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REVIEW PAPER

Complex networks and deep learning for EEG signal analysis

Zhongke Gao[1] · Weidong Dang[1] · Xinmin Wang[1] · Xiaolin Hong[1] · Linhua Hou[1] · Kai Ma[2] · Matjaž Perc[3]

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Abstract

Electroencephalogram (EEG) signals acquired from brain can provide an effective representation of the human's physiological and pathological states. Up to now, much work has been conducted to study and analyze the EEG signals, aiming at spying the current states or the evolution characteristics of the complex brain system. Considering the complex interactions between different structural and functional brain regions, brain network has received a lot of attention and has made great progress in brain mechanism research. In addition, characterized by autonomous, multi-layer and diversified feature extraction, deep learning has provided an effective and feasible solution for solving complex classification problems in many fields, including brain state research. Both of them show strong ability in EEG signal analysis, but the combination of these two theories to solve the difficult classification problems based on EEG signals is still in its infancy. We here review the application of these two theories in EEG signal research, mainly involving brain–computer interface, neurological disorders and cognitive analysis. Furthermore, we also develop a framework combining recurrence plots and convolutional neural network to achieve fatigue driving recognition. The results demonstrate that complex networks and deep learning can effectively implement functional complementarity for better feature extraction and classification, especially in EEG signal analysis.

Keywords Electroencephalogram signals · Complex network · Deep learning

Introduction

Real-world systems evolve over time and present complex system dynamics. Observing complex systems from different aspects can acquire diverse time-based measurements, namely, time series. Via learning the system dynamics from these acquired time series, one can better understand the external system behaviors and then predict the system accurately. After a long-term development, observing and characterizing complex systems from the observed time series has become a major filed of complex system sciences. Common methods applied into time series analysis mainly contain complexity theory (Aboy et al. 2006), symbolic theory (Keogh et al. 2003), chaos theory (Sugihara and May 1990), correlation theory (Podobnik and Stanley 2008), etc. Each of them specializes in a specific aspect of the time series and can capture the exclusive features. However, time series from real-world systems show obvious transient, nonlinear and non-steady features. Analysis based on one single point of view is no longer able to meet demands. To make matters worse, the complexity of the real-world systems continues to escalate. Time series analysis methods face enormous burden to effectively explore complex systems in such a context.

Human brain is recognized as an extremely complex and fascinating system. Human neocortex of brain contains up to 10^{10} neurons, which connect with each other and with cells in other parts of the brain via about 10^{12} synapses (Mountcastle 1997). All of these constitute a huge interconnected network, which is closely related to the human

✉ Matjaž Perc
matjaz.perc@um.si; matjaz.perc@uni-mb.si

Zhongke Gao
zhongkegao@tju.edu.cn

1 School of Electrical and Information Engineering, Tianjin University, Tianjin 300072, China

2 Tencent Youtu Lab, Malata Building, 9998 Shennan Avenue, Shenzhen 518057, Guangdong Province, China

3 Faculty of Natural Sciences and Mathematics, University of Maribor, Koroška cesta 160, 2000 Maribor, Slovenia

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behaviors and emotions. Many kinds of brain signals have been obtained and utilized to understand the brain, such as functional magnetic resonance imaging (fMRI), functional near-infrared spectroscopy (fNIR), near-infrared spectroscopy (NIRS), electroencephalogram (EEG), etc. Among them, noninvasive EEG is widely used because it is easy to access, of low cost and has a high temporal resolution (Shih et al. 2012; Kozma et al. 2008; Goshvarpour and Goshvarpour 2019). EEG records the scalp electrical signals and can effectively reflect the state of the brain. So far, a lot of progress related to EEG has been achieved in the fields of brain–computer interface (BCI), disease diagnosis, and cognitive analysis. For example, Subasi and Gursoy (2010) used PCA, ICA, LDA and support vector machines to predict epileptic seizure from EEG. Sharma and Pachori (2015) employed phase space representation of intrinsic mode functions to classify epileptic seizure and seizure-free EEG. Hassan and Bhuiyan (2016) proposed a single-channel EEG based method for sleep staging via complete ensemble empirical mode decomposition. Edelman et al. (2016) applied EEG source imaging to separate the multiple motor imagery tasks of the same hand, which helped the development of BCI systems with naturalistic and intuitive motor imaginations. Zhang et al. (2016) introduced a sparse Bayesian method by exploiting Laplace priors for EEG-based BCI classification.

Complex network theory has undergone an explosive growth in recent years (Newman 2003; Wang and Chen 2003; Jalili and Perc 2017; Boers et al. 2019; Donner et al. 2011; Li et al. 2019). Complex system with many interrelated components can be mapped into a complex network, where nodes represent the components and meanwhile the edges exactly illustrate the interactions among components. Plenty of achievements coming from diverse fields have demonstrated that complex network can efficiently cope with structural and dynamical problems of complex systems (Reijneveld et al. 2007; Agarwal et al. 2019; Diykh et al. 2017; Kurths and Agarwal 2019; Ekhtiari and Agarwal 2019; Rubinov and Sporns 2010; Gao et al. 2017, 2018; Li et al. 2018). Ref. Gosak et al. (2018) reviewed the study of complex biological systems based on methods of network science. In particular, complex network analysis of time series has been well developed (Zhang and Small 2006; Gao et al. 2017; Scarsoglio et al. 2017; Gao et al. 2017; Pasten et al. 2018; Gao et al. 2017; Weng et al. 2017; Nakamura et al. 2016; Rheinwalt et al. 2016). Via mapping the observed time series into a network framework, one can effectively understand the related complex system from network science. Obtained network topology, including the network edge distribution and community features, exactly mirrors the system characteristics implied in the observed time series. Viewing from the number of variables, complex network time series analysis can be divided into two categories. The first class of methods is the univariate time series complex network analysis. These methods allow to map one univariate time series into a complex network. The node can be defined via the time point (e.g. visibility graph) (Lacasa et al. 2008; Luque et al. 2009; Gao et al. 2016), or the motif from specific window (e.g. transition network) (Li et al. 2008; McCullough et al. 2015, 2017; Zhang et al. 2017), or the phase space vector (e.g. recurrence network) (Marwan et al. 2007; Zou et al. 2012; Donner et al. 2010; Riedl et al. 2015; Ngamga et al. 2016), etc. The other class is the multivariate time series complex network analysis (Gao et al. 2017, 2016). Multivariate time series present more rich information of the observed complex system from different viewing angles. By comprehensively studying the correlation between different channels of time series, one complex network can be built. Functional brain network is a typical example, where brain electrodes are set as nodes and edges can be determined via diverse correlation measures between electrodes. Many other types of complex network construction and analysis solutions have also been proposed, and have achieved good results in their respective research areas. A review of complex network analysis of time series can be seen in Gao et al. (2016). In addition to these single-layer network construction and analysis frameworks, multilayer network analysis has also received a lot of attention. This is because that real-world systems show obvious multiple characteristics, namely, the components of one complex system often present different associations from different perspectives. For example, in the transportation system, cities are connected via the road traffic and railway traffic with different characteristics. And in social networks, telephone networks and email networks within the group also present their own characteristics. Multilayer network, possessing different or same nodes in different layers with different types of edges, allows providing a more intuitive and accurate characterization of complex systems. Multilayer networks come in different forms (Gao et al. 2017, 2018; Boccaletti et al. 2014; Wang et al. 2014; Majhi et al. 2017). The operation of brain is inseparable from a large number of neurons, which connect into a large network. Therefore, studying the brain from a network view represents an effective direction. Actually, the application of network theory in brain research, i.e. brain network, has gained a lot of attention and made a lot of progress. In Ref. Betzel and Bassett (2017), the authors reviewed the multi-scale analysis of brain network. They discussed the content related to multi-scale topological structure, multi-scale temporal structure, and multi-scale spatial structure.

Machine learning (ML) is a branch of artificial intelligence, which shows great learning efficiency without the programming needs for specific tasks (Talebi et al. 2018).

