AFFECTIVE EEG AND FACIAL FEATURES BASED PERSON IDENTIFICATION USING THE DEEP LEARNING APPROACH

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Abstract - *The aim is to recognize person identity based on brain activity, measured by EEG signals. EEG data classification has attracted much attention with the development of machine learning algorithms, and various applications of brain–computer interface for normal people. Until now, researchers had little understanding of the details of relationship between different emotional states and various EEG features. With the help of EEG-based human identification, the computer can have a look inside user's head to observe user's mental state. We systematically perform feature extraction, feature selection, feature smoothing and pattern classification methods in the process. The features extracted are specified in detail and effectiveness is proven by classification results. Human identification based on Face recognition is one of the latest technology being studied area in biometric as it has wide area of applications. In image processing the Face detection is the challenging problem. The main aim of the face detection is to determine if there is any face in an image & locate position of a face .Face detection is the one of the first step towards creating an automated system which involves other face processing. The deep learning neural network needs to be created and trained with training set of faces and non-faces. All results are implemented in MATLAB 2013 environment. Database is collected for different persons from online EEG data base which is meant for research. One Time Password is also one of important aspects in field of personal security in this application.OTP is used for two ways authentication.*

***Key Words*:EEG signals , Machine Learning, Biometric, Face recognition, Image processing, Deep learning, Database, Neural network.**

1. INTRODUCTION

Person Identification (PI) can also be performed by using another method called Electroencephalography (EEG).The nature of the EEG signals, EEG-based Person Identification is done while a person is performing a mental task such as controlling the motor . However, few studies used EEG-based PI while the person is in different mental states(affective EEG).Our work is to develop a cascade of deep learning using a combination of Convolutional Neural Networks (CNNs) and Recurrent Neural Networks (RNNs). CNNs are used to handle the spatial information from the EEG while RNNs extract the temporal information. We evaluated two types of RNNs namely Long Short-Term Memory (LSTM) and Gated Recurrent Unit(GRU).The proposed method is evaluated on the state-of-heart affective dataset. The demand for personal identification in computerized access control has resulted in an increased interest in biometrics to replace passwords and identification card. They can be easily breached since the passwords can be divulged to an unauthorized user and ID card can be stolen. Biometrics which makes use of human features such as iris, retina, face etc can be used to verify person's identity if any spy or hacker who tries to interpret the transaction or personal security OTP is used as two way authentication in the application. The face recognition system has the benefit of being a passive, non-intrusive system for verifying personal identity. The proposed face recognition system consists of face verification and face recognition task. In verification task, the system known priori the identity of the user and has to verify this identity i.e. the system has to decide whether the a priori user is an imposter or not. It is useful to have a machine to perform pattern recognition. The machines which read face images are cost effective. Therefore this kind of application saves time and money and eliminates the requirement that a human perform such a repetitive task.

2. METHODS

2.1 PROCEDURE

Procedure: Mainly classified as two steps:
1. EEG based person Identification using deep learning.
2.Facial recognition using image processing.

1.EEG based person Identification using deep learning.

The study have been done by Tokyo institute of technology.

In this section, we first illustrated the DEAP(database for emotional analysis) affective EEG dataset that we used to conduct experimental studies and also described the pre-processing step of our solution. Since DEAP was created for mental state classification purposes, we described our data partition methodology used to accommodate the performance of the PI task. The proposed Deep learning approach and its implementation .

A. Affective EEG Dataset

In this we performed experiments using DEAP affective EEG dataset which is considered as a standard dataset to perform affective recognition tasks [1] . During EEG measurements they were asked to watch affective music videos and score subjective ratings (valence and arousal) during the EEG measurement. A summary of the dataset is shown in Table I .

TABLE I
AFFECTIVE EEG DATA FORMAT WITH LABEL

Array Name	Array Shape
data	32 x 40 x 32 x 8064 participant x video/trial x EEG x data
labels	32 x 40 x 2 participant x video/trial x (valence, arousal)

EEG dataset was preprocessed by using these steps:

- The data was down-sampled to 128 Hz.
- The Independent component analysis(ICA) is used to remove the EOG artifacts by using blind source separation technique.
- A band pass filter from 4.0–45.0 Hz was applied to the original dataset. The signal was further filtered into different bands as follows: Theta (4–8 Hz), Alpha (8–15Hz), Beta (15–32 Hz), Gamma (32–40 Hz), and all bands(4–40 Hz).
- The data was averaged to a common reference.
- Data was segmented into 60- second trials, and therefore the 3-second pre-trial segments were removed. Most researchers have been used this dataset to develop an affective computing algorithm and we used this affective dataset to study EEG-based Person Identification.

