A Sequential Graph Convolutional Network with Frequency-domain Complex Network of EEG Signals for Epilepsy Detection

Jialin Wang*¶, Shen Liang*, Dake He†, Ye Wang‡, Yingpei Wu*¶, Yanchun Zhang§¶✉
*School of Computer Science, Fudan University, Shanghai, China
†Xinhua Hospital Affiliated to Shanghai Jiaotong University School of Medicine, Shanghai, China
‡College of Computer Science and Technology, National University of Defense Technology, Changsha, China
§Institute of Sustainable Industries and Liveable Cities, Victoria University, Melbourne, Australia
¶Cyberspace Institute of Advanced Technology, Guangzhou University, Guangzhou, China
jialinwang16,sliang11@fudan.edu.cn, hedake@xinhuamed.com.cn, ss.colorsoflife@gmail.com, yanchun.zhang@vu.edu.au

2020 IEEE International Conference on Bioinformatics and Biomedicine (BIBM) 978-1-7281-6215-7/20/$31.00 ©2020 IEEE DOI: 10.1109/BIBM49941.2020.9313232

***Abstract*—Automatic epilepsy seizure detection based on electroencephalography (EEG) signals has been a hot topic in the bioinformatics community. Recently, graph representations named *complex networks* have been increasingly utilized to characterize EEG signals. However, existing time-domain complex networks often suffer from undesired intra-class variance due to phase shift. Addressing this problem, we propose to obtain complex network representations in frequency domain where perfect data alignment can be achieved. The transformation to frequency domain highlights the urgency to retain sequential information in the signals. To this end, we propose to further extract features from the complex network representation using a novel deep model called Sequential Graph Convolutional Network (SGCN). Specifically, we incorporate state-of-the-art graph neural network (GNN) architecture with a novel sequential convolution operation which is key to preserving sequential information. Extensive experiments demonstrate the effectiveness and interpretability of our method. Our source code is available at https://github.com/JL-Wang-source-code/SGCN-for-epilepsy-detection.**

***Index Terms*—Epilepsy detection, EEG, Graph representation, Complex network, Graph neural network.**

I. Introduction

EPILEPSY is a chronic neurological disease that affects 65 million people worldwide [1]. Accurate detection of epilepsy seizure has been subjected to extensive research. Clinically, neurologists rely on electroencephalography (EEG) signals (Fig. 1) to detect epileptic seizures. However, manual analysis of long-term EEG data is highly costly, which calls for automatic detection methods.

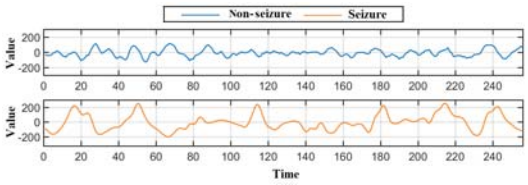

Fig. 1. An illustration of non-seizure (normal) and seizure EEG signals.

Automatic epilepsy detection is often formulated as a binary classification problem that labels a given EEG signal as epileptic or non-epileptic. Like other classification tasks, this requires an effective representation of the raw data. Traditionally, EEG signals are represented by handcrafted features [2], [3]. The feature selection process heavily relies on domain knowledge, and is often sensitive to the number of channels (electrodes) and the electrode placement. Lately, end-to-end deep learning methods have been increasingly applied to EEG mining [4], [5], which can automatically learn features from raw signals. However, the information that can be learned from raw data tends to be limited, and deep learning models often lack interpretability due to their black-box nature. All in all, the effective representation of EEG signals (especially 1D signals) remains a serious challenge.

Recently, graph representations called *complex networks* [6] have gained much interest from researchers. Specifically, a complex network transforms the original 1D signal into a graph, in which each data point corresponds to a node and each edge is created by some connection rule and connects two data points (Fig. 2). To the best of our knowledge, the first published complex network for signal processing is Visibility Graph (VG) [7], which has spawned numerous variants [8]–[10]. Capable of characterizing pairwise relationships between any two data points in the original signal, complex networks have been applied to various EEG mining tasks [6].

Fig. 2. An illustration of a complex network [6] which represents a 1D signal with some connection rule.

Despite their success, existing complex network-based methods are not without their drawbacks. Notably, these methods directly convert the original time-domain EEG signals to their graph representations. This makes them sensitive to phase shifts (i.e. misalignment) among different signals. As we will show later, this can lead to undesired intra-class variance.