In recent years, as a particular subset of ML methods, deep learning (Lin and Runger 2018; Bengio et al. 2013; Dang et al. 2019) has achieved lots of state-of-the-art results in diverse fields like object detection, speech recognition, and natural language processing. As the fundamental unit of deep learning, artificial neurons apply nonlinear transformation to the linear combination of its inputs, obtaining the high-level features. Stacking these neurons in different ways, variety of deep learning frameworks are built to implement effective feature extraction. Typically, deep belief network (DBN), convolutional neural network (CNN), and recurrent neural network (RNN) are three main frameworks in deep learning methods. DBN consists of a series of restricted Boltzmann machines (RBM), where the visible units and hidden units are held. Each RBM learns the compressed representation by maintaining the input and output the same as much as possible. In 2006, Hinton et al. (2006) proposed a layer-by-layer training scheme to handle the problem of vanishing gradient on DBN, which renewed the research focusing on deep neural network. Further, some functional modules, including sparse connections (Chen et al. 2016) and denoising structures (Vincent et al. 2010), was introduced into DBN. The DBN with these functional modules can guide the model to receive better representations of inputs. CNNs have achieved great progress in various tasks due to their unique structures. Improved from multilayer perceptron, CNN could extract local features through the convolution kernels while lightening the model by the shared parameters. Pooling layers can summarize the outputs of neighboring groups of neurons. Adopting these improvements, Krizhevsky et al. (2017) significantly improved the image recognition accuracy on ImageNet, showing the powerful abilities of learning effective features from the large amount of images. Further, the networks Inception (Szegedy et al. 2015, 2016) utilized deeper layers and detailed convolution, reaching excellent performance on the same dataset. He et al. (2016) proposed the residual learning framework, where extra paths were provided between some specific layers, enhancing the information transfer efficiency. Moreover, the densely connected convolutional blocks (Huang et al. 2017), connecting all layers with each other, promotes the interactions between these layers. As for the analysis of time series, RNN (Hochreiter and Schmidhuber 1997; Raghu et al. 2017) models have attracted great attentions due to its characteristic of extracting temporal dependencies. It consists of neurons that analyze both current input and previous state, which is possible for RNN to well explore the long dependencies along the temporal dimension on complex tasks. When solving the problems of vanishing or exploding gradients by selective adoption of the previous state, the new structures, long short-term memory (Hochreiter and Schmidhuber 1997) (LSTM) and gated recurrent units (Chung et al. 2015) (GRU), perform better than traditional RNN. Considering the information from both front and rear units, the bidirectional connection of RNN (Schuster and Paliwal 1997) ensures more comprehensive information fusion. The attention mechanism of RNN (Du et al. 2017) gives greater weights to the interested parts, enhancing the performance of RNN.

With the powerful analysis capabilities of complex networks and deep learning, effective characterization of brain system from EEG signals can be achieved. However, it should be mentioned that the advantages of these two theories are significantly different. Via setting nodes and defining edges, complex network can map complex relationships between different brain regions into network topology. Such mapping is purposeful and interpretable, allowing to understand and explore the complex dynamics and behavior of the brain. While deep learning enables to freely extract and combine diverse classification features, providing a good direction for the accurate identification of different brain states. Next, we will discuss the application of complex networks and deep learning in EEG analysis. And a framework combining complex network and deep learning is proposed to achieve driving fatigue recognition.

High performance brain–computer interface construction

Brain–computer interface (BCI) (Aggarwal and Chugh 2019; Lotte et al. 2007) utilizes the physiological signals from brain to control the external devices, where the physiological signals are intentionally induced by the specific activities of the subject. Widely accepted, BCI is an effective human–computer interaction technique, without relying on peripheral nerve pathways and muscle tissues. It is of great significance for studying and building BCI systems, especially for patients with severe dyskinesia disease. Among the various physiological signals, non-invasive EEG signals have attracted a lot of attention in BCI system research, mainly due to the fact that EEG signals have high resolution, are easy to access and inexpensive. So far, plenty of achievements related to EEG-based BCI system have been made, especially based on the steady-state visual evoked potential (SSVEP) (Zhang et al. 2013; Gao et al. 2018), event-related potential (ERP) (Wang et al. 2016; Gao et al. 2018), motor imagery (MI), etc. Typical analysis process of EEG signals in BCI system mainly contains three parts, namely, preprocessing, feature extraction and classification. The latter two points are highly valued in the existing researches. During the feature extraction, various time domain and frequency domain methods have been applied, such as fast Fourier transform

(FFT), autoregressive (AR) model, common spatial pattern (CSP), etc.

However, multi-channel EEG signals from BCI systems always present obvious channel coupling and rhythm dependence. In response to this characteristic, complex network theory with well complex relationship depicting ability has been introduced and utilized for EEG signal analysis. For example, BCI systems show obvious subject specificity, namely, when using the same BCI system, the performances of different subjects are obviously different. For some subjects, individual variations in brain structure would lead to lower classification accuracy of EEG signals. Zhang et al. (2013) carried out the SSVEP experiments and inferred the functional brain networks from the resting-state EEG signals. The coherence was used to determine the functional electrode connections. In the SSVEP-based BCI system, stimulus frequency plays the role of organizing the rhythms in the brain. They pointed out that resting-state EEG functional network topological properties were correlated with the SSVEP responses. Specifically, smaller clustering coefficient and larger characteristic path length would correspond to a larger SSVEP classification accuracy. This suggested that a less efficient brain state would facilitate SSVEP generation, providing a quantitative explanation for the inter-individual differences of SSVEP responses and BCI performances. Gao et al. (2018) built an SSVEP-based BCI system to achieve multi-directional motion control of robots. Figure 1 shows the visual stimulator of the experiments. For the fatigue phenomenon existing in the operation of BCI, they carried out systematic SSVEP experiments to conduct research. In detail, they utilized a complex network method and found that compared with the fatigue state, SSVEP-related brain network exhibited more obvious small-world properties under normal conditions. Quantitatively, for 10 studied subjects, the area under curve (AUC) of small-world-ness in the normal states was higher than that in the fatigue states. The results of two subjects are displayed in Fig. 2, as an illustration. In addition, different from SSVEP, steady-state motion VEP (SSMVEP) (Xie et al. 2012) utilizes the motion perception capabilities of the human visual system. Recently, Gao et al. (2019) combined limited penetrable visibility graph (LPVG) and broad learning system (BLS) to classify the SSMVEP-related EEG signals. The results were significantly better than the traditional methods.

P300 is evoked between 300 ~ 800ms from the stimuli onset, which belongs to endogenous positive ERP and is widely used to build BCI system. Wang et al. (2016) designed a multi-channel P300-based BCI system of lying detection. Figure 3 presented the schematic illustration of the system and steps involved in this analysis. Focusing on visual and auditory stimuli, multi-channel EEG signals corresponding to the guilty group and the innocent group were firstly acquired, respectively. They set the electrodes as the nodes, and employed nonlinear statistical interdependency to construct the functional brain network. By calculating cluster coefficient and characteristic path length, they found that the guilty group showed more obvious small-world characteristics. Moreover, by feeding calculated network measures into SVM, it is found that brain network analysis can effectively improve the classification accuracy of the P300-based BCI system, regardless of visual stimuli or auditory stimuli. Gao et al. (2018) derived wavelet multiresolution complex network for decoding brain fatigued behavior during the P300 application. They observed the enhancement of the small-worldness during the cognitive task in fatigue states. Kabbara et al. (2016) employed phase locking value (PLV) to infer brain functional connections in a P300 speller and revealed a clear difference between the case of target and non-targets visual stimuli.

During actual movement or mental rehearsal of movement (i.e. MI), the intensity of activity in the sensorimotor areas changes. In a MI-based BCI system, EEG signals can

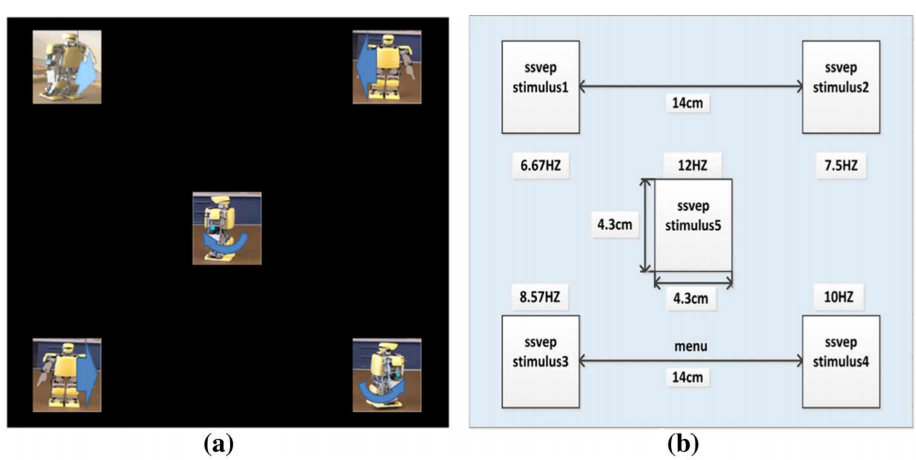


Fig. 1 The visual stimulator of the experiment. **a** The user interface shown to the subjects. **b** Detailed diagram of the user interface, including the description of the size, frequency, and location of the image. This figure is from Ref. Gao et al. (2018)

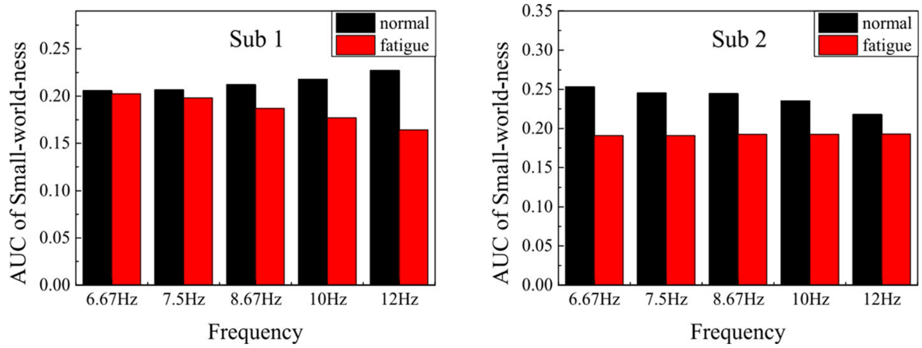


Fig. 2 The area under curve (AUC) of small-world-ness for 2 subjects at five different flicker frequencies. This figure is from Ref. Gao et al. (2018)