B. Sub sampling and Cross Validation

Affective EEG is categorized by the standard subjective measures of valence and arousal scores (1–9), with 5 as the threshold for defining low (score < 5) and high (score ≥ 5) levels for both valence and arousal. There were four affective states in total, as stated in Table II. To simulate practical PI applications, we randomly selected 5 EEG trials per state per person (recorded EEG from 5 video clips).Participants spent 5 minutes watching 5 videos for the first registration. Table II presents the numbers of participants in each affective state. The numbers were different in each state because some participants had less than 5 recorded EEG trials categorized into the state. Furthermore, we aimed to identify a person from a short-length of EEG: 10-seconds. In each EEG trial in DEAP, the video used as a stimulus lasted 60 seconds. Thus, we simply cut one EEG trial into 6 subsamples. Finally, we had 30 subsamples (6 subsamples × for 5 trials) from each participant in each of the affective states. The participant ID was used as label in our experiments (personal identification). Data and labels that have been used can be described.

TABLE II
NUMBER OF PARTICIPANTS IN EACH STATE AFTER SUBSAMPLING

Affective States	Number of Participants
Low Valence, Low Arousal (LL)	26
Low Valence, High Arousal (LH)	24
High Valence, Low Arousal (HL)	23
High Valence, High Arousal (HH)	32
All States	32

C. Deep Learning(DL) Approach:

In general, a single EEG channel is a one-dimensional (1D) time series. However, multiple EEG channels can be mapped into time series of 2D mesh (similar to a 2D image).For each time step of the input, the data point from each EEG channel was arranged into one 2D mesh shape of 9×9. 2D mesh size is empirically selected according to the international standard of an electrode placement (10-20 system) which covering all 32 EEG channels. The mesh point (similar to the pixel), which was not allocated for EEG channel, was assigned to zeros value throughout the sequences. The mean and variance for each mesh (32 channels) were normalized individually. In this study, a non-overlapping sliding window was used to separate the data into one-second chunks. Since the sampling rate of input data was 128 Hz, the window size was 128 points. Thus, for each 10-second EEG data, a 10×9×9×128-dimensional tensor was obtained.

D. Comparison of affective EEG-based Person Identification among EEGs from different frequency bands

EEG is conventionally used to measure variations in electrical activity across the human scalp. The electrical activity occurs from the oscillation of billions of neural cells forming the human activity across the human scalp. The electrical activity occurs from the oscillation of billions of neural cells forming the human brain. Most researchers usually divide EEG into frequency bands for analysis. Here, we defined Theta (4–8Hz), Alpha (8–15 Hz), Beta (15–32 Hz), Gamma (32–40 Hz), and all bands (4–40 Hz). Typical Butterworth band pass filter had incorporated to extract EEGs from different frequency bands. In the study, we questioned whether frequency bands affect PI performance or not. To answer the question, we incorporated CNN-GRU (stratified 10-fold cross-validation), CNN-LSTM, and SVM(as performed in Section II-C) for CRR comparison.

Note: according to the results of Section I-D, all bands(4-

40 Hz) provided the best CRR and we continued to use all bands for the remainder of the study.

E. Comparison of affective EEG-based Person Identification among EEGs from sets of sparse EEG electrodes

During this experiment, we hypothesized whether or not the number of electrodes might be reduced from thirty-two channels to 5 while maintaining a suitable CRR. The lower the amount of electrodes required, the more the system becomes user-friendly and practical the system. to research this question, we defined sets of 5 EEG electrodes as shown in Figure 1, including Frontal (F) Figure 1(a), Central and Parietal (CP) Figure 1(b), Temporal (T) Figure 1(c), The Occipital and Parietal (OP) Figure 1(d), and Frontal and Parietal (FP) Figure 1(e).Consistent with Section III-C and D, the DL approach significantly outperforms the normal SVM in PI applications. So we incorporated only CNN-GRU and CNN-LSTM during this investigation.

