelines are discussed. Finally, we conclude this study and present our ongoing and future directions in Section 6.

2. Experimental Paradigms in EEG-Based Face Recognition

The term familiarity is defined by the age of view of an individual as old, new, or one-seen (e.g., view of two pictures of an individual at two different ages). Therefore, to assess the underlying cognitive processes linked with familiar face recognition and unfamiliar face processing, extensive manipulations of the familiarity of the participants with the individuals whose face images are displayed is important.

The use of experimental paradigms represents the first and one of the major decisions to be made when designing an EEG experiment. In this section, studies on different EEG-based experimental paradigms are reviewed and compared based on familiarity vs. unfamiliarity and the number of face stimuli. The application of experimental paradigms carries through and results in clinical diagnosis for developmental prosopagnosia and neuropsychiatric disorders accompanying impaired face recognition. These experimental paradigms are not in the scope of this review but are of great interest to related concerns. Major experimental paradigms for both familiar and unfamiliar face recognition are reviewed in the rest of this section.

2.1. Event-Related Potentials (ERPs)

The event-related potential (ERP) method is a stable way to analyze brain activity for familiar and unfamiliar faces. It involves time-locked stimulus display and consists of the superposition of ERP components. ERP waveforms are separated into multiple positive or negative components, including P1, N170, N250, and P600. A thorough investigation of ERP signals for face perception involves determining changes in the ERP components for different types of face stimuli. Among these components, the N170 ERP component has shown adaptation and peak latency elongation effects in studies of overall form match tasks. N170 is a face-sensitive neural composite that consists of multiple double-peak negative components over the posterior portion of the scalp at approximately 170 ms after stimulus onset. It originates in the brain's occipitotemporal regions, near the occipitotemporal sulcus's overlapping.The other component, N200, is an ERP component that is locked to the match/non-match memory comparison for face stimuli. It emerges at approximately 200 ms after stimulus onset and indicates the retrieval of face-specific memory regardless of familiarity. P1 is an early positive component that emerges at around 125 ms after stimulus onset during face compared to a frame detector task. The P1/N170 complex has been extensively studied in normal face recognition mechanisms, including face perception, facial expression recognition, and holistic or configural processing of faces.

Standard ERP paradigms involve presenting participants with a series of familiar and unfamiliar faces while recording EEG responses. These paradigms help identify specific ERP components associated with face recognition. Podvigina and Prokopenya, for instance, examine EEG patterns related to the recognition of familiar and unfamiliar faces and words. Key findings reveal that the N170 component shows a higher amplitude for familiar faces, indicating early-stage familiarity recognition. The N250 component, observed in the 200-300 ms time window, is greater for unfamiliar stimuli, suggesting familiarity modulates this response. The N400 component, recorded in the 350-450 ms window, is more pronounced when participants focus on words, highlighting the influence of semantic processing and familiarity. The study involved 26 participants aged 19-35, who were presented with combined images of faces and words. EEG data were recorded and analyzed in specific time windows, concluding that familiarity significantly affects early and mid-latency ERP components (N170 and N250) and that semantic processing (N400) is more influenced by task type than stimulus modality [12]. The study is marked by a detailed methodology, employing a robust experimental setup with well-defined EEG recording protocols and analysis windows, which ensures reliable data collection and interpretation. Moreover, it identifies significant ERP components (N170, N250, and N400) influenced by familiarity, thereby contributing to the understanding of the temporal dynamics of face and word recognition. However, the study has limitations, including a small sample size of only 26 participants, which may restrict the generalizability of the findings. Additionally, task-specific instructions given to participants to focus on either faces or words might introduce task-related biases. Lastly, the use of Russian words limits the applicability of the findings to other languages and cultures.

In contrast Caharel and Rossion examine the N170 component of the human electroencephalogram (EEG) and its sensitivity to the long-term familiarity of face identities. The N170, a deflection peaking at approximately 170 milliseconds over the occipito-temporal cortex after the onset of a face stimulus, reflects perceptual awareness of a face. This study reviews 45 published studies comparing N170 responses to familiar and unfamiliar faces. Despite some inconsistencies, it finds that familiarity, particularly with personally familiar faces learned in natural conditions, significantly increases the N170 amplitude. This familiarity effect emerges between 150 and 200 ms, challenging the traditional neurocognitive models that distinctly separate perceptual and memory stages in face recognition. The study highlights that recognizing a face's familiarity may begin as early as the perceptual stage, suggesting that structural encoding for faces is influenced by previous experiences with specific facial identities. However, the review notes inconsistencies regarding the N170's sensitivity to familiarity, indicating a need for further research to resolve these discrepancies [13].