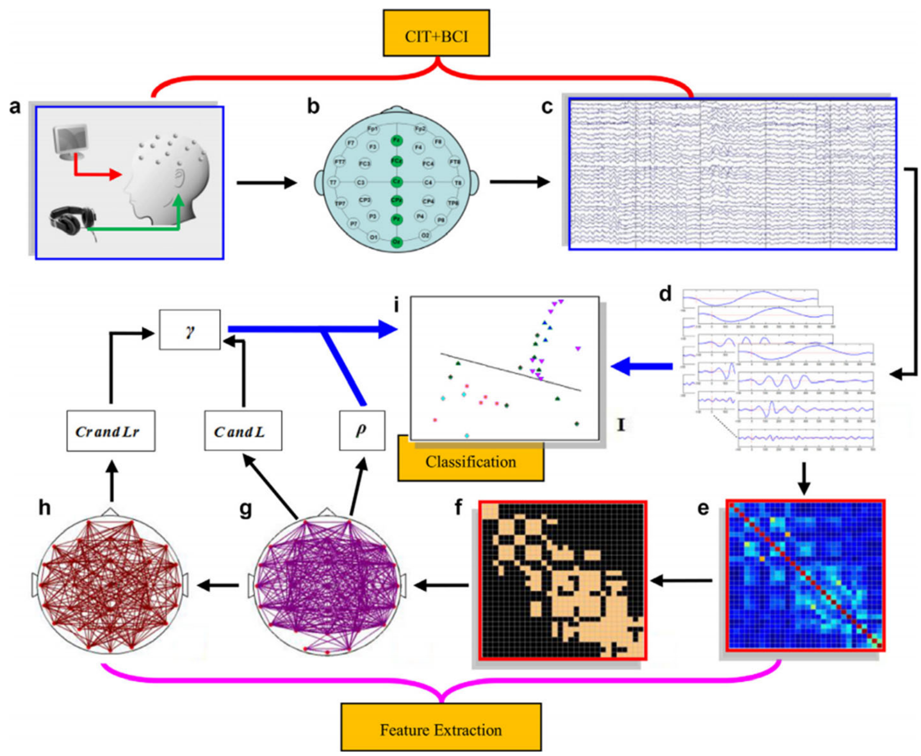


Fig. 3 Schematic illustration of the system and steps involved in the analysis. This figure is from Ref. Wang et al. (2016)

be collected when subject imagines specific movement, without the need of actual movement of the limb. Existing studies have shown that MI-based BCI systems can help improve cortical reorganization and functional recovery for disabled patients. For example, Wu (2020) used MI to assist the rehabilitation of subacute stroke patients. The results demonstrated that MI can improve the coordination between the multi-sensory and motor-related cortex and the extrapyramidal system. Carino-Escobar (2019) conducted the trend analysis of stroke patients' cortical activity during a BCI intervention aimed for hand rehabilitation. They found that the EEG trends in beta showed a higher association with time since stroke onset, compared to alpha, and a strong association with upper limb motor recovery. Moreover, plenty of studies have employed this mechanism to set up the EEG-based BCI system. For instance, Pichiorri et al. (2011) built an MI-based BCI system and introduced functional brain network to explore how the BCI system affects the brain plasticity. 61 channel scalp EEG signals were firstly obtained. Then imaginary coherence method was applied to infer the functional brain network. Global efficiency was calculated to quantitatively characterize the changes of brain network. They found that the global efficiency presented a significant decrease during the last session of BCI training for part subjects, which performed goal-directed like grasping. That is, the brain network configuration tends to organize itself by avoiding excessively long-distance connections in such a situation. Demuru et al. (2013) employed phase lag index (PLI) to infer functional brain networks and studied the brain state changes between imagery hand movements (both right and left) and resting state conditions. Particularly, functional connectivity analysis and minimum spanning tree parameters were both used to conduct the quantitative analysis.

They found that left hemisphere of the brain played a more relevant role for distinguishing imaginary hand movements. Daly et al. (2012) utilized empirical mode decomposition phase locking (EMDPL) to construct functional brain networks at all time-frequency locations. The significant differences between tap and no tap trials (or between left tap and right tap trials) can be characterized via the mean clustering coefficients. Through introducing the hidden Markov models (HMMs), they found that the network based approach achieved higher BCI accuracies for both executed and imagined taps compared with traditional band power based features. Stefano et al. (2018) constructed and analyzed the functional brain networks to classify MI-based EEG signals. Specifically, they set the electrodes as nodes and motifs synchronization method was utilized to infer the edges between nodes. Then five network measures, including strength, clustering coefficient, characteristic path length, betweenness centrality and eigenvector centrality, were extracted for MI analysis.

The development of deep learning has received a lot of attention in diverse fields. So far, many deep learning frameworks have been proposed and employed for feature extraction and classification in BCI systems. For instance, Zhu et al. (2019) combined common space pattern (CSP) and convolutional neural network (CNN) to extract the common features of different subjects for building the training free MI-based BCI systems. Figure 4 shows the workflow and the pipeline of the analysis model. They first transformed the original EEG signal into a fixed CSP space. Then, a separated channel convolutional network was proposed to capture information from CSP space. Finally, a recognition block was set to conduct classification. The results showed that this model achieved higher accuracies than classical methods under the training free condition (or transferring subjects learning). Wang et al. (2018) utilized long short-term memory (LSTM) to construct classification framework for MI-based BCI system. One dimension-aggregate approximation (1d-AX) and channel weighting technique were developed to concisely represent the EEG signals, which then eased the training of LSTM network. When applied on the public BCI competition dataset, they found that the proposed framework can achieve superior results. Figure 5 showed the prediction accuracies using EEG data of tow subjects, where the green column represented the proposed framework. Lawhern et al. (2018) proposed a compact convolutional neural network, named EEGNet, for EEG-based BCI system research. The architecture of EEGNet is displayed in Fig. 6. Depthwise and separable convolutions were used in this model. After comparing with some state-of-the-art approaches, they found that EEGNet generalized across paradigms better than, and achieved comparably high performance to, the reference algorithms when only limited training data was available across all tested paradigms. Tabar and Halici (2016) developed a novel deep learning approach to classify the MI signals. Convolutional neural networks (CNN) and stacked autoencoders (SAE) were both been considered and utilized. In particular, based on the short time Fourier transform (STFT), a new form of input combining the time, frequency and location information was set and fed into CNN part. Then, deep SAE network were built to distinguish the features extracted via CNN. The related results showed that this method can yield obvious improvement over the existing algorithms on BCI competition IV dataset 2b. Zhang et al. (2019) proposed two neural networks-convolutional neural network and wavelet neural network-to train the weights and classify two classes of MI-based EEG signals, where the wavelet neural network was designed via using wavelets to replace the convolutional layers. In a recent paper (Sakhavi et al. 2018), by using the filter-bank common spatial patterns methods, EEG signals were turned into new 250 temporal representations and a CNN framework was introduced for motor imagery EEG signal classification. The framework outperformed the existing results on the BCI competition IV-2a dataset. Moreover, Zhao et al. (2019) developed a deep convolutional network (ConvNet) to learn joint space-time-frequency features of EEG signals for BCI research. Li et al. (2019) developed a channel-projection mixed-scale CNN for decoding MI signals. Lee and Choi (2019) combined wavelet analysis and CNN to classify MI signals, and achieved some good results on two public BCI datasets. More related work can be found in Refs. Uktveris and Jusas (2017), Lu et al. (2017), Tang et al. (2017), Amin et al. (2019), Tayeb et al. (2019).

Based on the above information, we can find that complex network can specifically study the characteristics of EEG signals under different tasks during BCI, while deep learning mainly leverages multilayer framework to extract comparable features. They both provide effective classification schemes for the construction of BCI systems.