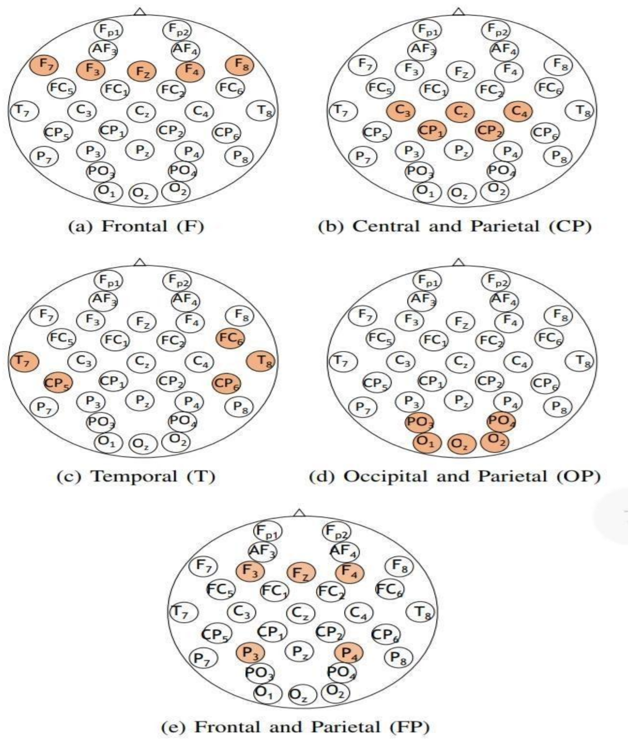

Figure 1: EEG Electrode set

F. Comparison of proposed CNN-GRU/CNN-LSTM and other relevant approaches towards affective EEG-based PI application

First, we evaluated our proposed CNN-GRU against a spatiotemporal DL model, namely which CNN-LSTM[2]. During this study, we measured the performance in terms of the mean CRR and therefore the the convergence speed as we tuned the dimensions of the models by varying the amount of CNN layers and the number of GRU/LSTM units. We also compared our greatest models against other conventional machine learning methods and relevant works, like Mahalanob is distance based classifiers, using either PSD or spectral coherence (COH) as features (reproduced from [3]) and DNN/SVM as, proposed in [4].

2. Face recognition using image processing.

A. Image Preprocessing

The process of operations with images at the lowest level of abstraction both input and output are intensity images called as pre-processing. The images captured are of same kind to iconic images which are cultured by the the sensors. With an intensity image usually represented by a matrix of image function values (brightness). The pre-processing is a process which is to improve the image data that suppresses unwilling distortions or enhances some image feature. Although geometric transformations of images which are classified by using the preprocessing method here since similar techniques are used.

B. Face Detection

Face detection is a process of computer technology which determines the location and size of face in arbitrary image. The facial features are detected and any other objects like trees, buildings and bodies etc. are ignored from the digital image. It can be regarded as a specific case of detection, where the task is to find the location and size of all objects in an image that belong to a given class .Face detection, is regarded as a more general, case for face localization. In face localization, the task is to find the locations and sizes of a own number of faces (usually one).Commonly there are two types of approaches to detect facial part in the given image i.e. feature base and image base approach. Face detection involves separating image windows into two classes; one containing faces and another background (clutter). It is difficult because although commonalities exist between faces, which can vary in terms of age, complexion and countenances. The problem which is complicated by differing lighting conditions, image qualities and geometries, also because the possibility of partial occlusion and disguise. An ideal face detector would be able to detect the presence of any face under any set of lighting conditions, and any background. The face detection task can be classified into two steps. The first step is to classify the task that capture some arbitrary image as input and outputs a binary value , indicating that there are any faces present in the image. The second step is the face localization task which aims to take an image as input and output the location of any face or faces within that image as some bounding box with (x, y, width, height).

C. Feature Extraction

For the purpose of feature extraction the viola jones method is used. Object detection was presented by the Paul Viola and Michael Jones. Paul Viola and Michael Jones proposed a fast and robust method for face detection which is 15 times quicker than any technique at the time of release with 95% accuracy at around 17 fps. The technique relies on the use of simple Haar like features that are evaluated quickly through the use of a image representation. Based on the concept of an Integral Image which generates a large set of features and uses the boosting algorithm. Ada-Boost is used to reduce the over complete set and the introduction of a degenerative tree of classifiers. The detector which is applied in a scanning fashion and used on gray-scale images. The scanned window can also be scaled, as well because the features evaluated.

2.2 Participants

Anybody can participate to his/her details safe so here we are assuming that this can be used in mobile banking or in atm machines. The participants need give their data (i.e., EEG of a person, face images) in order to use this application so after the data is taken from the user which is stored in the database whenever the user wants to access he need undergo some authentication process if successful he can access else not given access to him/her an alert mail will sent to the original or actual user so that if anybody other than him tries to access the user can be concise.

2.3 Model Development and Analysis

Assuming that this technology is used in mobile banking applications. The procedures as shown below:

- User enters the details.
- Application takes the users EEG signals.
- EEG signals matches the customer or the user the system provides the access.
- If EEG signals doesn't match the customer it will get OTP and if the customer enters the OTP correctly will take face of the user and matches the face he will be allowed to access the profile.
- If face didn't match that customer he will consider as unauthorized.

