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# An EEG based familiar and unfamiliar person identification and classification system using feature extraction and directed functional brain network

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ABSTRACT

People are extremely proficient at recognizing familiar person, but are much worse at matching unfamiliar one. However, the neural correlation of this proposed difference in neural representations of familiar and unfamiliar identities remains unclear. New methods of EEG data analysis, functional networks and time frequency analyses, are highly recommended to advance the knowledge of those brain mechanisms. Developing an EEG based pattern recognition system could potentially be used to improve the current person recognition strategies. In this study, we designed a multi-channel EEG based pattern recognition system for person recognition. To do this, a new feature extraction method combining directed functional network analysis and signal complexity of EEGs from different brain regions was proposed, which is the main contribution of this paper. The proposed method was tested in an experiment of 20 subjects underlying visual and auditory stimuli simultaneously. The features were calculated in delta, theta, alpha and beta band respectively, then SVM and KNN classifiers were applied to these feature sets and the results showed the recognition accuracies of these four bands are relatively stable with the best accuracy of 90.58% in delta band for SVM. In addition, theta and alpha band also showed good performance for the two classifiers. It indicated delta wave is the best sub band for person perception and SVM is better than KNN in this system. This work is the first time to construct the directed functional network in person recognition study, and it demonstrated the combination of non-linear complexities and network features are efficient for EEG based expert and intelligent system for person recognition.

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## 1. Introduction

Person recognition is an essential and effortless part in our everyday life. We encounter familiar and unfamiliar people in many different contents everyday (Gosling & Eimer, 2011; Haghighat, Abdel-Mottaleb & Alhalabi, 2016). People can recognize person which are familiar to them proficiently, but are poor at identifying unfamiliar one (Bate & Bennetts, 2014; Ewbank & Andrews, 2008; Gumus, Kilic, Sertbas & Ucan, 2010). For humans, the ability to recognize and distinguish one person from another generally depend on people's face or name, and other clues, such as voice and posture of the person also can help (Gainotti, 2013). People's action will be very different if they categorize someone as a stranger or a friend. People sometimes deliberately pretend not to know the person for their own benefit (Sun, Chan & Lee, 2012). For instance, a suspect might deny knowing the victim to avoid being arrest and prosecution. Person recognition, mainly distinguish familiar people from unfamiliar one, is also contribute to crime investigation (Lui, Lui, Wong & Rosenfeld, 2018), forensic inspections, security operations and mental illness research (Ewbank & Andrews, 2008; Phillips et al., 2018).

Humans' brain has developed a complex, multimodal person recognition system based on visual (face), auditory (voice) and verbal (name) perception channels ((Gainotti, 2013)). A larger number of researches based on neuroscience and behaviorism have suggested that person recognition is in fact a complex cognitive process which is mediated by a sequence of face, voice and verbal specific brain mechanisms (Gainotti, 2013; Gosling & Eimer, 2011). Lots of evidence shows that the processes in recognition of unfamiliar

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face, which is the visual identification of a person, is qualitatively different from familiar face (Ewbank &, Andrews,2008; Haghighat et al., 2016). Studies also suggested that representations of unfamiliar and familiar voice might dissociate in the human brain (Fontaine, Love, & Latinus, 2017; Gainotti, 2013); A grouping body of studies suggest that a different hemispheric specialization may exist for different modalities of person identification, with the right hemisphere is more activated in the recognition of familiar than unfamiliar faces and voices, and a left hemisphere superiority in the recognition of corresponding names (Gainotti, 2013). Identification faces, voices and names of familiar people depend on the coactivation of visual, acoustic and verbal areas and the cortical networks involved in person identify retrieval, whereas unfamiliar faces, voices and names identification should depend on the perceptual step of corresponding face, voice and name processing (Gainotti, 2013).

There has been lots of brain imaging studies of neural mechanisms underlying familiar and unfamiliar person recognition. Regions and activations related to person recognition in the cortices can be localized from EEG, which is the most commonly used brain imaging method as it is simple, economical and portable (Robertson,2018). Although neuropsychologist's research has already suggested that matching unfamiliar faces or voices is prone to error and may be utilized by swindlers wanting to deceive ID checkers. It is still heavily relied on the unfamiliar person recognition for identity verification in our national security (Robertson, 2018). It is very necessary to development the EEG based expert and intelligent system which can do familiar and unfamiliar person identification and classification, as lots of studies have found that neural mechanisms underlying of familiar person recognition is different from unfamiliar one. EEG based pattern recognition system, which is a new way of recognizing person, mainly consists of test system which including stimuli presenting, data acquisition and data processing, and pattern recognition system which including feature extraction and selection, and classification and decision making, as shown in Fig. 1.

Stimuli presenting section includes a paradigm for conducting the test and presenting the visual (face) and auditory (name) stimuli simultaneously, in which the names were converted into auditory stimuli. As experimental studies dealing with laterality effects in face, voice and name recognition in normal subjects are sparse and in part controversial (Gainotti, 2013). Schweinberger, Kloth and Robertson (2011) and González et al. (2011) studied the audiovisua integration of face and voice and found a direct information sharing between face and voice processing systems before access to the person identity areas in right hemisphere. O'Mahony and Newell (2012) have shown that faces are integrated with voices, but not with names (verbal) in person recognition. Besides the voice, among auditory stimuli, the own name is one of the most powerful and it is able to automatically capture subject attention

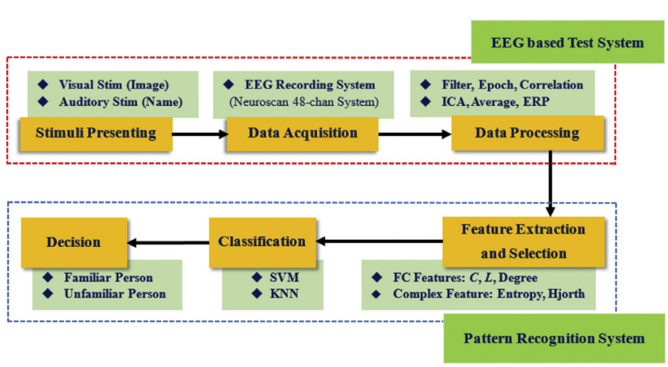


**Fig. 1.** Block diagram of the EEG based person recognition system.

and elicit a robust EEG response (Del Giudice et al., 2014). One way of investigating the level at which face and name information interact within the person cognitive system is presenting the name as auditory stimuli, which is the reason the name were presented as auditory stimuli simultaneously in this system.

Date recording and processing section was based on the Neuroscan system and the pre-processing of EEG data including filter, epoch, baseline correction and artificial remove. Feature extraction and classification is the most important section for building a usable and reliable multichannel EEG based person recognition system. Due to the high temporal resolution, the scalp EEG provide a real time measure of neural activities during person recognition, they constitute a well suited approach to compare not only the time courses of within- and cross-domain priming effects but also the interdependence between different brain regions during person recognition (Maguinness, Roswandodowitz & Von Kriegstein, 2018). As the difference between familiar and unfamiliar faces concerns not only their lateralization, but also their interhemispheric cooperation, and multichannel EEG recording distributes across the whole scalp surface and it can provide the spatial cooperation information for person recognition through functional brain networks.

In this study, a novel pattern recognition method was proposed for the EEG based person identification and classification system. Two types of features were calculated to characterize the temporal and spatial information of EEG signals. Firstly, functional brain network was constructed by phase transfer entropy to present the effect connectivity, and several network parameters which represent functional segregation and integration were calculated as the features. Besides, several entropies and Hjorth parameters, which represent the complex of EEG time series were calculated as another features. These two types of features were extracted from the four sub-band (delta, theta, beta and alpha) and fed into the SVM and KNN classifiers respectively to complete the identification and classification of familiar and unfamiliar person. The purpose of this study is to examine the feasibility of the proposed novel method by using EEG based lab person recognition experiment.

The remaining sections are organized as follows: first, a set of related works is presented, then the contribution and motivation is exposed. After that, the materials and methods are detailed in Section 2. The results obtained from the proposed method are described in Section 3, and Section 4 is the discussion of the obtained results. Finally, the conclusions, limitations and future work are presented in Section 5.

### 1.1. Related works

Recognition of familiar person is a fundamental biological function for the human beings, which usually based on the visual (face), auditory (voice), verbal (name) and other information of the person. Familiar face recognition has been the first cognitive model for analyzing the stages involved in recognition and identification of familiar people (Gainotti, 2013). Over the past few years, despite lots of neuroimaging studies focused on the neural basis of face processing, the neural correlations of familiar face recognition in humans remains largely unknown (Collins, Robinson, & Behrmann, 2018; Freiwald, Duchaine & Yovel, 2016). The role of person recognition and identification based on voices and name are less well explored. However, there are evidence that perception of familiar and unfamiliar voices (or names) is the result of different mechanisms and distinctive personally familiar voices (or names) are recognized more easily (Gainotti, 2013; Zaske, Volberg, Kovacs & Schweinberger, 2014). Voice and face, which are the cues to convey concordant information to support identity processing, have shown to be represented in a similar manner in the neurotypical brain(Maguinness et al., 2018) . There is no consensus of the question about how the brain distinguish familiar and unfamiliar person representations, and the effect of the interaction between voice and face remains unanswered (Gainotti, 2013; Murphy, Gray & Cook, 2017). Person perception and recognition involves multiple aspects of cognitive such as attention, emotion, pattern recognition, and identity processing, all of which might vary depending on the nature of the required task (Collins, Robinson, & Behrmann, 2018).