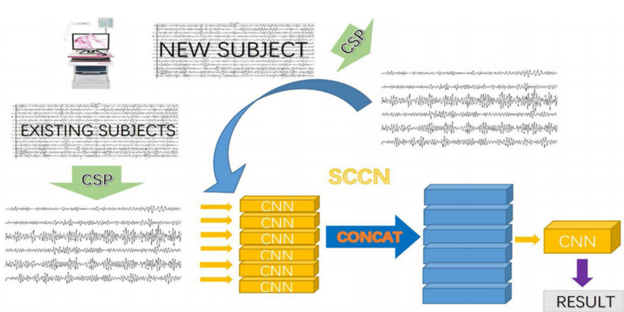


Fig. 4 The workflow and the pipeline of proposed model. This figure is from Ref. Zhu et al. (2019)

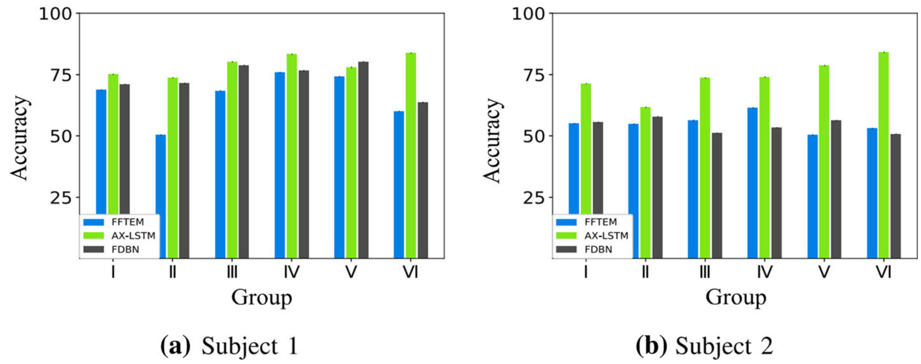


Fig. 5 Prediction accuracies using EEG data of two subjects. **a** Subject 1. **b** Subject 2. This figure is from Ref. Wang et al. (2018)

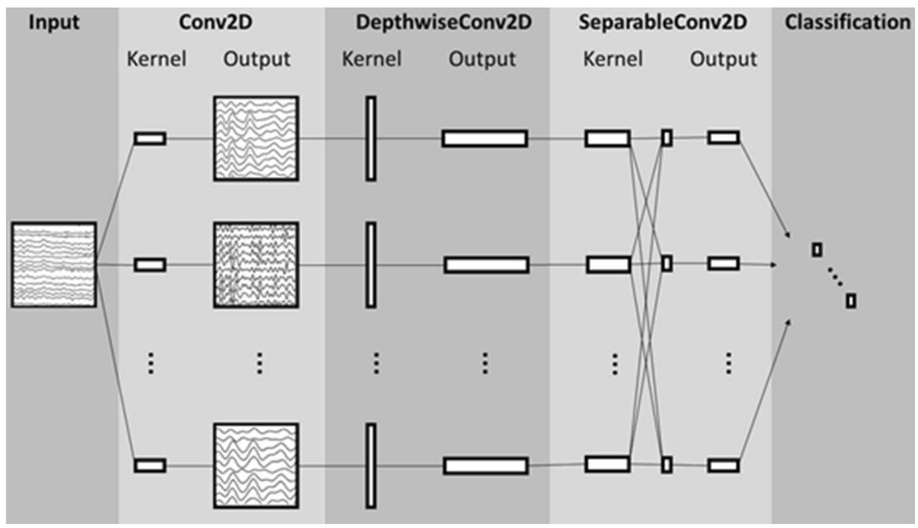


Fig. 6 Overall visualization of the EEGNet architecture. This figure is from Ref. Lawhern et al. (2018)

Brain neurological disorder analysis

Neurological disorders are related to the brain, spine and the nerves that connect them. They all involve malfunction or damage to the nervous system. A variety of neurological disorders severely affect the lives of patients, from infants to the elderly. So far, many existing work has been conducted from physiological signals to achieve detection and research of neurological disorders. Easy to access and harmless EEG signals have received widespread attention from researchers. Particularly, brain network derived from multi-channel EEG signals allows providing a data-driven methodology for understanding the neurological disorders from the lens of network science.

Epilepsy is a brain disorder corresponding to a patient's condition with frequent and spontaneous seizures. When severe epilepsy seizures, excessively synchronized neural activity can be detected in the cerebral cortex. Statistics show that people with epilepsy account for about 1–2% of the world's population, and the incidence and prevalence of epilepsy increases sharply in the elderly population. Research on epilepsy has important scientific and social value (Hejazi and Motie Nasrabadi 2019). Diykh et al. (2017) calculated statistical features to construct feature vectors and inferred distance-based brain network to classify epileptic EEG signals. They found that the network connectivity was significantly stronger in epileptic signals than in non-epileptic signals. Specifically, modularity, clustering coefficients, average degree and closeness centrality were all introduced and studied to quantify the brain network topologies. Eight pairs of combinations of EEG signals were classified by the proposed method. Figure 7 shows the performance of the proposed method across all the EEG groups based on the network attributes. The results demonstrated that brain network-based method can effectively detect epileptic seizures in EEG signals. Gao et al. (2017) proposed an adaptive optimal kernel time-frequency representation-based visibility graph (AOK-VG) to classify the epileptiform EEG. They firstly calculated the adaptive optimal kernel time-frequency representation and then extracted the energy time series from the joint time-frequency plane. Subsequently, visibility graph and some network measures were introduced to conduct the classification. The publicly available datasets provided by Andrzejak et al. (2001) were analyzed in this work. The datasets totally have five sub-datasets, corresponding to

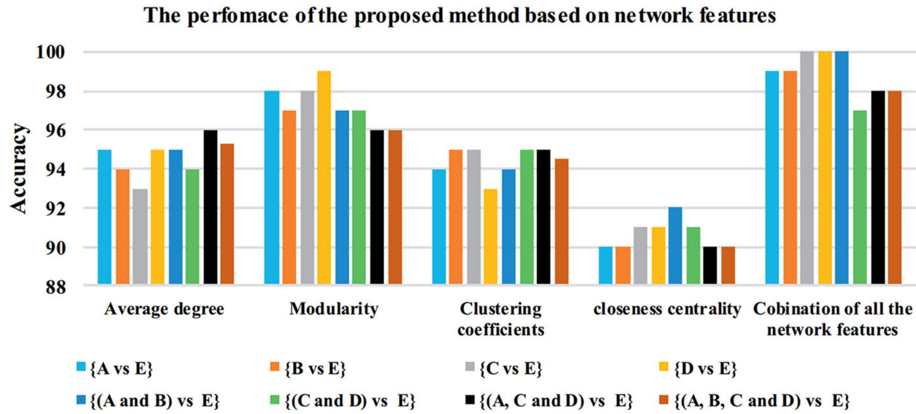


Fig. 7 Classification accuracy based on network characteristics. This figure is from Ref. Diykh et al. (2017)

normal (A, B), interictal (C, D) and ictal (E) states. The results showed that AOK-VG method can identify and classify healthy and epileptic seizure EEG signals (sets A and E; sets A, B and E) with an accuracy of 100%, and can classify seizure free interval and seizure EEG signals (sets C, D and set E) with classification accuracy exceeding 98%. Figure 8 presented the related results. Additionally, Kinney-Lang et al. (2019) constructed functional brain network in terms of cross-spectrum based method and effectively identified the candidate biomarkers of cognitive impairment in children with early-onset epilepsy. Supriya et al. (2016) presented a weighted visibility graph for automatic epilepsy detection.

Alzheimer's disease (AD), the most common form of dementia, is a disabling neurodegenerative disorder. In the early stages, AD mainly presents as a memory problem. As the disease advances, patients would have symptoms in terms of language, direction, behavior, etc. In more serious cases, AD may lead to death (La Foresta et al. 2019). Franciotti et al. (2019) utilized Granger causality (GC) to determine the strength and the direction of information transfer between electrode pairs, namely to infer the brain network. Based on the quantitative analysis from brain network view, they found that degree, indegree and outdegree values were lower in AD-MCI (mild cognitive impairment due to AD) and ADD (AD patients with mild dementia) than the control group for non-hubs and hubs vertices. Clustering coefficient was lower in ADD compared with AD-MCI in the right occipital electrode. Local and global efficiency values were lower in patients than control groups. The results denoted that topology of the brain network is altered in AD patients also in its prodromal stage. de Haan et al. (2009) studied the topological changes in large-scale functional brain networks of AD patients via resting-state EEG signals. Figure 9 presented the analysis framework. 20 patients with mild to moderate AD and 23 non-demented individuals were investigated. Synchronization likelihood was employed as a basis to determine the brain network connections. Some common network measures were calculated and analyzed, such as clustering coefficient, characteristic path length and degree correlation. They found that the large-scale functional brain network organization in AD deviated from the optimal 'small-world' network structure towards a more 'random' type. Moreover, Fallani et al. (2009) utilized spectral coherence to quantify the level of the synchronicity between multi-channel EEG signals and studied the functional brain networks of patients following stroke damage. Zeng et al. (2015) employed phase lag index (PLI) to assess the pair-wise synchronization of EEG signals in different frequency bands for amnestic mild cognitive impairment patients. Morabito et al. (2015) inferred functional brain network via mutual information to characterize the progression of AD in individual patients.