Meanwhile, figure 1 illustrates the grand average ERP waveforms elicited by various stimulus categories at occipito-temporal electrode sites. The figure includes data adapted from several studies: (A) Bentin et al. (1996), (B) Rossion and Jacques (2008), and (C) Rossion and Caharel (2011). The N170 component is consistently more pronounced in response to face images compared to other categories, and it is almost absent for meaningless stimuli. This face-selective response occurs shortly after stimulus onset, around 120–130 ms, and typically remains within this time window until about 200 ms [14-16].

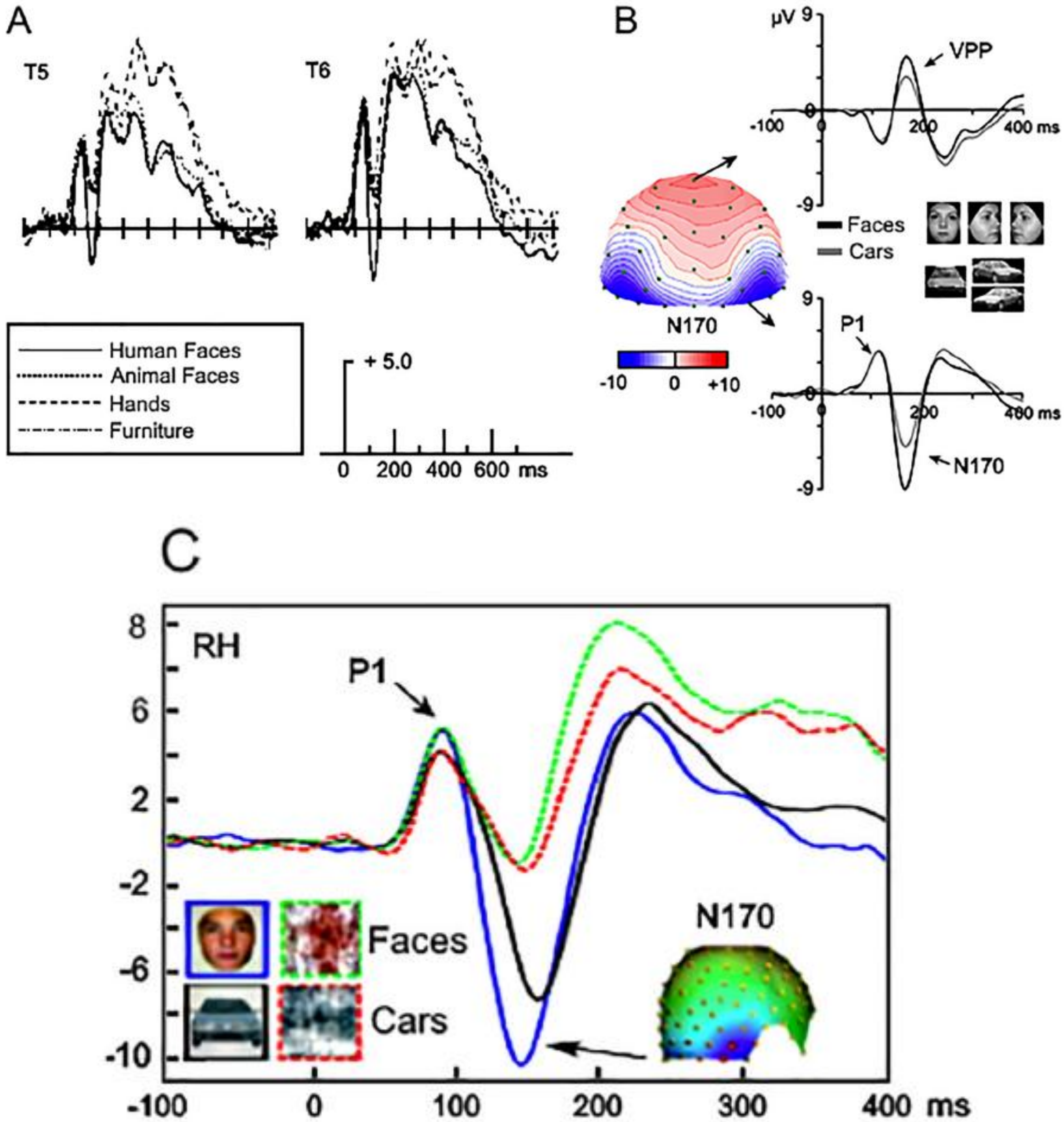

Fig. 1. Grand average ERP waveforms observed at occipito-temporal electrode sites in response to various categories of stimuli. The figures were derived from the research conducted by Bentin et al. (1996), Rossion and Jacques (2008), and Rossion and Caharel (2011) [14-16].

Moreover, Huang et al. investigate the cognitive processes underlying the recognition of familiar faces using event-related potentials (ERPs). The research focused on distinguishing between familiar and unfamiliar faces through various cognitive stages, identifying significant familiarity effects (FFEs) on ERP components such as P1, N170, N250, and P300. The study utilized a task where participants categorized upright and inverted famous and unknown faces, revealing that FFEs on early components (P1 and N170) reflected low-level visual differences, while later components (N250 and P300) were associated with cognitive recognition processes. The N250 component, particularly, emerged as the earliest correlate linked to the recognition of familiar faces in long-term memory, showing individual correlations with recognition speed and improvements through learning. The study underscores the importance of the N250 and P300 components in understanding the time course of face recognition and provides novel evidence supporting the role of cognitive discrimination in familiar face recognition starting no less than 200 ms after stimulus onset. The methodology robustly correlates ERP components with recognition speed and learning improvements. However, the focus on ERP components might overlook other relevant neural processes, and the experimental design may not generalize well to naturalistic settings where faces are encountered in diverse contexts. Additionally, the limited sample size might restrict the generalizability of the findings [17]. Lastly, Barragan-Jason et al. investigates the rapid recognition of familiar faces using scalp EEG recordings during a go/no-go famous/non-famous face recognition task with speed constraints. The research aims to determine how quickly the human brain can differentiate familiar faces from unfamiliar ones, with a focus on the ERP components N170 and N250. The study found that the N170 component, appearing around 140 ms after stimulus onset, showed modulation by familiarity and was linked to faster but less accurate recognition responses. A subsequent increase in