It has been reported in the literature that some brain regions related to face recognition are crucially activated (Lopatina, Komleva, Gorina, Higashida & Salmina, 2018; Zhao, Zhen, Liu, Song & Liu, 2018), but the results of face responsive areas in brain cortex have been inconsistent (Gainotti, 2013; Gobbini & Haxby, 2007). Numerous neuroimaging studies showed that some brain regions were activated by familiar face, including the medial temporal, lateral temporal and prefrontal areas (Collins, Robinson, & Behrmann, 2018; Leveroni et al., 2000). In another case, the temporal and frontal areas were related to personal identification. Furthermore, various studies also reported that different activations emerged in anterior ventral temporal for familiar from unfamiliar face, and other studies also reported differences in middle occipital gyrus, right infero temporal cortex, and right posterior fusiform gyrus areas (Collins, Robinson, & Behrmann, 2018). But some studies found that these regions also related to activations from familiar names and other external factors (Collins, Robinson, & Behrmann, 2018; Haxby, Hoffman & Gobbini, 2000). Thus it has no consistent result of activated brain regions between familiar and unfamiliar face perception. A group studies suggests that a different hemispheric specialization exists for different patterns of person identification, with a prevalent right hemisphere lateralization of the face and voice recognition system, and a prevalent left lateralization for verbal name recognition (Gainotti, 2013).

Numerous ERP based studies found that N170, later N200 and P300 are strongly involved in face perception, which clearly reflect the temporal dynamics of face processing as participants respond slower to unfamiliar than familiar faces (Collins, Robinson, & Behrmann, 2018; Gosling & Eimer,2011; Hanso, Bachmann & Murd, 2010). The results showed that N170 is related to early structural encoding of faces, which is insensitive to familiarity of a face (Lui et al., 2018), some studies found larger N170 amplitudes for familiar relative to unfamiliar faces, while some studies found contrary results (Huang et al., 2017). The perception and recognition of familiar faces is found to be associated with an increased amplitude of N200 and P300 (Hanso et al., 2010). Other studies found that later ERP components to be sensitive to recognition of familiar faces, which could elicit a larger amplitude of N400 and P600 compared to unfamiliar faces (Huang et al., 2017; Lui et al., 2018). Both the N400 and P600 were widely distributed over the scalp in the central-parietal area (Sun et al., 2012).

Potential components of familiar and unfamiliar voice recognition include the fronto-central mismatch negativity (~210 ms), and the parietal P3 (Zaske et al., 2014). Studies based on name stimuli found a decrease in alpha power in response, and a stronger theta event-related synchronization to subject's own name, and a higher delta synchronization for target than non-target stimuli (Del Giudice et al., 2014; Tamura, Karube, Mizuba & Iramina, 2012). Repetition priming experiment found a strongly left-lateralized inferior temporal negativity (N250r) for familiar names (Tamura et al., 2012). Evidence for audiovisual integration of faces and voices of familiar and unfamiliar person was found at multiple processing levels. Several articles showed that the topographic distribution of familiarity related N250 for face, voice and bimodal stimuli, was lateralized to the right hemisphere and showed larger amplitude at temporal sites (Gainotti, 2013; González, 2011; Schweinberger et al., 2011).

Although neuroimage based studies of person recognition have not yet provided a clear picture of the relationship between face, name and voice specific brain regions and brain processes involved in recognizing and identifying familiar person (Gosling & Eimer,2011; Ozbeyaz & Arica,2017), and also the links between ERP components and familiar person recognition remain completely unclear. These results showed that the ERPs from specific brain regions can be used as electrophysiological tools for structural encoding and face, name and voice recognition for familiar person (Olivares, Iglesias, Saavedra, Trujillo-Barreto & Valdes-Sosa, 2015). An alternative approach, the functional brain network, which based on interdependence analysis of multi-channel ERP recordings, can reflect the differences through the connectives from the whole brain for person recognition and identification between familiar and unfamiliar people (Van Diessen et al., 2015; Lynn & Bassett,2019).

Functional brain network has been successfully applied to the study of brain mechanisms and other cognitive process such as mental imagery, motor and language processing (Van Diessen et al., 2015; Lynn & Bassett,2019; Rubinov & Sporns,2010). It provides a new view of EEG based person recognition. In the previous study, we constructed the functional brain network using nonlinear interdependence for visual and auditory stimuli respectively. Comparative analysis of network parameters and the classification results showed that face (visual) stimuli is better than name (auditory) stimuli. Network features combined with classifiers can distinguish familiar person from unfamiliar one (Wang, Chang & Zhang, 2016). Another study compared the network structures and recognition effect between different interdependence measures, results showed lots of measures can obtain a good results which proves the universality of brain network analysis for face perception (Chang, Wang, Hua, Wang & Yuan, 2019). In addition, we found the identification and classification results is largely depend on the threshold and parameters selection of the network.

### *1.2. Motivation and contribution of the study*

In this paper, we studied the problem of EEG based person recognition under the integration of visual face and auditory name stimuli. As most of the studies for person recognition are based on face, while the voice and name based recognition effect are less well established. In this study, we converted person's name into auditory stimuli and presented them to the subjects combined with face simultaneously, which is a novel point of stimulus presentation and to our knowledge, it is the first time used to the person recognition, to investigate the effects of this visual (face) and auditory (name) interaction on person recognition.

To build an EEG based expert and intelligent system for person recognition, besides the stimulus presenting, another important point is feature extraction and classification. Previous studies have proved functional brain topology and parameter analysis are good at person recognition (Wang et al., 2016). Besides, the brain activities measured by EEG exhibits complex temporal features that are not simply attributable to erratic events but also indicative of nonlinear dynamic neural oscillations (Laprevote et al., 2017; Stam & Reijneveld,2007). Applying nonlinear indicators such as signal complexity to EEGs helps to explore this variability in human brain. Among various measures, entropy based methods are very popular and powerful for EEG analysis (Scarpa et al., 2017). We aimed to provide a new insight into EEG feature extraction combine with functional connectivity and signal complexity under the four sub bands during person recognition. The purpose of this study is to demonstrate that it is possible to identify familiar person from unfamiliar one using the proposed novel method for feature extraction from EEG data and try to develop a machine learn-

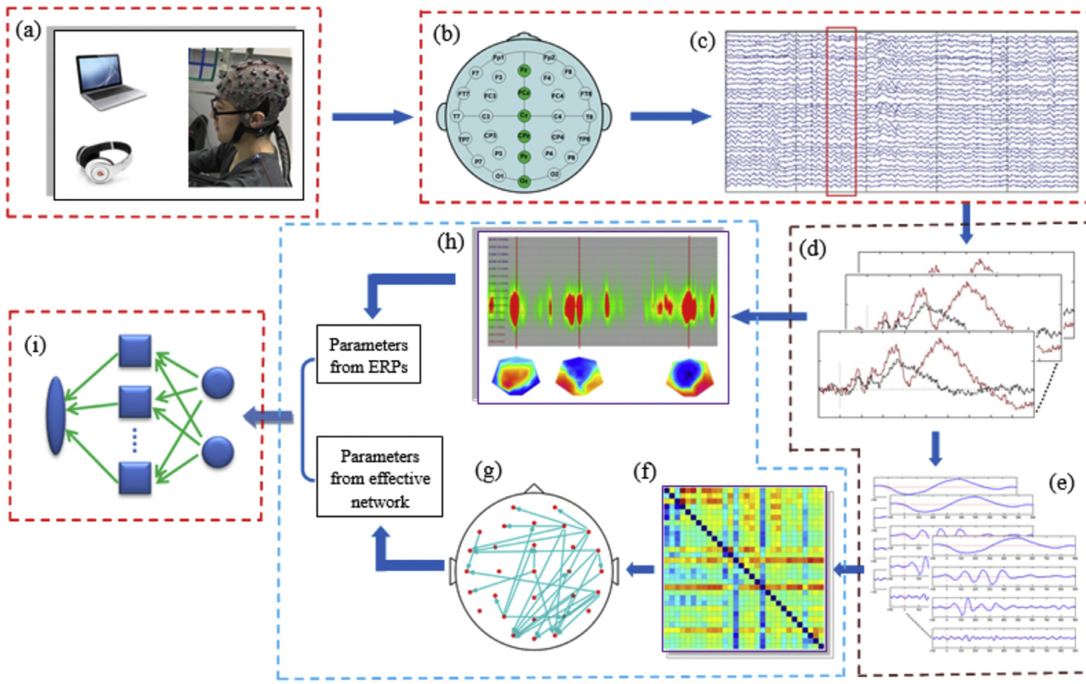


**Fig. 2.** Schematic illustration of the recognition system. Firstly, visual and auditory stimuli were presented to the subject simultaneously, and 30 channel EEG data were recorded, as shown in (a) is the stimuli presenting, (b) and (c) are EEG data recording. EEG data to different stimuli were segmented and averaged to get the ERPs, as shown in (d), and after the wavelet decomposition and reconstruction, get the four sub-band frequencies (delta, beta, theta, alpha), as shown in (e), which is the data processing section. Then as shown in (h), parameters for estimating ERPs' complexity were calculated, and in (f) and (g), effective brain networks were constructed and parameters for networks were calculated. The section (g),(f),(h) is feature extraction and selection. Finally, feature vectors consisted by parameters from ERP and effective network were used to several classifiers to complete the face recognition, as shown in (i) is the classification and decision making.

ing based intelligent system for person recognition. As shown in Fig. 2 is the schematic illustration of the recognition system.