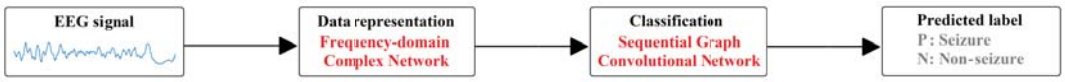

Fig. 3. Workflow of our epilepsy detection framework, with frequency-domain complex network and Sequential Graph Convolutional Network (SGCN) as its key design features.

To handle this problem, in this paper, we propose to first transform the time-domain signal using Fast Fourier Transform (FFT). The result is an ordered sequence of frequency-domain features that are perfectly aligned among all EEG signals with the same length and sampling rate. The complex networks generated from these frequency-domain signals[1] are no longer affected by the phase shift issue in the time domain. Moreover, since there is much domain knowledge on the relationship between epilepsy and EEG components on certain frequencies [11], [12], these frequency-domain complex networks can generate highly interpretable results.

However, the transformation from time to frequency domain can aggravate another potential problem. Specifically, in view of its excellent performance on graph learning [13], [14], we apply a graph neural network (GNN) [15] to further learn features from the graph representations and accomplish the classification task. However, many existing GNNs for graph classification mainly focus on characterizing the topology of the graph representation, yet for both time- and frequency-domain signals, the topologies of the complex networks alone cannot retain the sequential characteristics of the signals. Specifically, an existing GNN is likely to treat all nodes as being homogeneous without taking into account the fact that they represent data points in an ordered sequence. This problem can be more serious in the frequency domain. In this case, the signals are perfectly aligned, which makes it more crucial to retain the sequential information.

To fix this issue, in this paper, we propose a Sequential Graph Convolutional Network (SGCN), a novel GNN model that can preserve the sequential characteristics of 1D signals. Concretely, SGCN leverages a novel sequential convolution operation to learn sequential features from the input complex network. This can yield better classification performance than existing GNNs, especially in the frequency-domain setting. Also, SGCN exploits a learnable weight vector to assess the contribution of each node in the graphs to classification. As we will show later, when coupled with frequency-domain complex networks, this can lead to good interpretability. Combining the frequency-domain complex network with SGCN, we have our epilepsy detection framework shown in Fig. 3. Note that this framework is generic as it allows for different complex networks with varying connection rules [7]–[10].

Our main contributions in this paper are as follows:

- We extend the complex network representation of 1D EEG signal to the frequency domain, which can enhance data alignment and reduce intra-class variance.
- We propose Sequential Graph Convolutional Network (SGCN), a novel GNN-based model that further learns features from the complex network representation. Exploiting a novel sequential convolutional operation, the proposed model can preserve the sequential features of the 1D signals effectively, thereby improving classification performance, especially for the frequency-domain representation.
- Combining the aforementioned two design elements, we propose our novel epilepsy detection framework which can yield excellent classification performance and generate interpretable results. We conduct extensive experiments to demonstrate the effectiveness of our framework.

For the rest of this paper, Section II reviews the related works. Section III provides the preliminaries. Section IV presents our frequency-domain complex networks for 1D EEG signals. Section V introduces our SGCN classification model. Section VI reports the experimental results. Section VII concludes this paper.

II. Related Works

EEG-based epilepsy detection has been a hot research topic, in which the representation of EEG signals is of great importance to classification performance. Traditional epilepsy detection methods rely on handcrafted features (e.g. spectral and spatial features [16], waveform [2], wavelet [17], etc.) to represent the original signal. A classification model (e.g. SVM [2], decision tree [18]) is then applied to classify the data in the feature space. These methods require much domain knowledge and are less adaptive to varying datasets. In recent years, end-to-end deep learning techniques (e.g., CNN [4], LSTM [5]) have been increasingly applied to EEG analysis, which can learn representations from the raw signals. However, end-to-end learning with no explicit data transformation can have limited gain in detection performance, and the black-box nature of deep learning can lead to poor interpretability.

Recently, graph representations called *complex networks* [6] have been applied to EEG signal mining. For a given 1D signal, a complex network converts it into a graph in which each node corresponds to a data point in the original signal. Edges are created following some *connection rule*. Existing complex networks for EEG signals include Visibility Graph (VG) [7] and its variants, such as HVG [9], LPVG [8] and LPHVG [10]. Some of these methods have been deployed in EEG analysis. For instance, Wang et al. [19] transformed EEG signals with HVG. Zhu et al. [20] proposed a fast weighted HVG construction algorithm for epilepsy detection. Despite achieving some success, these methods simply convert the original time-domain signals to their graph representations, which are sensitive to phase shifts. In view of this, in this paper, we propose to apply complex networks in the frequency domain where strict data alignment can be guaranteed.