3. RESULTS

The result shows the implementation of a person identification and authentication system using a multi-level detection scheme such as a EEG signal and facial features. We run the EEG signals of a person to identify. the user enters his/her details, based on the data given .if the user matches with stored data then he will be identified as an authentic person and is given access to the further use of the system .The EEG signal authentication is as shown in the figure 2 below:

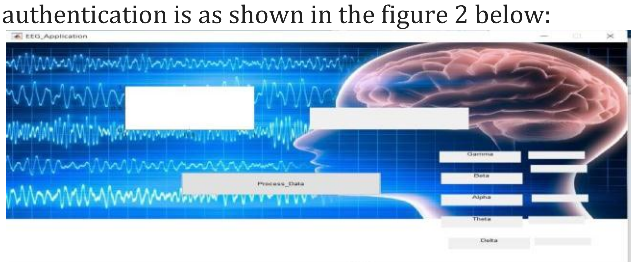

Figure 2: EEG signal Authentication

1. EEG Signal analysis and its phases

In EEG signal acquisition phase, raw EEG signals will be collected directly from the datasets. In signal acquisition and analysis the Identification and removal of artifact is a challenging process. There will be various factors like head motion and physical problems during the signal acquisition. This phase creates signals with abnormal frequencies. Next phase will be feature extraction where feature of signals can be derived using various signal processing techniques like Fourier transform, wavelet, principal component analysis and meaningful features are extracted .Forget transform categorize the signals into four frequency bands.

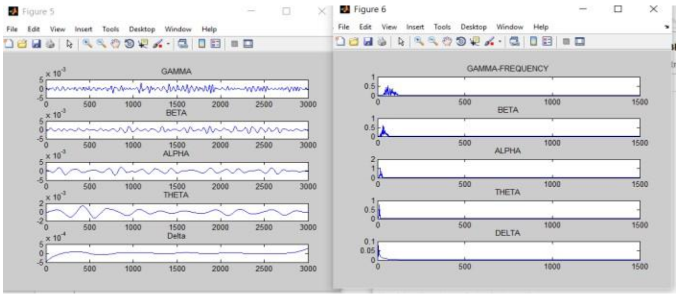

Chart 1:signal/frequency bands for processed data

EEG wave forms are generally classified according to their frequency, amplitude. The classification of wave forms such as alpha , beta, theta, delta and gamma are based on signal frequency.

2. Feature Extraction

The EEG signals are then processed into another phase i.e., training phase where the data of the person will be trained with the already stored datasets. The training set is created based on the complete data that has been stored in the network. Once the training set is created then the test input is taken whose initially all data is extracted using in built functions. Once the data is extracted it is matched with training set. Below figure 3 shows the stage wise output obtained. We are comparing the test input with database input where each part of the face is tested separately as shown in the figure 3 below. The data from each region is noted separately and stored in database.

Figure 3: Feature Extraction

After comparing the test input faces with the database images it displays the result as match. If the image does not match with the obtained data then an one time password is generated to registered mail id, the person/user enters the OTP to get authentication. Entered OTP is then processed to extract features of the person and classifies the image with the stored image. If that image is matched then that identifies the person/user as authentic and provides access to the further use of the system.

4. DISCUSSION

This section presents the design of authenticating a person for providing access to the system. The entire data analysis process, from acquiring data from external devices and databases, through preprocessing, visualization, and numerical analysis, to producing presentation-quality output and which is completely supported by MATLAB. In the given above figure , at first the user enters his/her respective card details. Based on the data given the EEG feature extraction will take place . If the EEG data of the user matches with the stored EEG data in the system which was taken before then the user will be identified as an authentic person and therefore access to the further use of the system will be given to the user which completes one level of authentication. If the EEG data is not matched then the process moves on to the second level of authentication which takes place through image processing. At this point an one time password (OTP) will be sent to the user. When the user enters the obtained one time password then the image of the person will be captured through webcam. In the image captured the face present in the image will be detected which is followed by the extraction of features and the features obtained will be classified with the Support vector machine (SVM).If this image matches with the stored one then the user will be identified as an authentic person and therefore access to the further use of the system will be given to the user which completes the second level of authentication.

5. CONCLUSIONS AND FUTURE ENHANCEMENT

In this paper, we explored the feasibility of using affective EEG for person identification. We have implemented a person identification also person authentication system using a multi-level detection scheme, one is using EEG signals of a person to identify and then Facial features for authentication. Further to this an application was developed which can be accessed upon once the right identity of the person is verified. Also an email based OTP notification system is plugged in to further assist in case of failure of EEG. Training algorithms used are Principle component Analysis (PCA) for facial features, and discrete wavelet transform (DWT) for EEG signals. Classification algorithms include neural network and support vector machine. The Entire Application was developed and linked using MATLAB, image processing and machine learning libraries. Results were found to be promising.

This approach is proposed for a significant improvement in both theory and practice, to meet the performance and requirements of a person authentication under different stages or from different devices. In future we can use various algorithms to increase the prediction results.

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