In current work, we investigated whether directed functional connectivity analysis can be used for person recognition and is there any difference of brain networks induced by familiar and unfamiliar face and name. The main contribution of this study is that we proposed a novel and efficient feature extraction method of multichannel EEG signals, in which directed functional network parameters and signal complexities were extracted as the features, combing with machine learning classifier to distinguish familiar person and unfamiliar one. To verify the proposed method, a person perception experiment based on familiar and unfamiliar visual face and auditory name was designed with multi-channel EEGs recording simultaneously. Directed functional brain network was constructed based on phase transfer entropy in the four sub-band frequencies. Network parameters together with several complexity estimators, including sample entropy, spectral entropy, approximate entropy and Hjorth parameters were used as the features for several classifiers. The results showed that this method can get a good result for person recognition, and therefore can easily be generalized in the future related to the development of person recognition intelligent system in different settings such as in the field of legal investigations, especially in the identification of suspects, as well as medical applications such as pre-diagnose of some brain disease. The experience obtained with the familiar/unfamiliar person classification may also be beneficial for the BCI researches. The identification based on EEG directional functional networks and signal complex as far as known is the first study used for person recognition. The general approach used to solve this problem here, namely using samples of EEG data obtained under visual and auditory stimuli and machine learning, is highly general and can be used to the study of other EEG classification issues, which is also a theoretical contribution to EEG based expert and intelligent systems.

## 2. Methods and materials

### 2.1. Experiment design

#### 2.1.1. Participants

Twenty right handed participants (seven female) from Northeastern University aged between 22 and 30 (mean age 23.45 years, SD is 3.6) years participated in this research. All subjects were recruited from our university and had normal or corrected vision and hearing. No subjects have any historical neurological diseases or psychoactive drugs. The study was approved by the Ethics Committee of our university and all subjects were paid for their participation after the test. Each subject was informed of the experiment procedures and signed the consent to participate.

#### 2.1.2. Experiment procedure

One week before the test, we asked each subject to provided two photos, in which one is their supervisor and another is their sibling, and also the corresponding names of these photos. These photos were scanned and converted to grayscale with the same contrast, brightness and resolution. All photos were united to 37.3 by 50.3mm$^2$. Their names were converted into audio files ("wav" format, 48 kHz sampling rate, 16 bits resolution) with the same overall sound pressure level by text-audio conversion software. Each wave file was composed by three Chinese words and lasted 1000 ms. All these procedures were accomplished using the same software and procedure (Abootalebi, Moeadi & Khalilzadeh, 2009; Wang et al., 2016; Fu, Tian, Bao, Meng, & Shi, 2019).

The test was designed as a typical oddball paradigm and each trial consisted by five irrelevant items, two probe items and one target item, in which familiar item as one probe and unfamiliar item as another probe. Twenty subjects were randomly divided into five groups and make sure they do not know each other. For each subject in one group, visual and auditory stimuli sequence were presented simultaneously, in which two photos or names (target and probe2) were from themselves and other six photos or names (five irrelevant and probe1) were from other three subjects. For half the subjects, the information of their supervisor served as target and the information of their sibling as probe2 (familiar group), while for other half subjects, the information of their sibling severed as target and their supervisor as probe2 (Fu, Tian, Bao, Meng, & Shi, 2019; Wang, Chang, & Zhang, 2016). This is similar to probe1 (unfamiliar group) and irrelevant items.

In the test, subjects were required to recognize familiar person by press one button and unfamiliar person by another button. They were seated in a comfortable chair at a distance of 80 cm from the computer screen. The visual and auditory stimuli sequence were edited and presented by STIM2 software. With the visual stimuli presented by the photos on the screen, the auditory files were simultaneously presented to the subjects binaurally through a headphone. The stimuli lasted about 1000 ms and the winder of the stimuli is 1500 ms with a 1700 ms interval between next stimuli. During the test, subjects were required to pay their attention to the stimuli and press the button correctly, avoid any body movement during the stimuli presented.

### 2.1.3. EEG recording

Experiment data was recorded under Neuroscan system with a 40 channel SynAmps amplifier. EEG data were recorded from 30 Ag-AgCl electrodes arranged according to the international 10-–20 system, with a contralateral reference to left and right mastoid derivation. The mid-forehead electrode severed as ground. Horizontal and vertical electrooculograms (EOG) were recorded from electrodes placed laterally to both eyes as well as below and above the left eyes to monitor the eye movements and blinks. Electrode impedances were below 5kΩ, the amplifier was set as band pass at 0.01 Hz to 100H and the sample rate is 1000 Hz. Trials with overt incorrect responses or amplifier blocked were eliminated from the EEG data. The EOG artifacts were reduced by means of an ocular artifact reduction algorithm implemented in Neuroscan software (SCAN4.5).

### 2.1.4. ERP extraction

For each subject, EEG data was segmented from 100 ms prior to onset of stimuli and ended at 924 ms after stimuli, and baseline correction was done using the pre-stimulus period data. Any epochs which larger than 100 mV were excluded. Through the overlaying and averaging of ERP epochs for all trials induced by the four stimuli (irrelevant, probe1, probe2, and target), we got the averaged ERP for each subject. In this study, the averaged ERP for each subject and the grand averaged ERP over all subjects were used. In order to get the four sub-band frequencies of EEG data, wavelet package decomposition was used to the EEG data and corresponding sub bands were reconstructed. The results were display in result section.

## 2.2. Directed functional connectivity

### 2.2.1. Phase transfer entropy

Phase transfer entropy (PTE) is a useful measure for directed functional connectivity in large-scale investigations of human functional connectome (Lobier, Siebenhuhner, Palva & Palva, 2014). It is more robust to noise and considerably more efficient computationally. For a given signal $X$(t) and a frequency band, define the corresponding analytic signal (after Morlet wavelet filter or Hilbert transform filter) as:

$$S(t) = A(t)\exp(i\theta(t)) \tag{1}$$

Where$\theta(t)$is the instantaneous phase time-series of signal $X$(t). Then Lobier et al. defined phase transfer entropy for a given analysis lag $\delta$ as (Lobier et al., 2014):

$$\begin{aligned}\mathrm{PTE}_{X\to Y} = {} & H(\theta_y(t),\theta_y(t'))+H(\theta_y(t'),\theta_x(t')) \\ & -H(\theta_y(t'))-H(\theta_y(t),\theta_y(t'),\theta_x(t'))\end{aligned} \tag{2}$$

Where $\theta_x(t')$and $\theta_y(t')$are the past states at time point $t' = t - \delta$: $\theta_x(t') = \theta_x(t-\delta)$and $\theta_y(t') = \theta_y(t-\delta)$. And the marginal entropy and joint entropy terms was defined as:

$$H(\theta_y(t),\theta_y(t')) = -\sum p(\theta_y(t),\theta_y(t'))\log p(\theta_y(t),\theta_y(t')) \tag{3}$$

$$H(\theta_y(t'),\theta_x(t')) = -\sum p(\theta_y(t'),\theta_x(t'))\log p(\theta_y(t'),\theta_x(t')) \tag{4}$$

$$H(\theta_y(t')) = -\sum p(\theta_y(t'))\log p(\theta_y(t')) \tag{5}$$

$$\begin{aligned}H(\theta_y(t),\theta_y(t'),\theta_x(t')) = {} & -\sum p(\theta_y(t),\theta_y(t'),\theta_x(t')) \\ & \log p(\theta_y(t),\theta_y(t'),\theta_x(t'))\end{aligned} \tag{6}$$

### 2.1.2. Network measures

Directed functional connectivity can be presented by a directed graph which defined as a set of nodes and corresponding sets of directed links. In this study, we constructed a directed network using PTE with the 30 channel EEGs under familiar and unfamiliar person group. The value of adjacent matrix can present the weight and direction of the network, and the network characteristics can be presented by some parameters of the directed network. The parameters we mainly discussed in this article are degree (in degree and out degree), clustering coefficient, characteristic path length, betweenness centrality and assortativity coefficient (Rubinov & Sporns, 2010; Stam & Reijneveld,2007).