Based on the complex network representation, many existing methods again rely on handcrafted features (e.g. average degree of the graph representation [21], entropy of the complex

[1]Here we use the word *signal* to refer to the frequency-domain sequence for consistency with time-domain signals.

network [22]) extracted from the graphs for classification. Recently, the advent of graph neural networks (GNN) [15] has shed new light on graph learning, which can learn both the graph structure and node features using its hidden layers. In EEG analysis, GNN is usually used to analyze multi-channel signals with each channel treated as a node in a graph [23], [24]. As far as we know, before this work, there was no attempt to incorporate GNN with complex networks. Outside the EEG mining community, existing general-purpose GNN models such as GraphSAGE [13] and GIN [14] cannot preserve the sequential information in the original EEG signals, which has motivated us to develop our SGCN model.

III. Preliminaries

Before introducing the proposed method, we define the concepts used in this paper.

Definition 1: EEG. EEG is a type of physiological signal which records electric activities of the brain. Formally, a 1D EEG signal can be written as $T = \{t_1, t_2, ..., t_n\}$, where each t_i is the data point at the ith timestamp.

Definition 2: Complex network. Given an EEG signal $T = \{t_1, t_2, ..., t_n\}$, a complex network $G = (V, E)$ is a graph representation of T. Here $V = \{v_1, v_2, ..., v_n\}$ is the set of nodes (vertices) where each node v_i corresponds to data point t_i. E is the set of edges, which are created by some connection rule. Let $e_{i,j} \in E$ denote the edge connecting v_i and v_j. Let $A = \{a_{i,j} | i = 1, 2, \ldots, n, j = 1, 2, \ldots, n\}$ be the adjacency matrix of G, where

$$a_{i,j} = \begin{cases} 1 & if\ e_{i,j}\ exists; \\ 0 & otherwise \end{cases} \tag{1}$$

To the best of our knowledge, there are currently no directed complex networks. Therefore, in this paper we restrict our discussion to undirected graphs. Hence, if $a_{i,j}$=1, then $a_{j,i}$=1.

IV. Frequency-domain Complex Network

In this section, we introduce our frequency-domain complex network. Here the main motivation for frequency domain transformation is to mitigate the impact of phase shift. This is shown in Fig. 4, in which the two raw time-domain signals belong to the same class and Signal 2 is a phase-shifted version of Signal 1. Clearly, the two signals have very different morphology which leads to different complex networks. However, when transformed to frequency domain (we will elaborate on this transformation later), the two signals are now semantically aligned and the corresponding graph representations are much more similar, which helps reduce intra-class variance.

The way we convert a time-domain signal into its frequency-domain complex network representation is shown in Fig. 5. To begin with, we transform the original time-domain signal $T = \{t_1, t_2, ..., t_n\}$ into frequency domain using Fast Fourier Transform (FFT). We write the resulting signal as $|F| = \{|f_1|, |f_2|, ..., |f_n|\}$ where

$$f_k = \sum_{i=1}^{n} t_i e^{-j\frac{2\pi}{n}k} \ (k = 1, 2, \ldots, n) \tag{2}$$

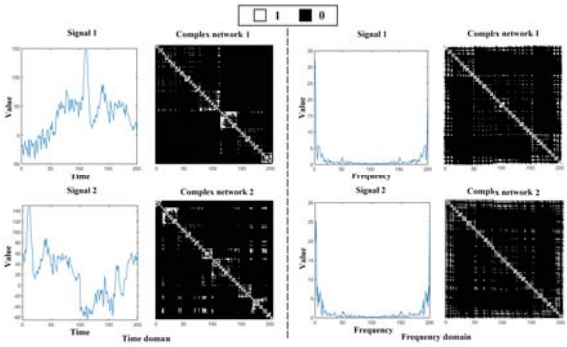

Fig. 4. A comparison of time- and frequency-domain complex networks. The two time-domain signals are from the same class with Signal 2 being a phase-shifted version of Signal 1. Directly converting them into their graph representations (here we use the VG [7] complex network for conversion) leads to very different results. By contrast, in the frequency domain, the results are much similar to each other.