decoding power, starting around 200 ms and continuing through the N250 component, indicated a more refined processing stage. These results suggest that familiarity recognition involves a cascade of neural processes, with an early coarse stage and a later, more detailed stage. By utilizing both ERP analyses and multivariate pattern analysis (MVPA), the study tracks the time course and dynamics of face recognition. However, the go/no-go task design might introduce motor response confounds, particularly in later ERP components like the N250. The focus on famous faces may not fully generalize to personally familiar faces or other types of face familiarity. Additionally, while speed constraints reveal early processing stages, they may not reflect typical face recognition strategies used in everyday life [18].

2.2. Steady-State Visual Evoked Potentials (SSVEPs)

Steady-State Visual Evoked Potentials (SSVEPs) technique records the human brain's response to a stimulus that is presented at a steady rate. The method is commonly used in the frame of Brain-Computer Interface (BCI). In the context of SSVEPs, face processing has also been studied. Using a specially designed SSVEP-based BCI system, the pair of classes (e.g., familiar and unfamiliar faces) are cell phone images of a familiar person and an unfamiliar person. The simple and natural face stimuli assure minimum visual attentional factor and guarantee the relatively clear observation for the face perception-related component, especially the early phase face processing stage, the N170 component [5].

Lui et al. investigates the possibility of detecting face recognition using steady-state visually evoked potentials (SSVEP). The study aimed to determine whether SSVEPs could reveal a person's recognition of faces by comparing responses to familiar and unfamiliar faces. In the experiment, 23 participants rated the familiarity of over 300 faces, from which ten familiar and ten unfamiliar faces were selected for each participant. The selected faces were presented at 6 Hz while participants performed a color change detection task. Results indicated that 12-Hz event-related spectral perturbations (ERSPs) at parietal-occipital electrodes were significantly lower when viewing familiar faces compared to unfamiliar ones, suggesting greater suppression of 12-Hz ERSP during familiar face viewing. This finding implies that SSVEPs can serve as a reliable index for face recognition, with familiar faces eliciting more negative 12-Hz ERSPs, reflecting decreased alpha activity associated with enhanced visual attention and memory retrieval processes. However, the study's exclusive focus on 12-Hz SSVEPs may limit the understanding of other frequency bands involved in face recognition. Additionally, the experimental tasks might not capture the full complexity of real-world face recognition scenarios. Furthermore, the lack of information regarding sample size and participant diversity raises concerns about the robustness and generalizability of the study's conclusions [5].