A node's degree is equal to the number linking to that node, and inDegree and outDegree is the edge number ingoing and outgoing of that node. For weighted network, another parameter for a node is flow, which is defined as the sum of the weight of edges linking to the node, and inFlow and outFlow is the weight sum ingoing and outgoing of that node. Network's degree and flow is the average of all nodes' degree and flow, which commonly used as a measure of "wiring cost" of the network. Clustering coefficient (C) measures the segregation of the network and is equivalent to the fraction of the node's neighbors that are also neighbors of each other (Rubinov & Sporns, 2010; Stam & Reijneveld, 2007). Characteristic path length (L) is known as the average of shortest path length between all pairs of nodes. Path length consequently estimates the potential for functional integration between brain areas, with shorter paths implying stronger potential for integration (Rubinov & Sporns, 2010). Betweenness centrality (BC) is a more sensitive measure for centrality, defined as the fraction of all shortest paths in the network that pass through a given node, which is an important measure for assessing the importance of individual nodes in the network (Rubinov & Sporns, 2010). Assortativity coefficient (ASS) is a useful measure of network resilience, which actually is a correlation coefficient between the degrees of all nodes on two opposite ends of a link (Rubinov & Sporns, 2010).

## 2.3. Complexity measures

Entropy is a useful measure of EEG signal complexity and can be used to quantify the potential feature for person perception (Greene et al., 2008; Mazher, Aziz, Malik & Amin, 2017). Spectral entropy has been suggested to be useful to present significant nonlinear dynamics properties of biological time series. The spectral entropy (SpEn) of EEG is defined as (Greene et al., 2008; Mazher et al., 2017):

$$\mathrm{SpEn}(X) = -\frac{1}{\log N_v}\sum_v P_v(X)\log_e P_v(X) \tag{7}$$

Where $P_v(X)$ is the probability density function (PDF) for EEG signal $X$, which is calculated by normalizing the power spectral density (PSD) estimate with respect to the total spectral power. The PSD is calculated separately in the four sub-band frequencies. $N_v$ represents the number of frequencies in PSD estimate (Greene et al., 2008; Mazher et al., 2017). The value was finally normalized to the range 0–1.

Approximate entropy (ApEn) can present robust estimate for non-stationary biological signals with a small data set (Nie et al., 2019). It can be used to characterize the changes of brain activities in person perception. For a $N$ points data set from a time series $\{x(\mathrm{n})\}$, $n = 1,2,3\ldots N$. ApEn was defined as following steps (Nie et al., 2019):

For the $t$-dimensional space reconstruction, the reconstructed $i$ th vector is defined as:

$$x_t(i) = [x(i), x(i+1), \ldots, x(i+t-1)], i = 1, 2, \ldots, N-t+1 \tag{8}$$

Where $t$ is the pre-selected mode dimension. Then the distance between one vector and other vector is computed as the maximum absolute difference between the two corresponding elements (Mazher et al., 2017; Nie et al., 2019):

$$d[x_t(i), x_t(j)] = \max_{0\le p\le t-1}(|x(i+p) - x(j+p)|) \tag{9}$$

For a given threshold $w$, for each $i$, the number of $d[x_t(i),x_t(j)]$ less than $w$, and the ratio of the number and the total distance ($N$-$t$) can be calculated and marked as$\phi_i^t(w)$. Then the probability of time series is defined as:

$$\Phi^t(w) = \frac{1}{N-t+1}\sum_{i=1}^{N-t+1}\ln\phi_i^t(m) \tag{10}$$

Increase the dimension to $t + 1$ and repeat the above steps to get $\phi_i^{t+1}(w)$ and $\Phi^{t+1}(w)$. Then the approximate entropy is defined as:

$$\mathrm{ApEn} = \Phi^t(w) - \Phi^{t+1}(w) \tag{11}$$

ApEn has one bias as it usually counts each sequence as matching itself to avoid the happening of ln(0). Then the sample entropy (SaEn) is proposed to overcome this drawback by reducing the bias (Mazher et al., 2017), which is defined as:

$$\mathrm{SaEn} = \ln\left[\Phi^t(w) - \Phi^{t+1}(w)\right] \tag{12}$$

where $\Phi^t(w) = \frac{1}{N-t+1}\sum_{i=1}^{N-t+1}\phi_i^t(m)$.

In this study, $t$ is set to 2 and $w$ is set to 0.2SD (SD is the standard deviation of the amplitude of the time points). Each 1024 points is used for ApEn calculation.

Hjorth parameters are one method to indicate statistical properties of a signal in time domain(Oh et al., 2014) . The parameters are activity, mobility, and complexity, which are commonly used in the analysis of EEG signals for feature extraction. Hjorth activity is the variance of a time function, which represents the signal power. It can indicate the surface of power spectrum in the frequency domain, which is defined as:

$$\mathrm{Activity} = \mathrm{var}(y(t)) \tag{13}$$

Where $y$(t) represents the signal.

Hjorth mobility is defined as the square root of variance of the first derivative of the signal $y$(t) divided by variance of the signal $y$(t). It represents the mean frequency or the proportion of standard deviation of the power spectrum, which is defined as:

$$\mathrm{Mobility} = \sqrt{\frac{\mathrm{var}(\frac{dy(t)}{dt})}{\mathrm{var}(y(t))}} \tag{14}$$

Hjorth complexity (HC) represents the changes in frequency. It indicates how the shape of a signal is similar to a pure sine wave, where the value converges to 1 if the shape of the signal gets more similar to a pure sine wave. It is defined as:

$$\mathrm{Complexity} = \frac{\mathrm{Mobility}(\frac{dy(t)}{dt})}{\mathrm{Mobility}(y(t))} \tag{15}$$

### 2.4. Classifiers and statistical analysis

In this study, support vector machine (SVM) and k-nearest neighbor (KNN) classifiers with several kernels such as linear kernel, coarse Gaussian kernel, cosine kernel and median kernel were applied to distinguish the EEG features induced by face image between familiar and unfamiliar group. It is said that SVM and KNN are good at using multidimensional nonlinear data to investigate the performance of features in a pattern recognition system (Bae, Yoo, Lee & Kim, 2017; Yin & Peng, 2012). In this article, the network parameters and signal complexities were discussed as the features for person recognition, but only the features that have statistical significance based on paired sample $t$-test ($p < 0.05$) were selected as the feature set for classifiers to distinguish familiar person from unfamiliar one. The selected features of classifiers were validated using 5 fold cross validations.

## 3. Results

EEG was segmented to epochs and trial average was done under the two conditions. As shown in Fig. 3(a) is the grand averaged ERP through all subjects. Compare to unfamiliar items, familiar person induced more positive ERP components, which means it has larger amplitude and latency. In this study, the features and directed connectivities were discussed under the frequency of delta, theta, alpha and beta band. Fig. 3(b) presents the four sub-band waves of grand averaged ERP after wavelet package decomposition and reconstruction. It can be seen that for familiar person the signal have more ERP components in delta and theta band.

After got the four band waves, we calculated several complexity measures for each band. Table 1 presented the result of SaEn, SpEn, ApEn and complexity of Hjorth. It can be seen that SaEn and ApEn is very small in the four bands, by contrast, SpEn is more larger and the value of Hjorth complexity is the largest one. Paired $t$-test was done for these measures between familiar and unfamiliar face group. The results showed that SaEn in delta band ($t$=−2.5651, $p = 0.0208$), SpEn in theta band ($t = 2.9043$, $p = 0.0103$), Hjorth complexity in delta ($t = 2.8064$, $p = 0.0127$), theta ($t = 3.1188$, $p = 0.0066$), alpha ($t = 2.3046$, $p = 0.0349$), and beta ($t = 2.3099$, $p = 0.0346$) band have statistically significance. Other measures in these bands have no significant difference.

Directed networks under the four bands were constructed using phase transfer entropy. In order to get a threshold to eliminate the unimportant edges, firstly we defined a measure for network node, which is the ratio of node flow and node degree (FDR):

$$\mathrm{FDR} = \frac{\mathrm{flow}}{\mathrm{degree}} \tag{16}$$

Where node flow is the sum of in-flow and out-flow, and degree is the sum of in-degree and out-degree. Then the calculation for the FDR of all nodes was performed. Fig. 4 presents the statistical distribution of node FDR and the probability density function (PDF) for grand averaged network induced by familiar and unfamiliar person. Lastly, the upper quantiles of each distribution were calculated as the threshold for each sub-band.