This way, each f_k corresponds to the same frequency for all input time-domain signals as long as they have the same sampling rate and length, thus achieving data alignment.

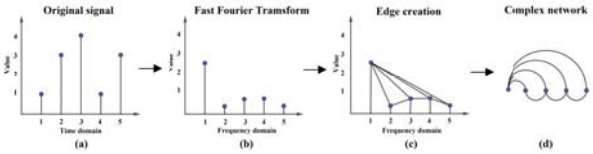

Fig. 5. The workflow of converting a 1D time-domain signal into its frequency-domain complex network representation.

Next, we construct the complex network representation for the frequency-domain signal. Specifically, we create a node for each data point in the signal, and create edges based on some connection rule. Here we use the connection rule of the aforementioned VG [7] complex network as an example. However, we note again that our method is compatible to other complex networks. The connection rule of VG is as follows: For two data points $|f_i|$ and $|f_j|$, if it suffices that for any point $|f_k|$ between them,

$$\frac{|f_k| - |f_i|}{k - i} < \frac{|f_j| - |f_i|}{j - i} \quad (i < k < j) \tag{3}$$

then we create an edge connecting the nodes for $|f_i|$ and $|f_j|$. In the resulting graph representation which can be written as an $n \times n$ adjacency matrix A^F, each edge indicates the pairwise relationship between two frequencies.

V. Sequential Graph Convolutional Network

With our frequency-domain complex network representation, we can now apply a classification model to accomplishing the epilepsy detection task. However, before predicting the labels, we would like to learn latent features from the graph representation with the advanced graph neural network (GNN) [15]. This brings about another challenge. Specifically, a complex network differs from a conventional graph in that each node in it corresponds to a data point in a signal, namely an *ordered* sequence. This sequential information cannot be naturally preserved by the topology of the graph. For example, in Fig. 6, Signal 2 is produced by swapping the second and

fourth data points in Signal 1. When converted to complex networks, the two have different adjacency matrices. However, the topology of the two graphs is the same.

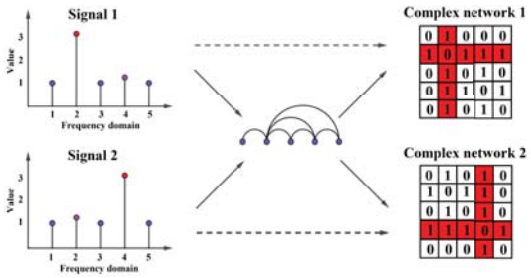

Fig. 6. An illustration of how sequential information can be lost in the topology of complex network. The two signals have the same topology under VG, yet their adjacency matrices are different.

Many existing GNNs consist of two steps: i) multi-hop aggregation of node neighbors, and ii) graph-level READOUT. Multi-hop aggregation updates the feature of each node by iteratively adding the feature of its neighbors, while READOUT uses the sum or pooling of the node feature vectors to learn graph-level representation. The use of READOUT results in the loss of node-level sequential information, making existing GNNs unsuitable for learning from complex networks. This problem can be made worse by our transformation into the frequency domain, as the perfect alignment of data makes preserving sequential information more important.

In view of this, we present a novel Sequential Graph Convolution Network (SGCN) which aims to retain sequential information within the GNN framework. The architecture of SGCN is shown in Fig. 7.

To be specific, for the input complex network $G = (V, E)$ with n nodes (namely it represents a length-n frequency-domain signal) in Fig. 7 (a), we follow the common practice for GNNs and feed it into a node aggregation module, shown in Fig. 7 (b). This module performs K-hop aggregation for all nodes in the graph, which is a process involving K iterations. Concretely, for any node v_i, let N_i be the set of its neighboring nodes and $h_{v_i}^k$ be the feature value of v_i in the kth iteration. At the beginning, we initialize $h_{v_i}^0 = 1$ for all $v_i \in V$. Then, in each iteration k $(1 \leq k \leq K)$, we perform the following summation [14] for each v_i:

$$h_{v_i}^k = h_{v_i}^{k-1} + \sum_{u_i} h_{u_i}^{k-1} \tag{4}$$

where $u_i \in N_i \cup \{v_i\}$. Repeating this operation K times, we have the feature values for all nodes. These form a feature vector $H^K = \{h_{v_1}^K, h_{v_2}^K, \ldots, h_{v_n}^K\}$ with the same order as the data points in the original frequency-domain EEG signal.