2.3. Other Paradigms

Various experimental paradigms have been employed to investigate EEG-based face recognition, focusing on the differentiation between familiar and unfamiliar faces. These paradigms often involve the presentation of faces in rapid sequences or with varying spatial resolutions, enabling the assessment of neural responses and their implications for face recognition.

One notable study by Yan, Volfart, and Rossion explored the behavioral and neural responses to familiar versus unfamiliar faces. Fourteen participants viewed rapid sequences of faces, where every fifth face was a different identity. The EEG recordings revealed a significant neural response to familiar faces, 3.4 times larger than to unfamiliar ones, observable at 1.2 Hz over the occipito-temporal regions. This neural response emerged approximately 180 ms after face onset and was consistent across individuals except in a case of prosopagnosia. These findings revealed a significant neural response to familiar faces, 3.4 times larger than to unfamiliar ones, observable at 1.2 Hz over the occipito-temporal regions, demonstrating a robust behavioral advantage. However, the limited sample size and exclusion of individuals with prosopagnosia may affect the generalizability of the results [1].

In another study, Deen, Husain, and Freiwald utilized optimized fMRI methods to investigate how the brain processes familiar faces, overcoming magnetic susceptibility artifacts. The research identified a specific area in the temporal pole (TP) that shows a strong response to familiar faces, distinct from a nearby region in the perirhinal cortex (PR) that responds specifically to faces but not to broader social cognition tasks. The TP was found to be functionally connected with a distributed network associated with social cognition, while PR was connected with face-preferring areas of the ventral visual cortex. This study suggests that the TP integrates visual information about faces with higher-order conceptual information about people, supporting separate processing streams for person and face recognition within the anterior temporal lobe. This study highlighted the integration of visual and higher-order conceptual information but was limited by the temporal accuracy of fMRI and potential magnetic susceptibility artifacts [7].

Yan, Goffaux, and Rossion examined the spatial resolution necessary for the human brain to recognize familiar faces. Sixteen participants were shown images of unfamiliar faces alternating with images of familiar celebrities at 1 Hz, while the spatial frequency content of the images either increased (coarse-to-fine) or decreased (fine-to-coarse). The study found that the neural response for familiar faces emerged abruptly in the occipitotemporal regions at about 6.3–8.7 cycles per head width and reached amplitude saturation quickly. When the spatial resolution decreased, the neural response for familiar faces disappeared below 12 cycles per head width. These results indicate that rapid automatic recognition of familiar faces is achieved with coarser visual inputs than previously thought. This supports a coarse-to-fine processing dynamic in the human brain but was limited to the occipitotemporal regions and a relatively small sample size. Collectively, these studies provide a comprehensive understanding of the neural and behavioral responses to familiar faces, the role of specific brain areas, and the importance of spatial frequency in face recognition [6].

3. Signal Processing and Feature Extraction Techniques from EEG Signals

The EEG recording is seriously affected by the presence of a number of artifacts, which may occur as spontaneous electrical signals or as a result of environment or subject-generated activities. The important EEG artifacts occur due to the muscular potentials of craniofacial muscles of different lengths and actions, which include the facial, neck, and ocular muscles, which also occur even at times of an individual's relaxation [19]. Oculomotor artifacts (eye blinks, vertical and horizontal eye movements) are usually the most common and salient artifacts in EEG signals, to which the EEG is most heavily susceptible. Smooth pursuit is voluntary, and saccadic velocity acceleration, vergence movements, and fixation may produce frequency and distinct topographical patterns related to gaze direction and visual attentional tasks. As there is a big difference between the interpretable raw EEG data and its preprocessing outcome, it is important to focus on the state-of-the-art preprocessing methods. Signal filtering techniques, independent component analysis (ICA), and wavelet denoising are among widely used preprocessing methods in different EEG fields. Electrode placement is another important step of the EEG data preprocessing as the outcome of applying different signal processing methods is highly affected by the signal quality. Commonly used standards of EEG electrode positioning are the 10/20 system and the 10/10 system [19, 20].