For the weighted network, some connections may be caused by the noise between signals and the weak connections cannot represent the real causality between different brain regions. Thus it is necessary to eliminate these weak connections using a threshold. As shown in Fig. 5 is the topology network of directed weight connections after selection using the threshold discussed above. We

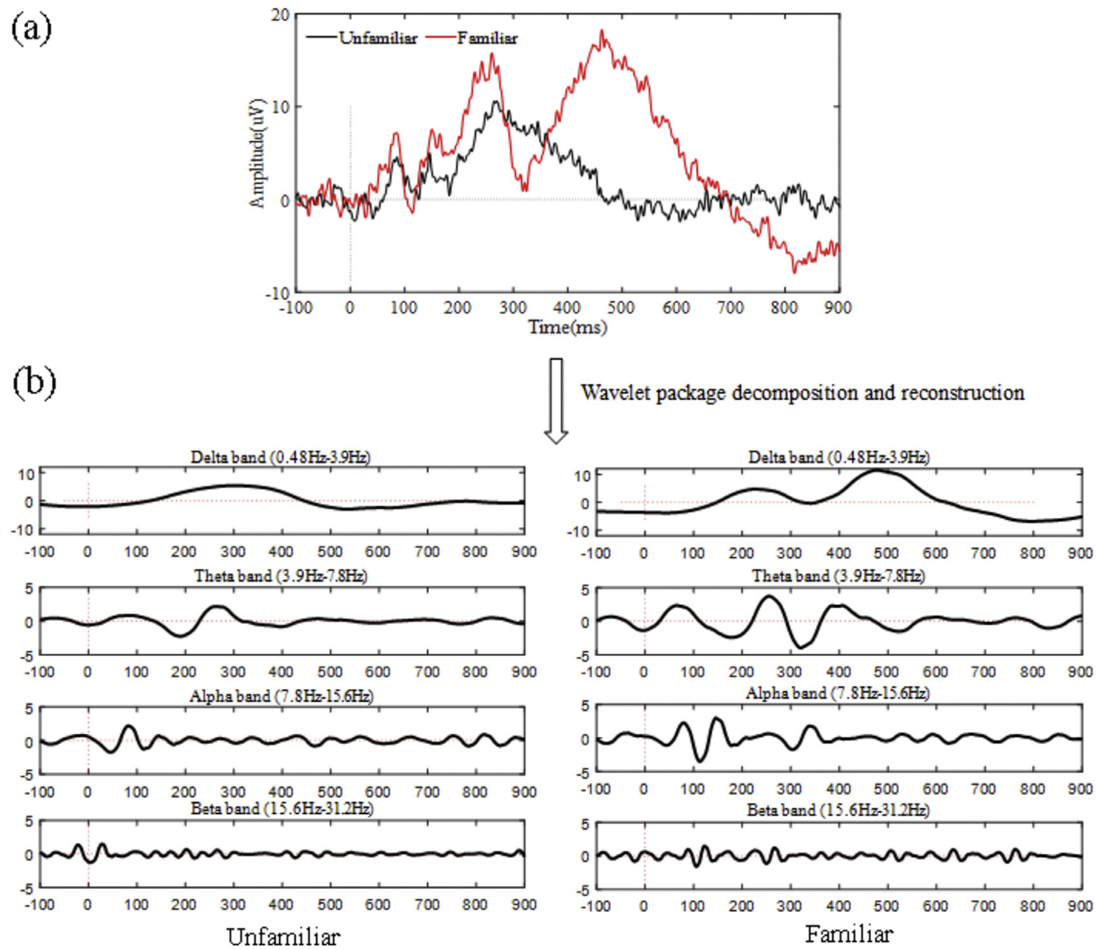


**Fig. 3.** ERP signal and the corresponding four band waves in familiar and unfamiliar face group. (a) grand averaged ERP, (b) the four band waves in the two conditions.

**Table 1**
Complexity measures of the four band waves for unfamiliar and familiar person group (mean/SD).

| | Band1-Delta | | Band2-Theta | | Band3-Alpha | | Band4-Beta | |
|---|---|---|---|---|---|---|---|---|
| | Cod1 | Cod2 | Cod1 | Cod2 | Cod1 | Cod2 | Cod1 | Cod2 |
| SaEn | 0.0489* (0.0091) | 0.0577* (0.0085) | 0.0033 (0.0012) | 0.0029 (0.0008) | 0.0011 (0.0004) | 0.0010 (0.0005) | 0.0001 (0.0001) | 0.0001 (0.0001) |
| SpEn | 0.6075 (0.0423) | 0.6037 (0.0498) | 0.6355* (0.0391) | 0.6068*(0.0426) | 0.4362 (0.0215) | 0.4266 (0.0219) | 0.5839 (0.0365) | 0.5737 (0.0338) |
| ApEn | 0.0720 (0.0074) | 0.0698 (0.0032) | 0.0063 (0.0021) | 0.0056 (0.0011) | 0.0031 (0.0011) | 0.0026 (0.0005) | 0.0007 (0.0005) | 0.0007 (0.0004) |
| HC | 0.8987* (0.1613) | 0.7636* (0.0803) | 1.2504* (0.0781) | 1.1574*(0.0986) | 1.1323*(0.0926) | 1.0451*(0.1280) | 1.0234* (0.1093) | 0.9252* (0.1417) |

Cod1: unfamiliar group, Cod2: familiar group,"*" means has statistical significance between familiar and unfamiliar person stimulus ($p$<0.05).
person stimulus ($p < 0.05$).

kept the connections that edge value larger than the threshold, and delete the connections that below the threshold. It can be seen that the difference of network topology between familiar and unfamiliar is significant in the four bands. In delta and alpha band, the connection density of familiar network is higher than unfamiliar network, but in theta and beta band, there are more connections in unfamiliar network than familiar network.

In order to carry on quantitative analysis of the weighted network, several network parameters were calculated and statistical analysis were done between familiar and unfamiliar person group. It can be seen from Fig. 6 that the value of clustering coefficient in unfamiliar condition is significant lower than familiar condition in delta band ($t = 2.4824$, $p = 0.0245$), whereas in other bands, the difference is not significant. For characteristic path length, there is not too much difference between these two conditions, but the value in alpha band is significant low ($t = 2.4641$, $p = 0.0254$) in familiar condition than in unfamiliar condition, and it is significant high ($t$=−2.3063, $p = 0.0348$) in beta band. As in directed network, one node's in-degree is another node's out-degree, so in this article, we only calculated in-degree of the network. As shown in Fig. 6, we can see that compare to familiar condition, it is higher in unfamiliar condition in theta and beta band, and lower in delta and alpha band. The $t$-test shows the difference between the two conditions is significant in the four bands (delta: $t = 2.375$, $p = 0.0304$; theta: $t = 2.1701$, $p = 0.0454$; alpha: $t$=−3.1365, $p = 0.0064$; beta: $t = 2.2018$, $p = 0.0427$). The situation for network density is exactly the same as in-degree. There are some differences for assortativity coefficient and betweenness centrality. It can be seen assortativity coefficient in familiar condition is a litter higher than unfamiliar condition in theta band, but the difference is not significant, while it is significant higher in unfamiliar condition in alpha ($t = 2.4035$, $p = 0.0287$) and beta ($t = 2.2802$, $p = 0.0366$) band. Difference of betweenness centrality within subjects is not clear and the statistical analysis shows

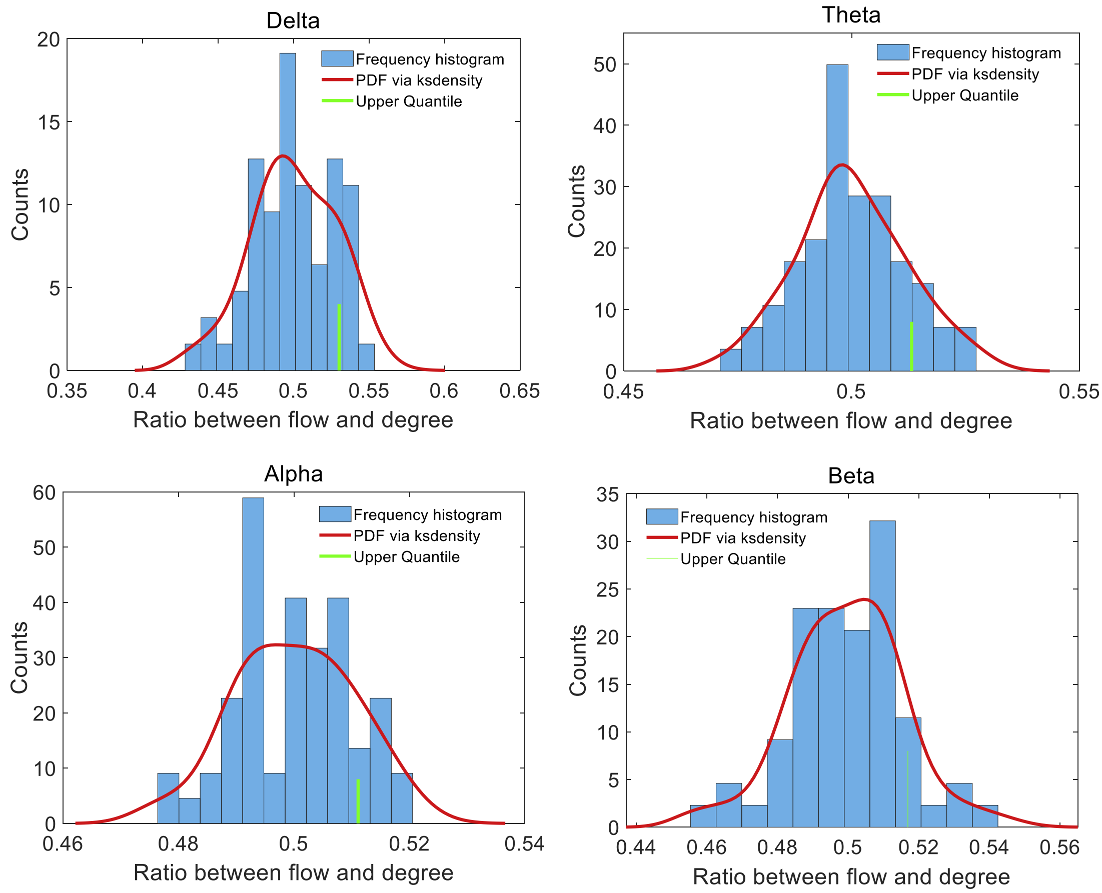


**Fig. 4.** Statistical distribution of node FDR and the probability density function (PDF) for grand averaged network induced by familiar and unfamiliar person in the four bands. Finally, the threshold for delta, theta, alpha, and beta band is 0.5274, 0.5120, 0.5101 and 0.5123 respectively.