After aggregation, we move on to the node sequential convolution module, which is the most important and original design feature of SGCN. The idea is to preserve sequential information and enhance model interpretability. As is shown in Fig. 7 (c), we first introduce a learnable vector $W = \{w_1, w_2, \ldots, w_n\}$ to weight each element in the aforementioned feature vector. Concretely, for each i, the weighted feature value is

$$o_i = w_i \cdot h_{v_i}^k \tag{5}$$

Note that in the frequency domain, each weight w_i corresponds to a specific frequency and can be interpreted as the importance of this frequency to epilepsy detection. This introduces interpretability into our model. After weighting all features, we have a weighted feature vector $O = \{o_1, o_2, \ldots, o_n\}$.

Next, We pad O and feed it to a series of P sequential convolutional layers to extract the sequential information of the graph. Each of these layers performs a 1D convolution operation that maps O to the output feature map $y^c \in \mathbb{R}^n$ with the following:

$$y_i^c = \sigma\left(\sum_{u=1}^{n} \omega_u \cdot o_{i+u+1} + b\right) \tag{6}$$

where $\omega_u \in \mathbb{R}^m$ is the weight parameter with m being the kernel size, b is the bias parameter, and σ is the ReLU activation function. The stride of the convolution kernel is 1. The size-m convolution kernel extracts features for m consecutive nodes in the graph. In other words, it preserves the sequential information for m consecutive frequencies in the original frequency-domain signal.

After convolution, we perform max pooling to y^c that maps it to $y^{pool} \in \mathbb{R}^{\lfloor n/2 \rfloor}$. The filter size of max pooling is 2. Next, we move on to Fig. 7 (d) where we flatten y^{pool} to a 1D vector and feed it to Q consecutive fully connected layers. This replaces the READOUT function in existing GNNs. As was mentioned earlier, using the latter would lose all sequential information. Finally, Softmax is used to obtain the classification result.

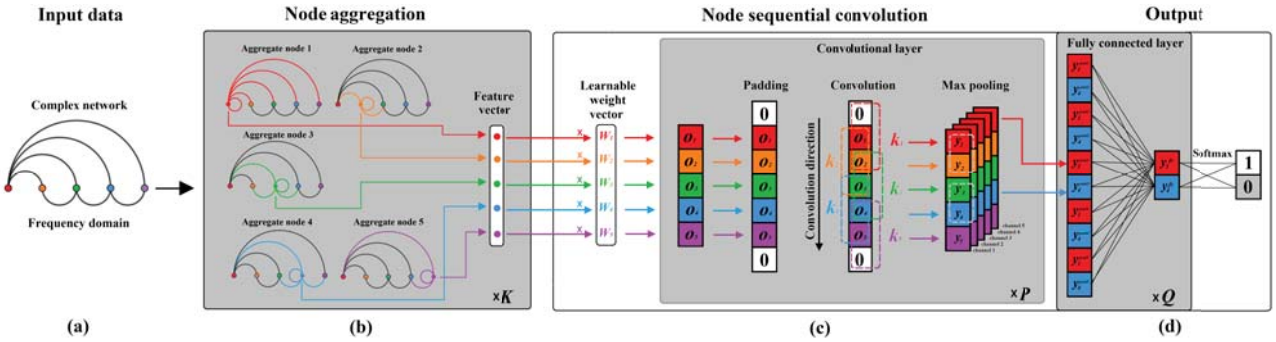

Fig. 7. The architecture of SGCN. Note that the sequential information (indicated by five different colors) is preserved throughout the process.

In summary, our SGCN uses two design elements to preserve sequential information. First, the sequential convolution operation learns features from consecutive nodes (i.e. consecutive frequencies) in an order-preserving fashion. Second, the use of fully connected layers (instead of READOUT) further retains the sequential information. In addition, our model has good interpretability in that the learnable weight vectors in Fig. 7 (c) can be seen as contributions of each frequency to epilepsy detection. As will be shown later, this can be fused with medical domain knowledge.

VI. Experiments

We now present our experiments. We begin by stating that all our source code is publicly available at https://github.com/JL-Wang-source-code/SGCN-for-epilepsy-detection for reproducibility.