In addition to brain network analysis, deep learning has also been applied to the studies of neurological disorders. For example, Chen et al. (2019) proposed a CNN-based deep learning framework to study the attention-deficit/hyperactivity disorder (ADHD). The proposed framework can achieve a good performance with accuracy of 94.7% on the test data. Particularly, authors also calculated the correlation between the deep features and 13 hand-crafted network measures, aiming at validating what was learned by the CNN model. The results demonstrated that the CNN model can effectively capture global and some additional patterns from the EEG signals of ADHD children. In Phang et al. (2020), based on the EEG signals, a multi-domain connectome CNN was proposed for the study of schizophrenia. The authors adopted a parallel ensemble of 1D and 2D CNNs to integrate the features from various domains and dimensions using different fusion strategies. In Acharya et al. (2018), a 13-layer convolutional neural network was developed for seizure detection, which achieved a mean accuracy of 88.67%. In an interesting paper (Golmohammadi et al. 2017), two types of recurrent units, including long short-term memory (LSTM) and gated recurrent units (GRU) were compared on the seizure detection task. The results showed that convolutional

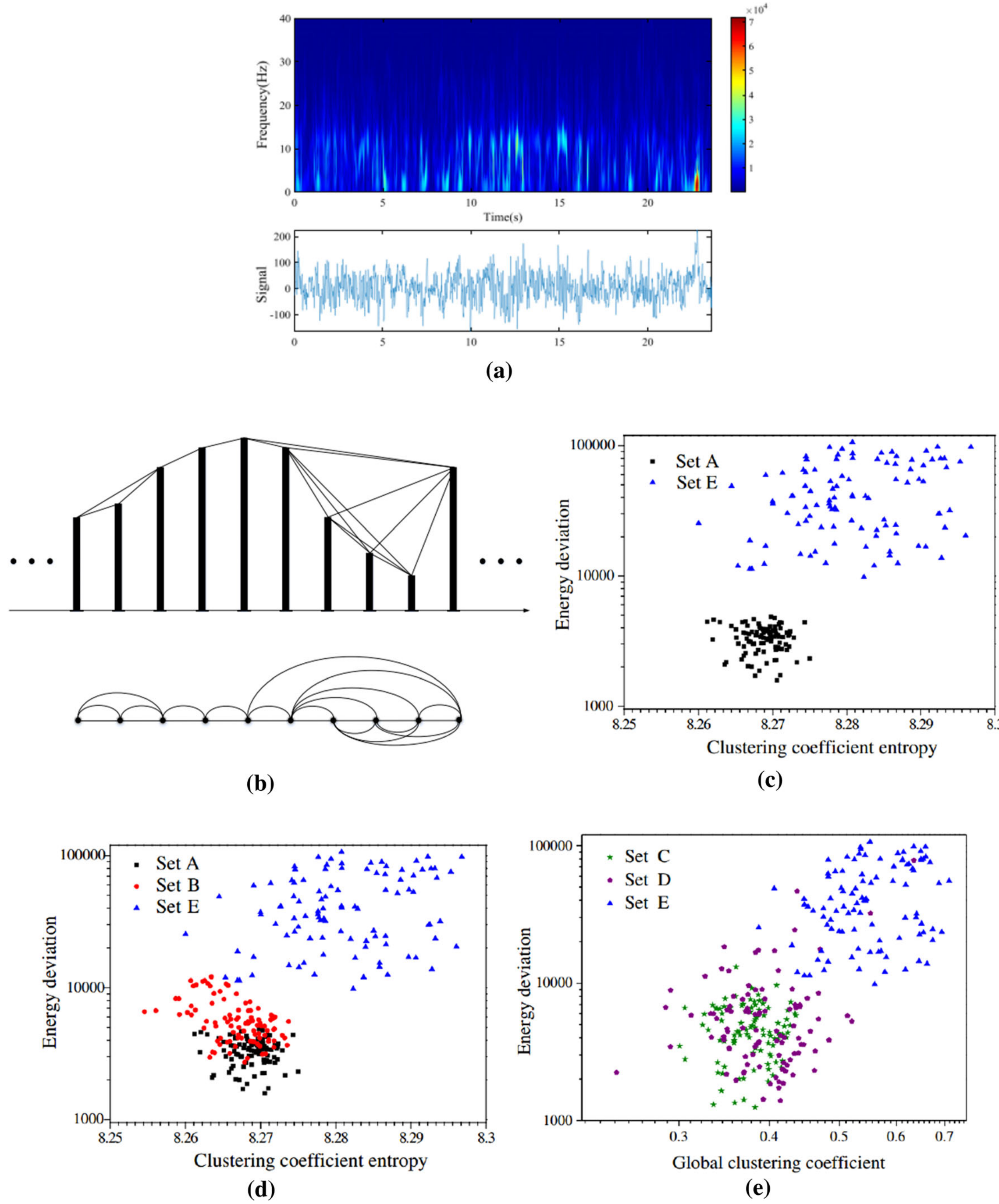
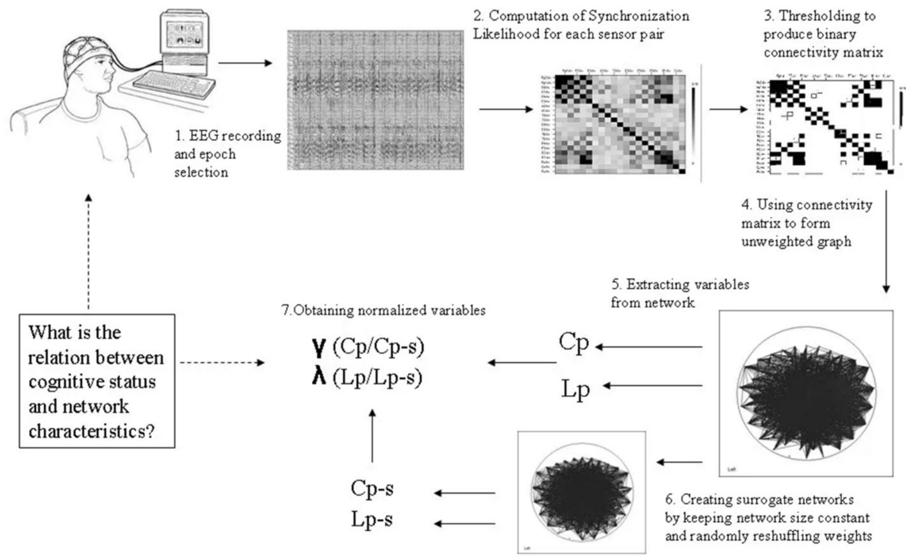


Fig. 8 **a** Adaptive optimal kernel time-frequency representations; **b** Visibility graph; **c–e** Joint distributions of clustering coefficient entropy and energy deviation for different sub-datasets. These figures are from Ref. Gao et al. (2017)

LSTM architecture can achieve significantly better performance on the TUH EEG dataset. Its architecture is shown in Fig. 10. In Ref. Lesmantas and Alzbutas (2020), a CNN was developed to classify seizures based on a heterogeneous clinical EEG dataset. In Ref. Gao et al. (2020), a deep learning-based classification methodology, namely epileptic EEG signal classification (EESC), was proposed. The methodology first transformed epileptic EEG signals to power spectrum density energy diagrams (PSDEDs), then applied deep CNNs and transfer learning to automatically extract features from the PSDED, and finally classified four categories of epileptic states (interictal, preictal duration to 30 min, preictal duration to 10 min, and seizure). In Truong (2018), a generalized retrospective and patient-specific seizure prediction method was proposed. Three different intracranial and scalp EEG

Fig. 9 From EEG recording to unweighted graph. Multi-step procedure to obtain normalized network-derived variables. This figure is from Ref. de Haan et al. (2009)