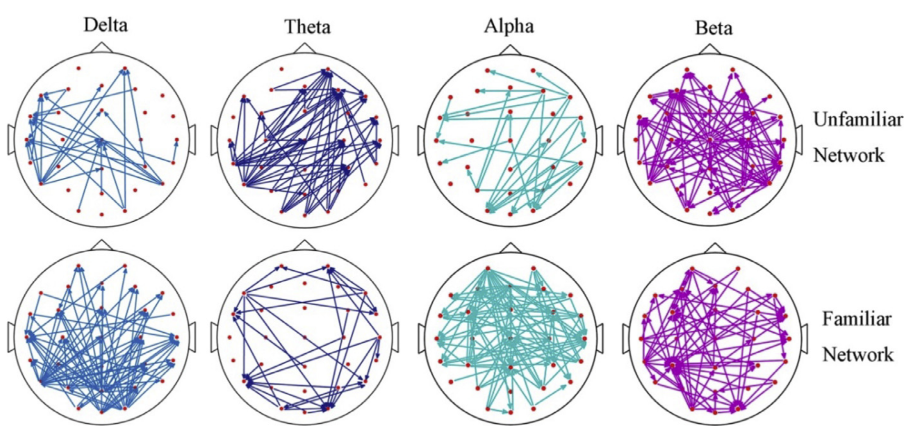


**Fig. 5.** Topology networks of directed weight connectivity in different condition.

that there are no significant differences between familiar and unfamiliar condition in the four bands.

From the results discussed above, it can be seen that the value of network parameters is very different in the four frequency bands between familiar and unfamiliar group, which means the directed network constructed by ERP signals in the four bands present different network features. We can make a hypothesis that the four bands present different cognitive activities and has different cognitive functions during person perception and recognition.

After the discussion of complexity measures and weighted network parameters, these features which have significant difference between familiar and unfamiliar person condition in each band were defined as the extracted feature set and applied to the classifiers. SVM with linear kernel and coarse Gaussian kernel, and KNN with cosine kernel and median kernel were applied to the extracted features to distinguish familiar person from unfamiliar one. The classification was performed for each sub band respectively. In delta band, the extracted features are SaEn, Hjorth complexity, clustering coefficient, degree, and density. In theta band, they are SpEn, hjoth complexity, degree, and density. In alpha band, they are Hjorth complexity, characteristic path length, degree, density and assortativity, and in beta band, they are Hjorth complexity, degree, density, characteristic path length, and assortativity. Fig. 7 shows the classification results for the four bands. It can be seen

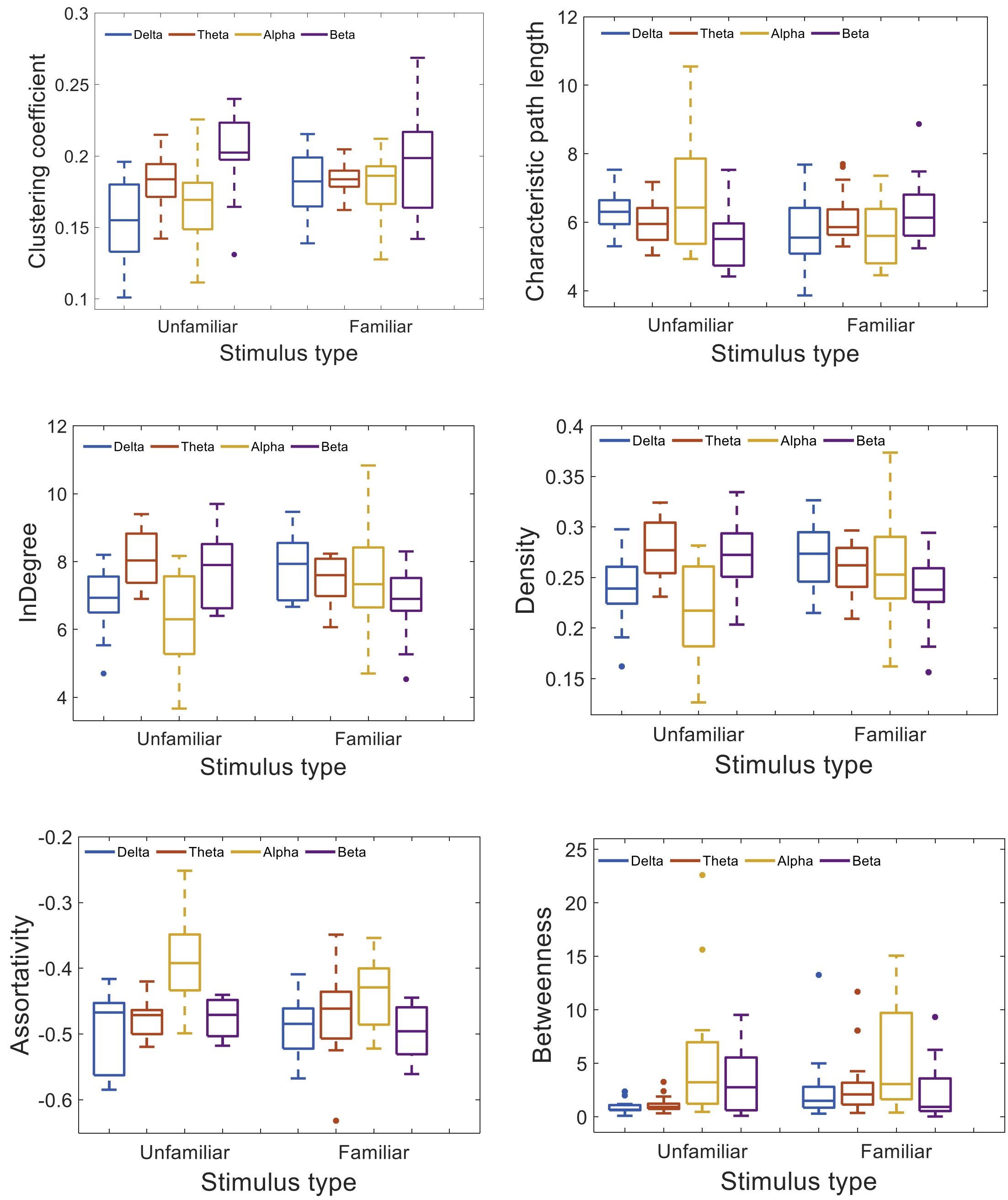


**Fig. 6.** Network measures of the four bands in familiar and unfamiliar condition.

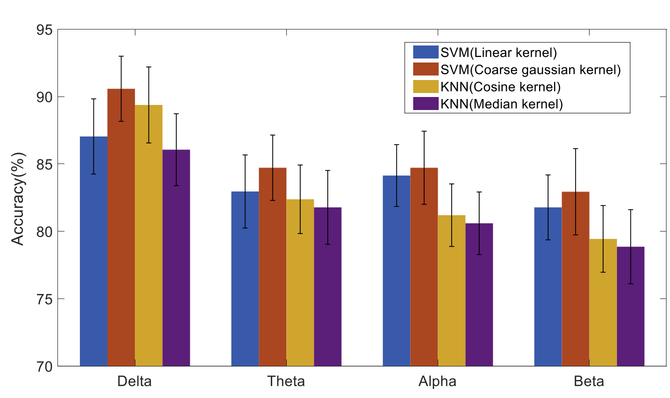


**Fig. 7.** Classification accuracy of different classifiers in the four bands.

that no matter what classifier kernel were used, the delta band got the highest classification accuracy, which is 87.04%, 90.58%, 89.38% and 86.06% for SVM with linear kernel, SVM with coarse Gaussian kernel, KNN with cosine kernel and KNN with median kernel respectively, all of which are over 86%. Besides delta band, theta and alpha band also achieved good results, the accuracy of classifiers are all above 82%. Beta band has the lowest accuracy, but the effect is not so bad with the accuracy of 78.86%, proved the effectiveness of the proposed method. Comparison results of different classifiers in the four bands shows that SVM with coarse Gaussian kernel has the best performance, and SVM classifiers are better than KNN classifiers for this analysis. The results identify delta band as the best measure frequency for face recognition, but to some extent, theta and alpha bands are also proved to be a good measure frequency.

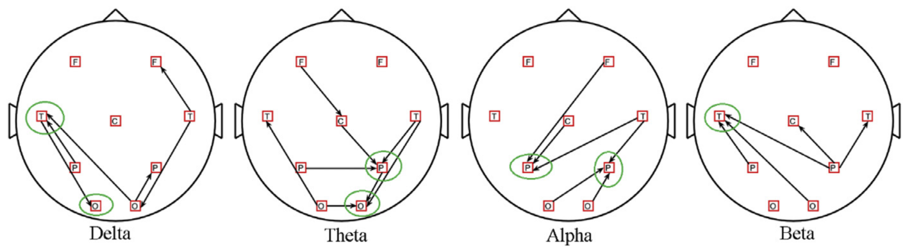


**Fig. 8.** Statistical result of directed functional connectivity among sub brain regions between familiar and unfamiliar face condition ($t$-test, $p < 0.05$).