A. Experimental Settings

We use two data sources for our experiments. First, we consider the well-known Bonn dataset [25], which includes five subsets named Sets A to E. Among them, Sets A to D are non-seizure EEG signals collected in various conditions, while Set E contains seizure signals. Each subset consists of 100 EEG signals. Each signal has a sampling rate of 173.61Hz and contains 4097 data points. In our experiments, unless otherwise noted, we use the first 4096 data points in each recording and split them into 16 non-overlapping length-256 segments, as using less data for prediction is more desirable in real-world applications. Also, we divide our experiments on the Bonn dataset into four binary classification tasks, namely A vs. E, B vs. E, C vs. E, and D vs. E. This division is consistent with practices in various previous works [4], [5], [17], [20], [21], [26]. In each task we consider the performance of four-fold cross-validation.

The second data source is a private EEG dataset called SSW. Unlike the Bonn dataset which is intended for conventional seizure detection, SSW is intended for detection of a special type of epilepsy called absence epilepsy [2], [4], which is more difficult to uncover than conventional ones. This dataset is collected from 10 patients at a local hospital. The sampling rate is 200Hz. By domain knowledge [27], we split the original recordings into segments of 1 second (i.e. with 200 data points). The dataset contains 10473 positive segments and 10473 negative ones. We use 16,000 segments for training, and 4,946 segments for testing.

As with parameter settings, K, P, Q in Fig. 7 are set to 5, 2, 2, and the detailed structural parameters of SGCN are shown in Table I. We use cross-entropy as the loss function and Adam as the optimizer, with the number of epochs set to 100 and the learning rate set to 0.001. We implemented our method with Pytorch. All experiments were run on a server with an Intel i7-6850k CPU @3.6GHz and four NVIDIA Titan XP GPUs.

B. Results and Discussion

We now present and discuss the experimental results.

TABLE I
Structural Parameters of SGCN

Layers	Model	Output size
Input	-	$1\times n\times n$[1]
Aggregate	$1\times1\times n$	$1\times1\times n$
Convolution 1	$8\times1\times9$	$8\times1\times n$
Max pooling 1	$8\times1\times2$	$8\times1\times(n/2)$
Convolution 2	$16\times1\times9$	$16\times1\times(n/2)$
Max pooling 2	$16\times1\times2$	$16\times1\times(n/4)$
Fully connected 1	$1\times4\times n$	1×50
Fully connected 2	1×50	1×2
Softmax	1×2	1×2

[1] n is the length of the EEG signals.

1) Determining the Best Practice: We begin by determining the best approach for complex network-based epilepsy detection. Concretely, we consider three design elements. The first concerns the choice of the complex network. Here we consider **VG** [7], **LPVG** [8], **HVG** [9] and **LPHVG** [10]. Relevant parameters are set as those used in the original papers [8], [10]. The second concerns the choice between time (**T**) and frequency (**F**) domain. The third concerns the choice of the classifier, where we consider the following.

- **SVM [21]**: A non-deep learning method that relies on handcrafted features extracted from the complex network. Here we inherit the features used in [21] except that we replace modularity with the variance of node degrees, as we found that the latter can yield better results. Also, we use RBF kernel as it performs better than linear kernel.
- **GNN**: a GNN network which is our SGCN without node sequential convolution.
- **CNN**: a 2D-CNN network modified from our SGCN by eliminating node aggregation and replacing node sequential convolution with 2D convolution on the adjacency matrix.
- **GIN [14]**: a recently proposed GNN network, which can be seen as a modification from our SGCN by eliminating node sequential convolution and replacing our fully connected layers with READOUT.
- **SGCN**: our method.

As with parameter settings, for SVM, the variance parameter for the RBF kernel is set to 0.5. As to the deep learning methods, for the modules they share with SGCN, we set the relevant parameters to the same as those in SGCN (see Table I) for comparable results. For CNN, the two convolutions and two max poolings in Table I are extended to 2D. For example, for Convolution 1, the output size is now $8 \times n \times n$ and the model parameters are now $8 \times 9 \times 9$. Similar rules apply for Convolution 2 and the max poolings. For GIN, the READOUT function is parameter-free.

The combination of the aforementioned three design elements leads to numerous epilepsy detection approaches, whose classification accuracies are shown in Fig. 8, from which we draw the following conclusions.