3.1. Time -Frequency-Domain Features

The time-domain features have been widely considered by studies in the field, especially those related to unfamiliar face recognition using ERPs. These features are directly extracted from the spatial-temporal voltage changes related to different processes involved in face recognition.

Traditional face recognition methods mostly utilize appearance-based approaches to extract the spatial information from the face images. These methods have shown strong performance in terms of detecting internal or external facial features. However, they usually fail to deal well with varying illumination and large-scale rotations. To address these challenges, frequency-domain features selection and extraction techniques have been suggested, such as PCA (Principal Component Analysis), LDA (Linear Discriminant Analysis, DWT, PSD, FFT. The frequency-domain features used in discriminating biomarkers and classifying through an optimized set of sub-bands were highly recommended. The different frequency-domain features can give different descriptive domain from the actual functions. The explorations of these features found that the combined approach targeting different practical issues to achieve good results were considered [19].

3.2. Artifact Removal

Artifact removal, artifact detection and rejection, removal of bad channels, and detection and correction of blinks and eye movements are among widely used artifact preprocessing methods which are essential in applications of EEG analysis. Preprocessing techniques, which are used widely in emotion, face recognition, character recognition fields are generally divided into conventional and state-of-the-art methods. However, the artifacted periods cannot be completely removed using the ART algorithm as the sensitivity and robustness of the ART algorithm need to be optimized, and especially in visual stimulation, the artifacted periods cannot be fully corrected even if the ART algorithm is optimized. However, a deep learning approach can also be used for selecting high quality data from low quality.

In the paper contacted byVanzara, Shah, and Vithalani, the authors, for instane, investigate the neural mechanisms underlying face recognition using event-related potential (ERP) responses from EEG signals. The study involves 18 subjects who were shown stimuli of familiar, unfamiliar, and scrambled faces. The EEG data recorded from these subjects were analyzed to determine if there are significant differences in brain activity when processing different types of faces. The study employed PCA and ICA for artifact removal and feature extraction, with results compared between the two methods [17]. The methodology included preprocessing steps such as extracting EEG channels, adding fiducials, resampling data, and removing noise using EEGLAB in MATLAB. The ERP data were then analyzed using both ICA and Single Trial PCA Based Artifact Removal (SPA). The results indicated that familiar face stimuli evoked distinct ERP components, particularly the N170 component at 170 ms and a slower potential shift at 250 ms. However, the independent T-test statistical analysis showed no significant difference in EEG signals between familiar and unfamiliar faces at these time points, suggesting that while there may be observable differences in the ERP data, they are not statistically significant across subjects. The study concludes that patterns in the EEG data indicate different processing for familiar and unfamiliar faces. However, the study's impact is somewhat limited by the lack of statistically significant differences between familiar and unfamiliar faces. Furthermore, the small sample size, consisting of only 10 usable subjects, may affect the robustness and generalizability of the findings. The variability in ERP responses, coupled with the absence of significant differences, could also be attributed to individual differences within the sample, thereby influencing the overall conclusions drawn from the study [20,21].

4. Machine Learning and Deep Learning Methods for for EEG-Based Familiar/Unfamiliar Face Classification

In recent years, machine learning (ML) and deep learning-based (DL) methodologies have been integrated into EEG signals for familiar/unfamiliar face recognition or classification. ML offers several advantages, including automated learning and classification models based on the training dataset, while producing reliable and effective prediction and classification results [19]. In contrast to traditional ML methods, DL models consist of deep neural networks and maintain a large number of hyperparameters. Different types of machine learning and deep learning methods can extract different features from EEG signals to distinguish familiar and unfamiliar faces, and some of the methods achieve better performance compared with other methods [18]. From the discussion, we found that most existing deep learning-based classification methods applied to EEG signals have a pre-processing step to extract frequency or time domain features from multi-channel EEG signals. However, most are simple operations, like the Welch method, ICA, or other standard methods. Therefore, in-depthdata analysis before end-to-end learning is minimized [20].