## 4. Discussion

In this article, by using EEG as a bridge for investigating the human face and name perception system in the brain, we aimed to present the cognitive processes and different features between familiar and unfamiliar person perception, and combined with classifiers to achieve the identification and classification of familiar and unfamiliar person. The present study is the first time to show the directed functional connectivity in person recognition, and how familiar person influence the EEG response and network topology in the context of person perception and recognition. Besides, four complexity measures of EEG signals were extracted and combining with the network parameters, it can efficiently classifier the familiar person from unfamiliar one.

Previous researches have demonstrated ERPs can be used as the electrophysiological markers to investigate the neural processes underlying face recognition (Gosling & Eimer, 2011). Lots of ERP studies focused on the N170, a negative-going ERP peaking around 170 ms after stimulus onset, which is related to early structural encoding of faces ( Hanso et al., 2010; Huang et al., 2017). However, some studies found larger N170 amplitude for familiar relative to unfamiliar faces, while some studies found contrary results. Several studies have suggested that very early stages of face processing are not modulated by familiarity (Johnston & Edmonds, 2009). The majority of studies failed to find any differences of N170 between familiar and unfamiliar faces (Lui et al., 2018;Huang et al., 2017), which is similar to the ERP result in this study. As show in Fig. 3(a), we did not find any significant difference from 100 to 200 ms, mainly because of the integration of visual and auditory stimuli.

Some researches also found that N200 and P300 are associated with person recognition. Even though N200 components are triggered reliably by repetitions of unfamiliar faces, familiar faces usually elicited larger amplitude of N200 and P300 (Gosling & Eimer, 2011; Hanso et al., 2010; Lui et al., 2018), which is supported by our results in this study. As show in Fig. 3(a), comparing with unfamiliar person, familiar person elicited not only an enhanced amplitude but also the larger latency. Other studies also found that later ERP components were sensitive to recognition of familiar faces and names: familiar visual face and auditory name elicited larger amplitude of N400 and P600 (Huang et al., 2017; Sun et al., 2012), but this study did not find any significant difference. The reason we think is that the later N200 and P300 generally been associated with higher-level, view-invariant processes such as face perception, auditory processing, working memory and decision making, and are therefore characteristics of the familiar person (Collins, Robinson, & Behrmann, 2018). In summary, ERP based person recognition has not yet provided a clear picture of the links between face and name-specific ERP components and brain processes involved in recognizing and identifying familiar person (Gosling & Eimer,2011). This is the reason that in this study we did not focus on an ERP component, but focus on the signal complexity and the directed functional connectivity of the ERPs from the whole brain in the four sub bands.

The directed functional network was constructed using phase transfer entropy, which is suited for the estimation of directed phase-based connectivity in investigations of human functional connectivity (Lobier et al., 2014; Vicente, Wibral, Lindner & Pipa, 2011). Because of the noise from the environment, there are lots of weak connectivities which is not important for feature representation and it is necessary to use a threshold to eliminate these connections (Reijneveld, Ponten, Berendse & Stam, 2007; Stam & Reijneveld, 2007). In this study, we proposed a threshold selection method for directed functional network, in which the threshold is defined as the upper quantile of the distribution of node's FDR for the networks from the two conditions. Thus, the connections after threshold filtering can distinguish the networks of the two conditions properly, with the parameters of the most important connections.

Fig. 5 shows the directed connectivity for the four bands in the two conditions. It can be seen that there are obvious differences of the network topology in delta, theta and alpha band, and the region of key connections located in different position. In general, compare to unfamiliar condition, it has a higher global connectivity in familiar condition in delta, alpha band and lower connectivity in theta and beta band. The reason is that neural oscillations in different frequency bands are thought to support different cognitive functions(Henry et al., 2014) ), and the cognition presentation to familiar and unfamiliar person in different bands are not exactly the same. Transfer entropy investigates whether the past of both source and target time-series would influence the ability to predict the future of the target time-series (Lobier et al., 2014; Vicente et al., 2011; Wollstadt et al., 2014)), which can be used to check whether the past activities in one region have effect to other regions' activities. Regions involved in person perception in the skull can be localized from EEG and we can provide some information about the causal dependence between different regions. As show in Fig. 8 we presented the significant connection between different brain regions, which means the phase transfer entropy from this region to another one has significant difference between familiar and unfamiliar group. We can see that there are some differences of the significant connection between the four bands.

In delta band, the direction of main significant connection is from right temporal to right occipital, and to left temporal then to left occipital. Delta are the slowest wave and some studies have shown it involves motivational process (Knyazev,2007). There is evidence that behaviors associated with unconstrained urge towards biologically relevant rewarding objects is accompanied by enhanced delta activity (Knyazev,2007). Delta EEG power has been shown to correlate positively with the amplitude of P300. In this study, the response to familiar person is assumed to be a specific motivation and it can induce strong P300 component, while the motivation from unfamiliar person is a little weak. It is the motivational process causing the significant directed connection among different brain regions between the two conditions, in which the connection end up in left temporal and left occipital regions. Mainly because occipital is associated with visual processing, such as visual recognition and visual attention, and temporal is respon-

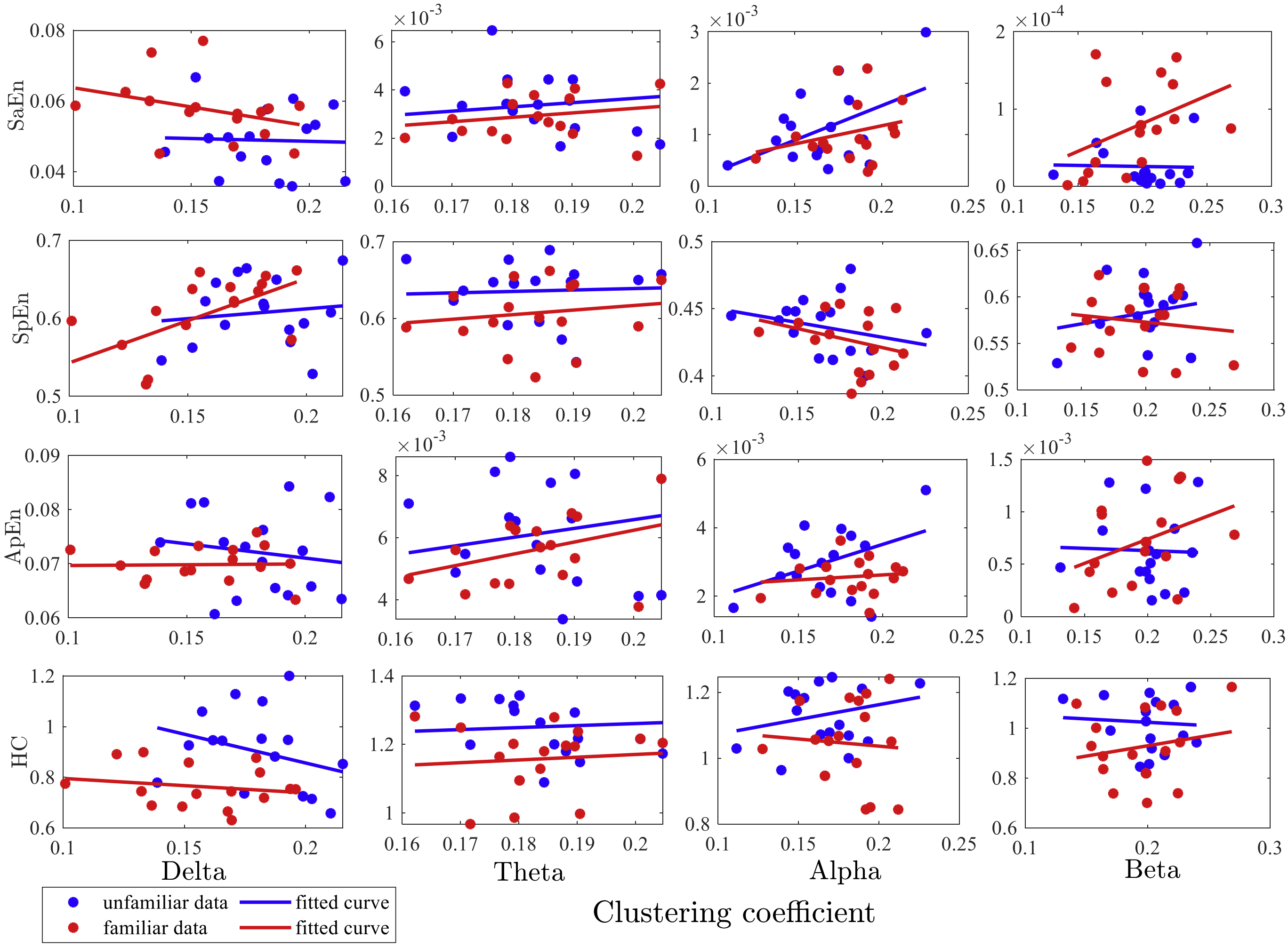


**Fig. 9.** Between subject correlation between network parameters and signal complexity.

sible for long-term memory and auditory memory processing. It indicates that the integration of visual and auditory cognition process of familiar person is different from unfamiliar one and the corresponding memory information in the brain has significant difference.