- As expected, complex networks in the frequency domain have better overall accuracy than those in the time domain.
- Our SGCN, along with CNN, is generally better than SVM, GNN, and GIN. This is likely because the former two

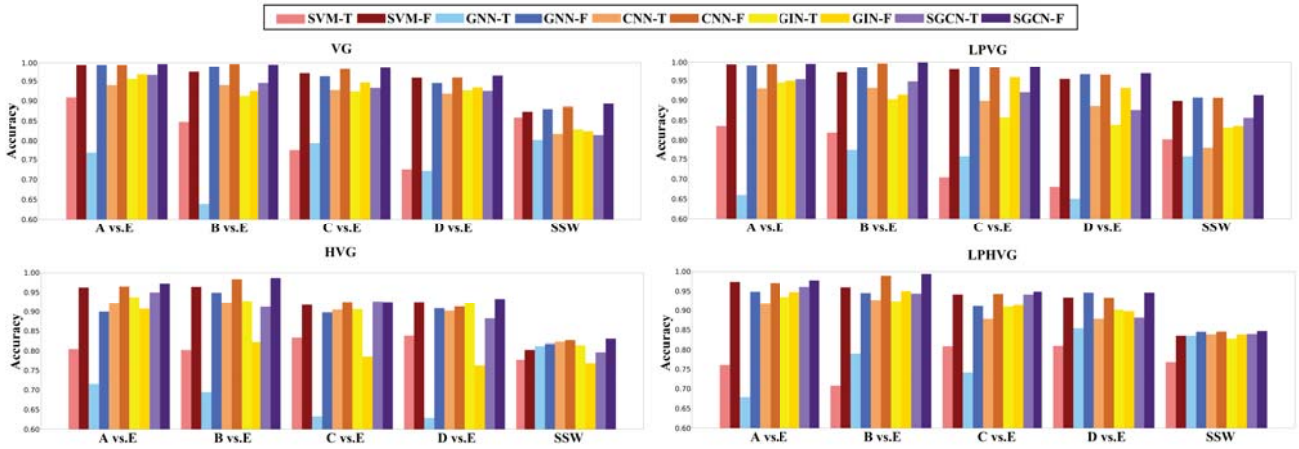

Fig. 8. Classification accuracies for all combinations of complex network, time/frequency domain (T/F) and classifier.

can take into account the sequential information. SGCN does so with its sequential convolution operation and fully connected layers, while CNN directly learns from the format of the adjacency matrices which in itself encodes the original order. In the frequency domain, our SGCN has slightly better performance than CNN. Besides, SGCN is more space-efficient than CNN thanks to its 1D convolutions.

- When transformed from time to frequency domain, SVM and GNN enjoy the greatest enhancement among all five classifiers. Since SVM and GNN are the weakest models in the time domain, this huge improvement showcases the superiority of the frequency-domain feature space. As with the other three models, CNN and SGCN enjoy more enhancement while GIN suffers from a decrease in performance on some occasions. This validates our claim that the need for preserving sequential information is more urgent in the frequency domain.
- When paired with SGCN in the frequency domain, VG and LPVG yield better results than HVG and LPHVG.

In conclusion, in terms of accuracy, the best practice for complex network-based epilepsy detection is to use the combination of VG/LPVG in the frequency domain (F) and SGCN. In particular, we recommend using VG for its relative simplicity.

2) Comparison with Rival Methods: We now compare our recommended method VG-F-SGCN with some existing methods. The results are shown in Table II, which includes three metrics: accuracy (Acc), specificity (Spe), and sensitivity (Sen). For the Bonn datasets, we use the results reported in the original papers for comparison, and the signal lengths are set to those in the original papers for comparability. For SSW, we selected two existing works on absence epilepsy detection (which SSW is intended for), re-implemented them and applied them to our own data. As is shown, our method can yield highly competitive results on all datasets. In particular, it achieves perfect performances in many cases, and generally outperforms its rivals on the four Bonn datasets.

3) Comparison Between Time and Frequency Domain: We further investigate the reason why our transformation into the frequency domain can yield better results. Concretely,