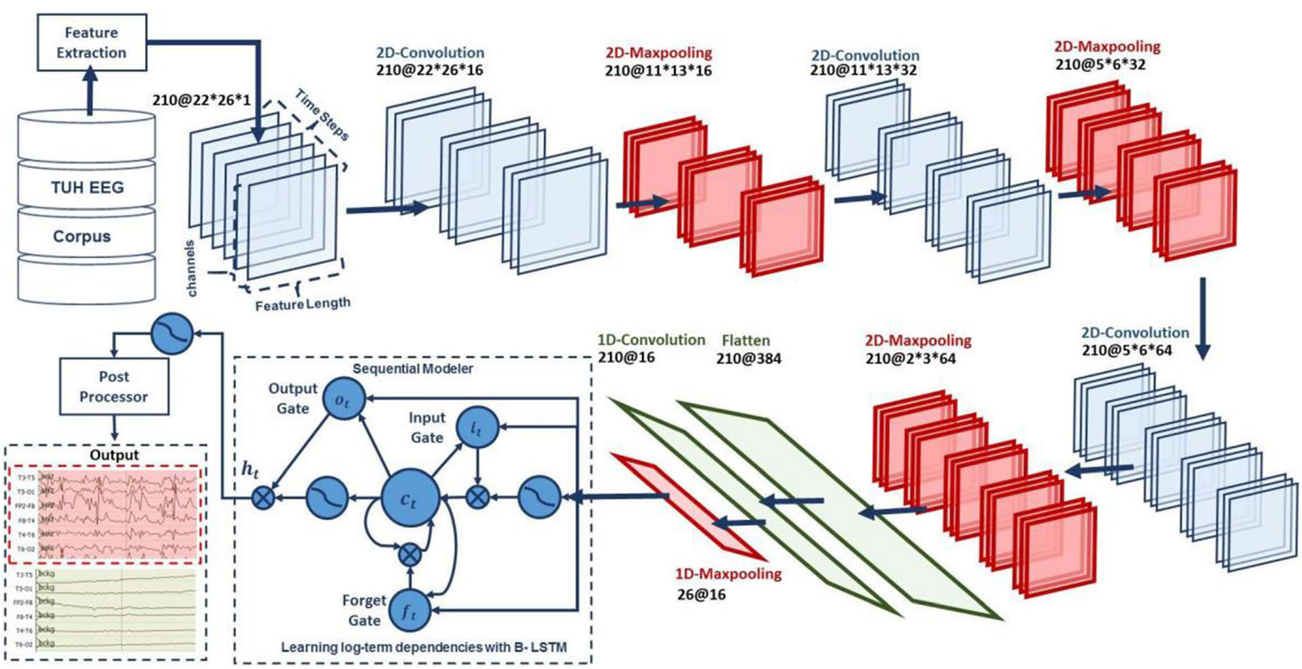
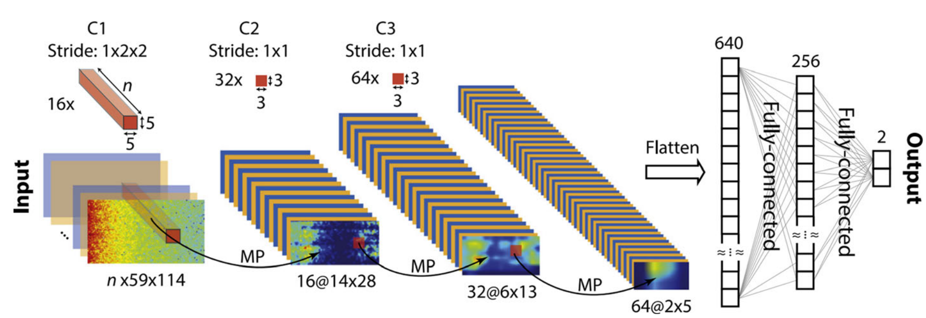


Fig. 10 A deep recurrent convolutional architecture from EEG signal decoding that integrates CNNs and LSTM networks in Ref. Golmohammadi et al. (2017)

Fig. 11 Convolutional neural network architecture. This figure is from Ref. Truong (2018)



datasets were used to evaluate the method performance. Figure 11 shows the CNN architecture applied in this work. In detail, short-time Fourier transform (STFT) was first used to translate raw EEG signals into a two-dimensional matrix containing both frequency and time domain information. Then three convolution blocks and two fully connected layers were appended to classify preictal and interictal segments. The results showed that such method can achieves sensitivity of 81.4%, 81.2%, and 75% on the Freiburg Hospital intracranial EEG dataset, the Boston Children's Hospital-MIT scalp EEG dataset, and the American Epilepsy Society Seizure Prediction Challenge dataset, respectively. Oh et al. (2019) developed a CNN-based detection system for the diagnosis of Schizophrenia (SZ). Considering that there were significant differences between the different subjects, they designed two models for non-subject based testing and subject based testing, respectively. The results showed that the model generated classification accuracies of 98.07% and 81.26% for above two testing, respectively. Golmohammadi et al. (2018) utilized the TUH EEG Seizure Corpus to evaluate some hybrid deep learning structures, including convolutional neural networks and long short-term memory networks. They demonstrated that the deep learning architectures integrating the spatial and temporal contexts can deliver state-of-the-art performances on EEG analysis. More related work can be found in Refs. Li et al. (2017), Kim and Jo (2020), Hassan et al. (2019), Salama et al. (2018).

In summary, it can be found that network-based methods and deep learning frameworks can both achieve good performance for neurological disorders researches. It is worth noting that network-based methods tend to quantitatively interpret the topological changes of the brain networks from the perspective of network measure analysis, which then allows to explore the changes of brain with neurological disorders. While deep learning frameworks utilize a variety of deep structures to extract some combinations of features, which are finally used for classification and prediction of neurological disorders.

Brain cognitive analysis

Cognitive processes use existing knowledge to generate new knowledge. Cognitive analysis is essential for human beings to understand themselves. Emotion is a cognitive process. And human beings express different emotions when facing different scenes. The reflection of emotions in the brain is a very important research topic at present. So far, based on the EEG signals, much work has been conducted to understand and further recognize the emotions. Existing studies showed that listening to music involves various psychological processes and can specially induce a variety of emotions (Koelsch 2010). Shahabi and Moghimi (2016) constructed and studied the effective brain networks associated with joyful, melancholic, and neutral music. Directed transfer function (DTF) technique was introduced to characterize the causal interactions between multichannel EEG signals and further inferred the brain network. They studied the correlation of brain network connectivity patterns with the self-reported evaluations of the musical selections, and found that the perceived valence was positively correlated with the frontal inter-hemispheric flow, but negatively correlated with the parietal bilateral connectivity. In addition, Rotem-Kohavi et al. (2017) denoted that an infant's ability to perceive emotional facial expressions was critical for developing social skills. They inferred brain network from EEG signals to study the functional organization of the brain that supports the processing of emotional faces in infants. In detail, three network measures, including density, modularity and clustering coefficient, were calculated. Figure 12 displayed the group average functional connectivity graphs of the infant group (top), and the adult group (bottom). Through analyzing from the global and the regional views, they found that while the global organization for the emotion perception was still immature in infancy, the basic functional network organization at the regional level is already in place early.

In addition, long-term monotonous work, such as driving, can easily cause mental fatigue (Chen et al. 2018). This may leads to extremely serious traffic accidents. Research on brain state during driving fatigue helps to provide a better physiological basis for solving this problem. Chen et al. (2018) studied the driver drowsiness using

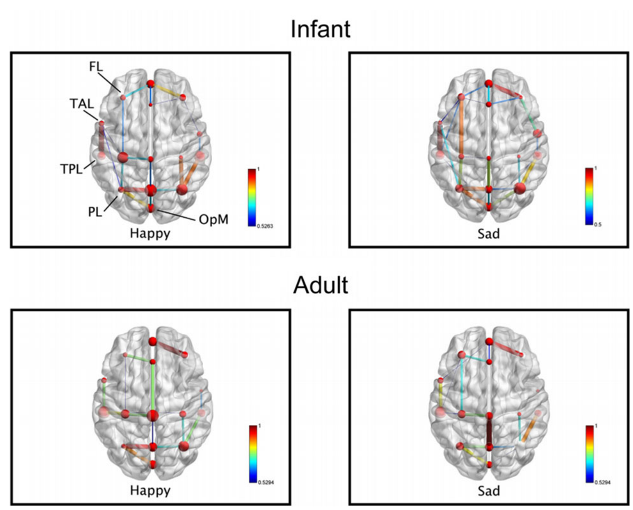


Fig. 12 Group average functional connectivity graphs of the infant group (top), and the adult group (bottom), in an axial view, for the observation of happy and sad facial expressions. This figure is from Ref. Rotem-Kohavi et al. (2017)

EEG signals from the view of functional brain network. General block diagram of the proposed methodology was shown in Fig. 13. They first utilized wavelet packet transform (WPT) to decompose the EEG signals into multiple bands. Then synchronization likelihood (SL) and minimum spanning tree (MST) were employed to infer and analyze the functional brain network. Based on the network features, they found that the difference between alert state and drowsy state were significant. Four classifiers were considered for classification of alert state and drowsiness state. The highest average classification accuracy was 98.6%, obtained by k-nearest neighbors. Dang et al. (2018) mapped the multi-channel EEG signals to a time-frequency multilayer network for driving fatigue analysis. The schematic diagram of the method is shown in Fig. 14. Specifically, they first performed continuous wavelet transform on each electrode of EEG signals. Then mutual information was employed to infer single-layer brain networks in different frequency bands, which ultimately constituted a time-frequency multilayer network. Analysis results suggested that a greater synchronization of neural assemblies was achieved as the brain state changed from alert to mental fatigue. Zhao et al. (Shih et al. 2012) studied the changes of brain network topology modulated by mental fatigue. EEG signals were first acquired from systematic simulated driving experiments. Then coherence was introduced to infer functional brain networks in different EEG bands. In the brain network topology analysis, they found that clustering coefficient increased in beta, alpha, and delta bands and characteristic path length increased in all bands. These suggested that functional network topology can shift the network topology structure toward a more economic but less efficient configuration during mental fatigue states. Moreover, some other researchers (Dimitrakopoulos et al. 2018; Fonseca et al. 2018; Kong et al. 2017; Wang et al. 2018) used diverse methods to construct

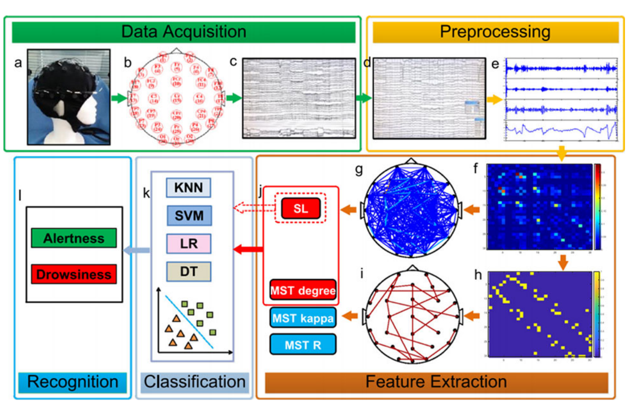


Fig. 13 General block diagram of the proposed methodology. This figure is from Ref. Chen et al. (2018)

functional brain network, aiming at exploring the brain state during fatigue driving.