In theta band, the main connection is from central, left parietal and right temporal to right parietal and end up to right occipital. Studies consistently report that theta is generally associated with brain processes underlying mental workload or working memory (Klimesch,1996), for example, during focused attention and information uptake. In this study, we think during the person perception, familiar face and name (in auditory form) draw more attention of the subject and thus increase the mental workload of the subject, which is the main reason of the difference for significant connection in theta band. Similarly, the direction connection finally end up to right occipital which is responsible for visual processing and right parietal which plays important roles in integrating sensory information from various parts of our body, and here in this study, it was primarily for visual and auditory perception.

In alpha band, the significant connection is mainly from right frontal, central and right temporal to parietal, and from right temporal, right and left occipital to right parietal. The underlying assumption for EEG asymmetry research is that alpha waves simply indicate the idling state of the brain(Grimshaw and Carmel, 2014) . Alpha suppression constitutes a valid signature of states of mental activity and engagement. In this study, the connection presents the difference of brain's activities and engagement in the recognition of familiar and unfamiliar face and name. The connection finally end up to right and left parietal, as discussed in theta band, the parietal cortex is responsible for merging of visual and auditory information. Therefore, we think the difference presents the brain's process of visual and auditory merging for the mental activity and engagement of face and name stimuli underlying different conditions.

In beta band, the main connection is from right parietal to left temporal, central and right temporal, from right occipital, left parietal to left temporal. Active, busy or anxious thinking and active concentration are generally known to correlate with higher beta power. Studies have shown that band activity also serves as a carrier for attention activation (Gola, Magnuski, Szumska & Wróbel, 2013). It is indicated that the attention activation of the brain for familiar and unfamiliar person are not exactly the same, the result shows in beta band the significant connection mainly focus on left temporal, which usually controls memories related to facts and information, along with the ability to recognize faces and objects (Gola et al., 2013). The conclusion is that during the face and name perception of familiar and unfamiliar person, the attention activation in left temporal which related to face and name recognize and memories has significant difference.

In the present study, attempts to understand the cognitive process for the human brain during person perception was conducted by computation of features based on phase transfer entropy and signal complexity among the recorded EEGs. The networks discussed above can present the directed connectivities among different brain regions qualitatively. We also found that some network parameters in familiar group are significantly different from unfamiliar group, which enables us to differentiate familiar person from unfamiliar one. As shown in Fig. 6 these significant parameters are averaged clustering coefficient and inDegree in delta band, inDegree in theta band, and in alpha and beta band they are characteristic path length, in-degree and associativity. Additional analysis present the complexity of signal, including spectral entropy, approximate entropy, sample entropy and Hjorth parameters were completed. Statistical analysis shows that some parameters have significant difference between the two conditions in a particular band. Finding features which have significant difference between the two conditions and classifying the groups using machine learning can be a useful tool for person recognition. Four classifiers namely SVM with linear kernel and coarse Gaussian kernel, and KNN with cosine kernel and median kernel were employed for classification. We successfully trained and tested several features in the four bands separately using five-cross validation and obtained satisfactory results. In summary, the result illustrate the effectiveness of the proposed method and it suggests this analysis can be a useful tool for the EEG based person recognition.

In this study, we also investigated the relationship between network parameters and signal complexity, as shown in Fig. 9 is the correlation between clustering coefficient and signal complexities. The current study identified a significant correlation between some parameters. That is in delta band, it is between C and SaEn ($r$=−0.4926, $p$ = 0.0445), C and SpEn ($r$ = 0.6740, $p$ = 0.003), L and SpEn ($r$=−0.6275, $p$ = 0.007), InDegree and SpEn ($r$ = 0.6158, $p$ = 0.0085) in familiar group, and L and ApEn ($r$ = 0.5613, $p$ = 0.0191), InDegree and ApEn ($r$=−0.5325, $p$ = 0.0278) in unfamiliar group. In theta band, it is between BC and HC ($r$=−0.5980, $p$ = 0.0112), ASS and HC ($r$ = 0.4142, $p$ = 0.0019) in familiar group. In alpha band, it is between BC and SpEn ($r$=−0.5656, $p$ = 0.018), BC and HC ($r$ = 0.7665, $p$ = 0.0003), ASS and HC ($r$ = 0.7819, $p$ = 0.0002) in familiar group, BC and SpEn ($r$=−0.6716, $p$ = 0.0032), BC and HC ($r$ = 0.5319, $p$ = 0.0280) in unfamiliar group. In beta band, it is between C and SaEn ($r$ = 0.5729, $p$ = 0.0162), BC and ApEn ($r$=−0.4969, $p$ = 0.0424), ASS and ApEn ($r$ = 0.4884, $p$ = 0.0467) in familiar group, ASS and SaEn ($r$=−0.5098, $p$ = 0.0366) in unfamiliar group. It can be seen that there are more significant correlations in the familiar group, which means compared to unfamiliar person, the complexity of ERP signal for familiar person tend to be more closer to the network parameters. Therefore, works to find whether the network parameters or the signal complexity is better for person recognition in these highly correlated parameters are needed in the future, finding features after optimization of the parameters with high correlation may further improve the accuracy of person recognition.

## 5. Conclusion, limitation and future work

In this study, an EEG based expert and intelligent system for person recognition has been proposed. We investigated whether directed EEG-based functional networks of familiar person are different from those of unfamiliar person. An objective approach based on network parameters, signal complexity and various classifiers was proposed to recognize familiar person from unfamiliar one. The signal complexity, including sample entropy, spectral entropy, approximate entropy and Hjorth complexity, combined with network parameters were calculated as the feature set. Two well known classifiers, namely SVM and KNN were employed for classification, satisfactory results were obtained using five-cross validation for training and testing of the classifiers. In which SVM with coarse Gaussian kernel in delta band got the highest accuracy of 90.58%, other classifiers in delta band also got an accuracy over 86%. Besides, to some extent, theta and alpha band also proved to be have a good performance, which got an accuracy all over 82% with different classifiers. The results indicated that delta wave was the best wave for person recognition and SVM was better than KNN in this system. This study demonstrated that the feature extraction method of EEG which combining the network parameters of directed functional network and signal complexity, together with machine learning classifiers is an effective approach to identify familiar person from unfamiliar one. The combination of functional brain network and machine learning method provide a new insight for EEG classification, and other details need more discussion in the further.

In terms of any practical implications, the developed method and person recognition system can be used as an expert and intelligent system for deception detection which is also a key part of forensic and security operations, feigning memory loss or amnesia detection, and brain disease diagnosis such as prosopagnosia. Besides, some brain computer interfacing studies adopted familiar or unfamiliar face and voice in experimental paradigm to strength ERPs generated by the stimuli of categories. The proposed person identification and classification method may also be beneficial for the BCI studies.

There are some limitations for the proposed methods. At first, the limited number of electrodes of the EEG device may be a drawback of this article. Although the scalp regions which responsible for person identification and classification are mostly covered, as the limited channels and the low resolution of EEG device, the information presented by the topology network is very limited. Besides, the network constructed in this study is based on PTE, which mainly focused on the causal dependence of different EEG signals. It does not consider the common source issue, a common problem of statistical interdependences in EEGs because of volume conduction and common reference, which is one of the reason we set threshold to delete the connection with low weight.

Based on the limitations discussed above and the development of neuroimaging technology and machine learning algorithm. Some future directions related to the proposed work to produce more robust expert and intelligent system for person recognition should be focused. Though the proposed system gives good performance on the test dataset. Firstly, it is necessary to use the proposed system on other dataset and compare the obtained results with the state-of-the-art to verify the universality of the proposed pattern recognition method. Secondly, as the neural and cognitive mechanism underlying person recognition is still not clear, this issue needs further research to enhance our understanding. The fMRI based functional brain network analysis of person recognition should be further considered as it has a higher spatial resolution. The third possible issue is to make a comparison of the recognition effect about visual (name), auditory (voice), and verbal (name) stimuli respectively, and the integration within these stimuli paradigm. For the fourth one, network based feature extraction such as network representation learning (NRL) is a promising and novel approach to learn the network features which could be used for classification. Whether NRL can been applied to the classification of functional brain networks is an open question to be considered. Besides, deep learning based EEG feature extraction and classification is another further direction, combined 1D-CNN and LSTM, or spectrogram and the 2D-CNN should be good at EEG based person identification and classification, which should be addressed in future work. In summary, the ultimate goal for all these future directions is to develop an efficient expert and intelligent system which can be used for person recognition.

## Declaration of competing Interest

None

## Credit authorship contribution statement

**Wenwen Chang:** Conceptualization, Methodology, Software, Visualization, Investigation, Writing - original draft, Writing - review & editing. **Hong Wang:** Supervision, Resources, Conceptualization, Methodology, Writing - review & editing, Funding acquisition. **Guanghui Yan:** Visualization, Resources, Validation, Conceptualization, Funding acquisition. **Chong Liu:** Software, Formal analysis, Investigation, Data curation, Visualization.

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