The capacity of ML models to generate a feature hierarchy for pattern recognition is an attractive solution for data with high dimensionality, a key characteristic of electrical brain activity related to facial recognition, such as EEG. The most common models used to classify EEG data are the Support Vector Machine (SVM), the Naïve Bayes (NB), the k-Nearest Neighbors (k-NN), the Artificial Neural Network (ANN), and the Convolutional Neural Network (CNN).

The SVM models can classify linear separable datasets with high accuracy by modeling the data space in high or infinite dimensions using the kernel trick, hence the reason for their wide use in EEG. Another renowned technique that has been used to classify EEG data is the k-NN; however, due to its characteristic of producing locally sensitive classification, it is not commonly applied, but may serve as a reference for comparing other data classification methods. The NB model relies on irrelevant or dependent characteristics but is difficult to implement, even if it can handle exponentially growing combinations of irrelevant or dependent data points; this attribute makes it a commonly used reference method in EEG classification [18-20].

Additionally, ANNs, which are characterized by mapping complex (usually linear impenetrable) nonlinear patterns of data, have been extensively used for processing temporally sensitive data like EEG. ANNs replicate several sophisticated techniques in EEG time series classification; however, they need a large number of trials to improve their dimensionality and learning velocity. Currently, CNNs are also a prominent technique among classes of deep learning in EEG data, because they can avoid issues of temporality arising from complex hand-crafted characteristics for lower-level feature extraction. These automatic learning techniques perform hierarchical learning from a broad pool of data that the model itself may classify, according to its sensitivity or specificity; hence, due to its highly hierarchical characteristics, the CNN algorithm is preferred for dropout algorithms compared with simpler models such as the k-NN, the SVM, or the ANN [3,4].

Recent progress in neural networks and deep learning techniques which are suitable for dealing with large-scale data in a wide range of applications increase the attention of a model of deep features which are used for face recognition. In the paper [10] the authors, Blauch, Behrmann, and Plaut, investigate the differential processing of familiar and unfamiliar faces. They use a high-performing deep convolutional neural network (DCNN) to explore how visual experience impacts face recognition capabilities. Their findings indicate that while humans are generally adept at face recognition, their ability to identify unfamiliar faces is significantly less reliable compared to familiar faces. This disparity is attributed to the fact that unfamiliar face recognition suffers from the need to learn each identity from scratch, as most identity-invariant visual variability is unique to each face. The study demonstrates that extensive training on faces leads to substantial generalization in identity verification tasks, emphasizing the role of identity-invariant information in face images. Moreover, familiarization with specific face identities enhances verification performance, highlighting that familiarity benefits stem primarily from learning at the level of identity readout from a fixed expert representation rather than from perceptual representations. These findings reconcile the large familiar face advantage with the notion that both familiar and unfamiliar face processing depend on shared expert perceptual representations, suggesting that human expertise in face recognition involves both domain-specific and domain-general learning mechanisms [10].

Moreover, Liu et al. presents a novel method for classifying familiar and unfamiliar faces using EEG signals. This method employs a filter-bank differential entropy (FBDE) feature extraction technique combined with a support vector machine (SVM) classifier with Gaussian kernels. The study involved recording multichannel EEG signals from ten participants exposed to three different face-recall paradigms. The EEG signals were temporally segmented and filtered using a filter-bank strategy to extract discriminative features. The F-score was used for feature ranking and selection, revealing that the delta band in the prefrontal region significantly contributes to face recognition tasks. The proposed method achieved a mean accuracy of 74.10%, demonstrating its effectiveness in practical applications [3].

The study conducted by Chang et al. explores the neural mechanisms underlying the recognition of familiar and unfamiliar persons using EEG data. The study designed a multi-channel EEG-based pattern recognition system incorporating a novel feature extraction method that combines directed functional network analysis and signal complexity from different brain regions. Twenty participants were exposed to visual and auditory stimuli, and features were calculated in delta, theta, alpha, and beta bands. The study found that delta waves provided the best accuracy for person recognition using SVM classifiers, with an accuracy of 90.58%. The research demonstrated that combining non-linear complexities and network features is effective for EEG-based person recognition systems, suggesting potential applications in forensic investigations and medical diagnostics [2].