Additionally, researchers have also tried to use deep learning frameworks for cognitive analysis. A hierarchical convolutional neural network was trained in Li et al. (2018) with 2D maps generated from differential entropy features, which was found efficient in emotion recognition tasks. EEG sequences were converted into 2D graph matrixes with spectral filtering and then fed into dynamical graph CNNs, which showed excellent performances for EEG emotion recognition (Song et al. 2018). Deep belief networks were introduced with differential entropy features to construct EEG-based emotion recognition model for three emotions, whose average accuracy was 86.08% on the SEED dataset (Zheng and Lu 2015). Note that, The publicly available SJTU Emotion EEG Dataset (SEED) dataset, contributed by Duan et al. (2013), focuses on EEG-based emotion recognition tasks. SEED dataset collects EEG signals from 15 subjects (7 males and 8 females), and contains 3 categories of emotions (positive, neutral and negative). In a recent paper (Zhang et al. 2019), a spatial–temporal recurrent neural network (STRNN) was proposed to integrate the information along the spatial–temporal dimensions from EEG signals. The final accuracy for emotion recognition reached 89.5%. This model employed a quad-directional spatial RNN layer to scan each temporal slice from different angles, and then stacked a bi-directional temporal RNN layer on the former layer to capture long-term temporal dependencies, whose architecture was shown in Fig. 15. In a more recent paper (Yang et al. 2018), combining with recurrence quantification analysis on EEG signals of different frequency bands, a novel channel-frequency convolutional neural network was developed to recognize different emotional states, which provided a high emotion recognition accuracy of 92.24% with an excellent stability (Kappa value 0.884). Its architecture is shown in Fig. 16. These studies have proved the deep learning methods can learn robust representations from the extracted features of EEG signals on emotion recognition tasks. In the paper (Gao et al. 2019), a novel spatial–temporal convolutional neural network (ESTCNN) was developed to detect driver fatigue through EEG signals. Firstly, core block was introduced to deal with the temporal information. The core block consisted of three convolutional blocks and a pooling layer. Each convolutional block orderly consisted of a 1×3 convolution, a rectified linear activation, and a batch normalization. Secondly, dense layer was employed to extract spatial information among the brain electrodes. The model fulfilled a better classification accuracy of 97.37% than the eight competitive methods, whose structure is shown in Fig. 17. Moreover, a detailed survey was presented in Ref. Schirrmeister et al. (2017), which reviewed how to design

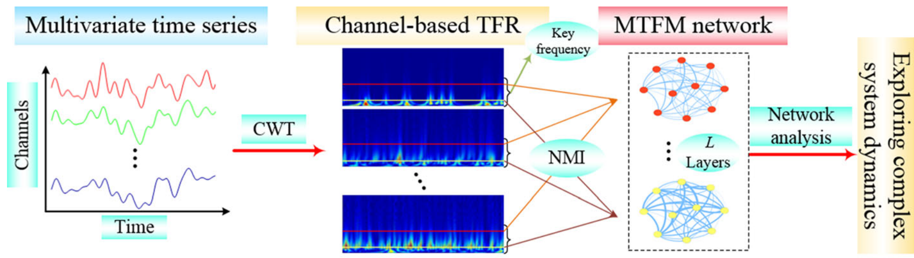


Fig. 14 A schematic diagram of MTFM network analysis framework for exploring the system dynamics from multivariate time series. This figure is from Ref. Dang et al. (2018)

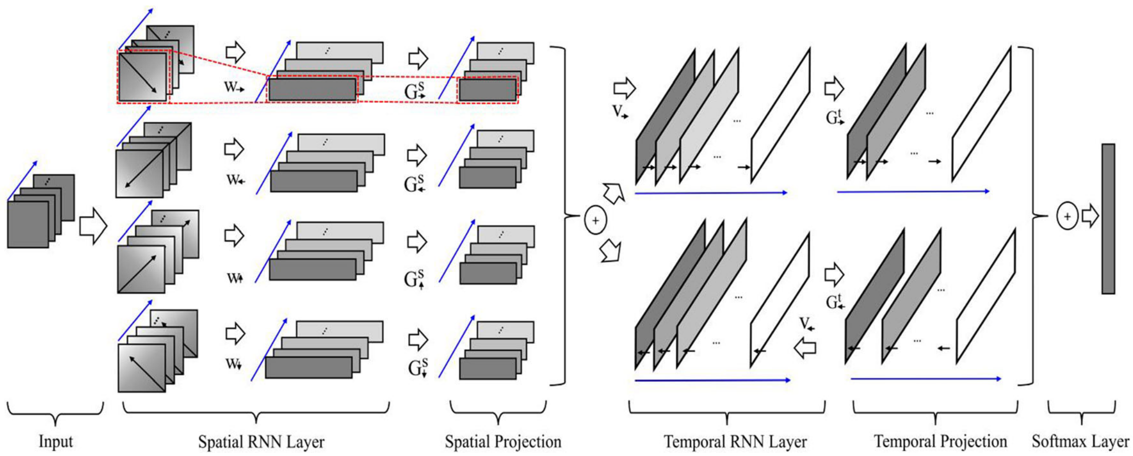


Fig. 15 The proposed STRNN framework in Ref. Zhang et al. (2019). The spatial and temporal RNNs are jointly learned to capture vital information from EEG signals

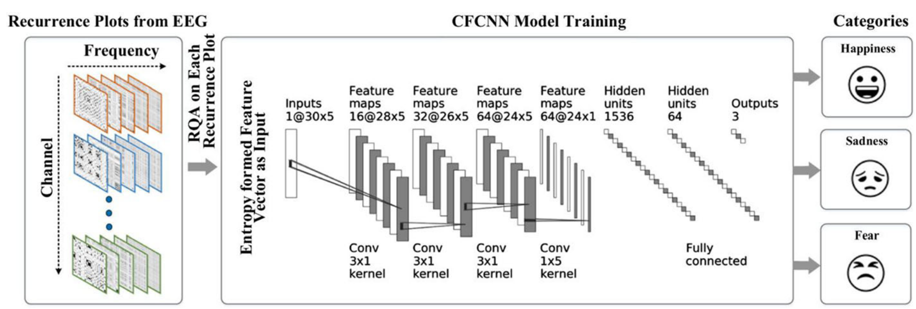


Fig. 16 The architecture of channel-frequency convolutional neural network in Ref. Yang et al. (2018)

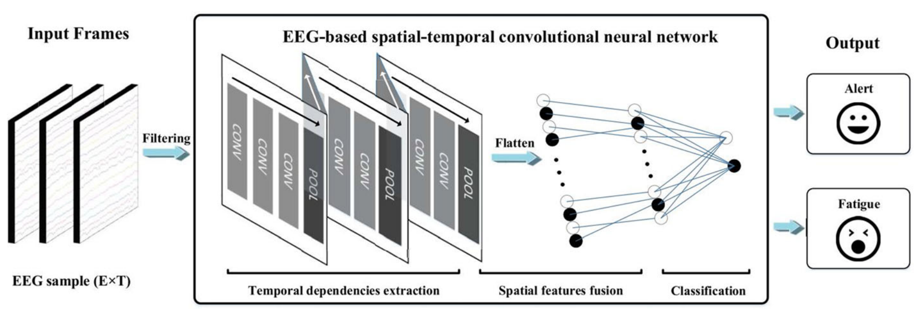


Fig. 17 The structure of ESTCNN model in Ref. Gao et al. (2019)

and train CNNs without handcrafted features for EEG-based brain mapping. Similar to the previous section of neurological disorder research, network-based methods and deep learning frameworks both can use their own characteristics to achieve EEG-based cognitive analysis, whether it is to analyze the internal brain mechanism or improve the accuracy of identification.

Conclusion

EEG signals with multiple channels contain a wealth of information, which directly reflect the state of the brain. Aiming to effectively study the EEG signals and then characterize the corresponding brain state, complex networks and deep learning have both been developed, with a variety of forms and variants. In this work, we review the application of complex networks and deep learning in EEG signal analysis. According to the existing work, it can be said that complex network theory can analyze the EEG signals in a targeted manner. The design of the network scheme is always specific to the specific research problem. The connection between the theory and the obtained results can also be explained. Namely, the analysis process shows a certain degree of interpretability. For example, in a brain network, brain electrodes are usually defined as nodes. However, the ways to determine the edges are varied, and allow to infer diverse network topologies. When combined with appropriate network measures (e.g., clustering coefficient, degree, characteristic path length, etc.), one can effectively reveal the brain mechanisms from various angles. Interestingly, deep learning uses a layer-by-layer learning framework to continuously extract feature information, which can be then used to distinguish different states in EEG signals. The feature extraction process is driven by lots of data. Note that, these features are different from the network measures mentioned above. They are often some abstract information, no specific meaning, but can achieve better classification. In particular, the size of the data set has a relatively large impact on the effect of deep learning. Large data sets can often train better models.