Lastly, in the paper [11], Chao Chen et al., present a novel approach to recognizing familiar and unfamiliar faces using EEG data. They designed an experiment based on the Complex Trial Protocol (CTP) and collected EEG data from 147 subjects, using self-face information to evoke responses. The proposed method, EEG-FRM, combines a multi-scale convolutional neural network with an attention module and supervised contrastive learning to enhance classification performance. The multi-scale convolutional network extracts temporal and spatial features from the EEG data, while the attention module and contrastive learning module improve focus on discriminative features and enhance the model's discriminative power, respectively. Experimental results revealed that familiar face stimuli evoked significant P300 responses, particularly in the parietal lobe, achieving a balanced accuracy of 85.64%, a true positive rate of 73.23%, and a false positive rate of 1.96%. This performance surpasses other methods, demonstrating the model's effectiveness in familiar/unfamiliar face recognition using EEG data [11].

5. Challenges and Future Directions

EEG-based face recognition has demonstrated significant potential, yet it faces several challenges that need to be addressed to fully harness its capabilities. One of the primary challenges is the presence of signal noise and artifacts, such as those caused by muscle movements, eye blinks, and external electrical interference. These artifacts can obscure the critical features necessary for accurate face recognition, necessitating the development of advanced noise reduction techniques like independent component analysis (ICA) and adaptive filtering to mitigate their impact. Additionally, there is considerable individual variability in EEG signals due to factors such as age, gender, and cognitive state, which complicates the development of generalized models that perform consistently across diverse populations. To address this, personalized models and adaptive algorithms that continuously learn and update based on individual EEG patterns are essential for improving the generalizability and accuracy of recognition systems.

Another significant challenge in the field is the limited availability of large, high-quality EEG datasets specifically for face recognition. Collecting and labeling extensive EEG data is time-consuming and expensive, which restricts the development and validation of advanced models. Data augmentation techniques and the generation of synthetic data using methods such as generative adversarial networks (GANs) and variational autoencoders (VAEs) can provide more training samples, enhancing model training and performance. The computational complexity of advanced feature extraction and classification methods, particularly those involving deep learning algorithms, also poses a challenge. These methods require substantial computational resources, which can limit their applicability in real-time or resource-constrained environments. Optimizing these algorithms for real-time processing can facilitate their deployment in practical applications.

Furthermore, EEG face recognition has attracted considerable attention not only to reduce the privacy risks of face recognition, but it also has applied in proper care and people with temporary or permanent conditions that cannot allow the use of face recognition. Most EEG-based face recognition studies have used visual attention, special object recognition for natural scenes, a similarity of waveforms and functional neuroimaging data, and characteristics of the visual evoked potentials. Most face images come from different directions, and psychological experimental designs are different from common characteristics of EEG. The facial EEG signals are fast, with milliseconds in length, of low amplitude, and with limited sparsity on the topographic scalp. EEG has some inherent characteristics which are essential for a high temporal resolution in employed signals. It is a non-invasive technique, so it is sensitive to sensor noise, electric field radiation, sensor noise, and consumer headwear when capturing data.

Overall, integrating EEG with other biometric modalities, such as facial recognition or voice recognition, can enhance the accuracy and robustness of recognition systems. However, achieving seamless integration presents technical and methodological challenges, requiring sophisticated multimodal fusion techniques and synchronization methods. Another critical aspect is the scarcity of studies focused on classifying familiar and unfamiliar faces using machine learning or deep learning. Although some research has shown promising results, there is a need for more comprehensive studies that explore various machine learning and deep learning approaches to improve the classification performance in this specific context.

6. Conclusion

This paper reviews feature extraction techniques, classifier choices, and the performance of EEG-based face recognition algorithms. Although still in development, these algorithms have shown reasonable performance, achieving 90% accuracy in recognizing unattended faces. The study aims to provide a foundational benchmark and promote advancements in familiar face classification using EEG signals.

Key insights suggest that class learning will become a major research focus, with opportunities for improving modeling techniques and exploring innovative training and testing approaches. Integrating pre- and post-processing methodologies is recommended to enhance deep learning model performance. Open-access resources will support ongoing research, providing neural network designs, validation data, and evaluation procedures.

Longitudinal studies and real-world applications are crucial for addressing practical challenges and enhancing system usability. Future research should focus on noise reduction techniques, personalized models, data augmentation strategies, efficient algorithms, and multimodal integration methods to advance the field of EEG-based face recognition.

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