With all these in mind, combining complex network with deep learning may be a valuable research theme. The combination of targeted and interpretable features (from brain network) with data driven (i.e. deep learning) would help to take advantage of both, and then open up new venues for analysis of EEG signals. In one latest work (Dang et al. 2020), based on the multi-channel EEG signals, a frequency-dependent multilayer brain (FDMB) network, combined with deep convolutional neural network (CNN), was developed to detect the major depressive disorder (MDD), with state-of-the-art accuracy of 97.27%. The model architecture is shown in Fig. 18. FDMB network was set as the input of the deep learning part. The experimental results confirmed that such design can help deep learning to effectively learn the rich network topology characteristics hidden in the brain network.

Here an example combining recurrence plots and deep learning for driving fatigue recognition is also presented. Figure 19 displays the detailed architecture, named RP-based spatial-frequency CNN (SFCNN).

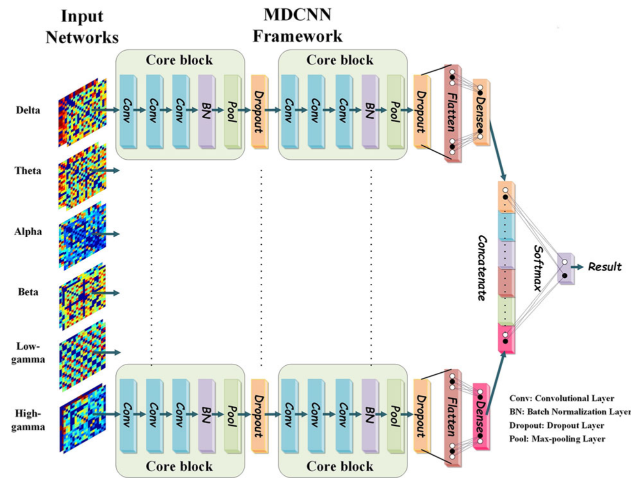


Fig. 18 The architecture of the FDMB network and the multilayer deep CNN, in Ref. Dang et al. 2020

For a M-channel EEG signals $\{x_{k,j}\}_{i=1}^{L}, k = 1, 2, \ldots, M$ with length L, we firstly divide the raw signals into a number of epochs with a sliding window without overlap. And then we filter the signal into four specific frequency bands (delta: 1–3 Hz, theta: 4–7 Hz, alpha: 8–13 Hz, beta: 14–30 Hz). Next, we reconstruct the phase space from the signals in each frequency band as following:

$$x_i(t) = (x_{i,t}, x_{i,t+\tau}, x_{i,t+(m-1)\tau}), t = 1, 2, \ldots, N \tag{1}$$

where m, τ represent the dimension and time delay, respectively. And then we obtain the RP from the phase space trajectory x_i through the following equation:

$$R_{i,j} = \Theta(\epsilon - \|x_i - x_j\|), i, j = 1, 2, \ldots, N \tag{2}$$

where $\Theta(\cdot)$ is the Heaviside function, ϵ is the threshold predefined, $\|\cdot\|$ represents the Euclidean norm, and N is the number of data points of phase space trajectory. Generally, ϵ is selected by:

$$\epsilon = 0.15 * \sigma \tag{3}$$

where σ represents the standard deviation of the data. For quantitatively characterizing the obtained RPs, we conduct channel-wise RQA on each epoch and calculate the recurrence rate (RR) (Webber and Zbilut 1994). The recurrence rate is proposed for quantifying the density of recurrence points in each RP and can be defined by:

$$RR = \frac{1}{N^2} \sum_{i,j=1}^{N} R_{i,j} \tag{4}$$

Finally, for each epoch, we obtain a feature matrix based on recurrence rate with size 30×4 (number of channels $\times$ number of frequency bands), respectively.

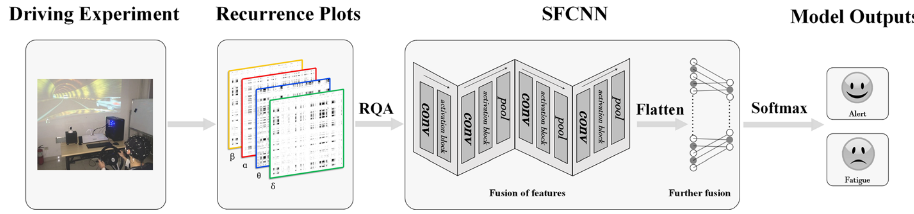


Fig. 19 The architecture of RP-based SFCNN

In the following step, the obtained feature matrices are fed into the SFCNN, which is constructed to recognize the category of these feature matrices and is implemented by the deep-learning library Keras. Generally, CNN is a multi-layer architecture that consists one or more groups of convolutional and pooling layers, followed by several continuous dense layers. Its deep architecture allows to extract a set of significant features at multiple levels. As can be seen that the SFCNN consists of four convolutional layers, one dense layer and one softmax layer, where the number of filters in the convolutional layers are 16, 32, 64 and 64, respectively. In our model, the first three convolutional layers only move forward in channel dimension for fusing the spatial information, where the kernel sizes are set as 3×1 with default stride 1. And the last convolutional layer is designed to fuse different frequency features with the kernel size 1×4. All the convolutional layers are followed by an activation block, which consists of a batch normalization layer and a rectified linear activation. Additionally, except for the first activation block, each activation block is connected to a dropout layer. In the next level, a flatten operation is conducted to transform the feature maps into a one-dimensional vector. Then two fully connected layers with size of 128 and 2, respectively, are connected to the model following the flatten operation. In the meanwhile, a softmax layer equipped with the cross-entropy objective function is applied to produce the probability for each category. The predicted label is set as the category corresponding to the maximum probability. During the model training process, the model optimization process is realized by the Adam optimizer with the learning rate of 0.001, decay of 10^{-3}, and momentum of 0.8. Besides, the number of learning iterations is 64 and the batch size is set as 128.

For testing the performance of above framework, we conduct our analysis on the dataset from fatigue driving experiments. The simulation experiments are conducted in the Laboratory of Complex Networks and Intelligent Systems at Tianjin University. The experimental system is consist of a Neuroscan data acquisition device, a driving simulator, a computer, and a screen. Eight right-handed volunteers (5 males and 3 females) were recruited to conduct the experiments. We define the first 10 min during the driving task as alert state, and define the last 10 min during the driving task as fatigue state. EEG signals is recorded at sampling rate of 1000 Hz. In this work, we apply a one-second sliding window to divide the raw signal into a number of epochs. In particular, we downsample the epoch data to 200 Hz for the sake of computational simplicity before conducting RQA. Finally, 600 epochs for each category were obtained from single subject. During the training, we use 5-fold cross validation method to assess the performance of our model. For each subject, we select randomly 80% of all samples as the training set and the remaining 20% as the testing set. The accuracies from the RP-based SFCNN model of all subjects are shown in Fig. 20. As can be seen, the classification accuracies of all subjects over than 95%. Particularly, Subject.1 and Subject.6 obtain the accuracies exceeding 99%. On the average, the accuracy of all subjects is about 97.87%. All the results indicate that the combination of complex network and deep learning has a powerful capability to recognize the driving fatigue. At the same time, this also illustrates that such combination may be an effective direction for studying EEG signals. We look forward to more research in the future to complement complex networks and deep learning for EEG signal analysis.

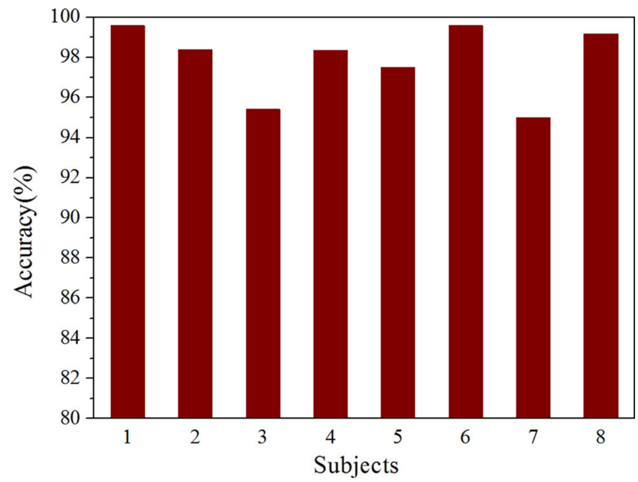


Fig. 20 Accuracy (%) results of RP-based SFCNN for driving fatigue recognition

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Compliance with ethical standards

Conflict of interest The authors declare that they have no conflict of interest.

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