TABLE II
COMPARISON WITH RIVAL METHODS

Datesets	Methods	Signal Length	Acc	Spe	Sen
A vs. E	CT-LS-SVM [26]	4097	**1.000**	**1.000**	**1.000**
	PSO-SVM [17]	4097	0.994	0.995	0.993
	LSTM [5]	4097	0.970	0.980	0.960
	VG-F-SGCN	4097	**1.000**	**1.000**	**1.000**
	FWHVA [20]	1024	0.990	0.990	**1.000**
	VG-SVMKNN [21]	1024	**1.000**	**1.000**	**1.000**
	VG-F-SGCN	1024	**1.000**	**1.000**	**1.000**
B vs. E	CT-LS-SVM [26]	4097	0.995	0.992	0.998
	LSTM [5]	4097	0.925	0.940	0.910
	VG-F-SGCN	4097	**1.000**	**1.000**	**1.000**
	FWHVA [20]	1024	0.970	0.960	0.990
	VG-SVMKNN [21]	1024	0.973	0.952	**0.995**
	VG-F-SGCN	1024	**0.988**	**1.000**	0.975
C vs. E	CT-LS-SVM [26]	4097	0.964	0.948	0.980
	LSTM [5]	4097	0.920	0.950	0.890
	VG-F-SGCN	4097	**1.000**	**1.000**	**1.000**
	FWHVA [20]	1024	0.980	0.990	0.980
	VG-SVMKNN [21]	1024	0.983	0.980	0.985
	VG-F-SGCN	1024	**1.000**	**1.000**	**1.000**
D vs. E	CT-LS-SVM [26]	4097	0.940	0.820	0.940
	fApEn-SVMRBF [28]	4097	0.958	0.956	0.961
	LSTM [5]	4097	0.910	0.870	0.950
	VG-F-SGCN	4097	**1.000**	**1.000**	**1.000**
	FWHVA [20]	1024	0.930	0.970	0.890
	VG-SVMKNN [21]	1024	0.933	0.963	0.906
	VG-F-SGCN	1024	**0.969**	**0.975**	**0.962**
SSW	AdaBoost [2]	200	0.587	0.942	0.548
	SeizNet [4]	200	0.886	**1.000**	0.772
	VG-F-SGCN	200	**0.893**	0.911	0.874

we compare the average degree distributions of time- and frequency-domain complex networks. Average degree distribution is a widely-used [6], [10], [21] evaluation metric for complex network-based methods. To be specific, for a given graph representation, its average degree is the average value of the degrees of all its nodes. Combining the average degrees for all complex networks from a certain class, we have the average degree distribution for that class.

The average degree distributions on the Bonn and SSW datasets are shown in Fig. 9. As is indicated, the distributions of the seizure classes (E and SSW) are generally more dissimilar to the non-seizure ones in the frequency domain, which

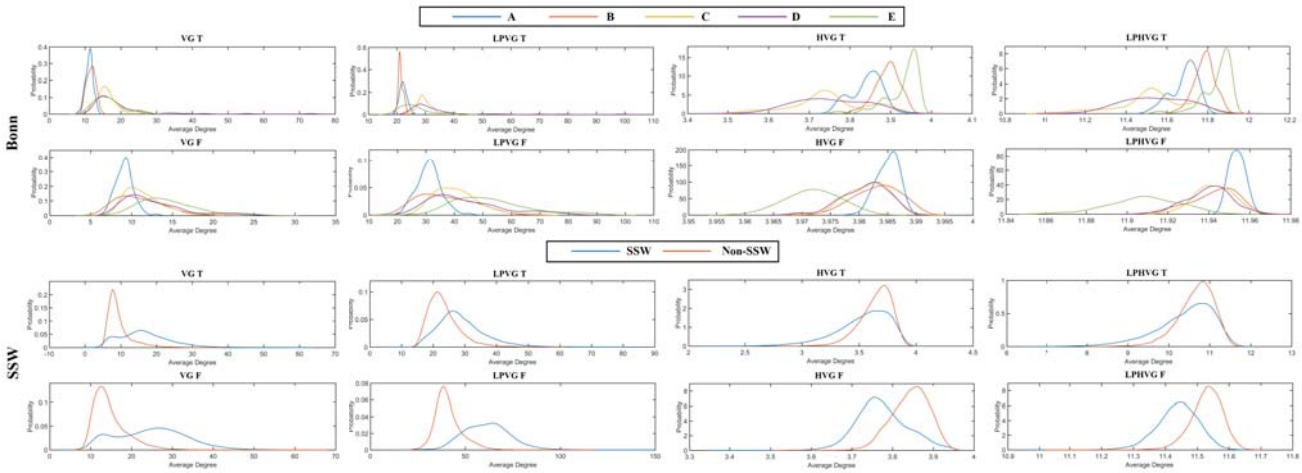

Fig. 9. Average degree distributions of complex networks. The distributions in frequency domain are more discriminative than those in time domain.

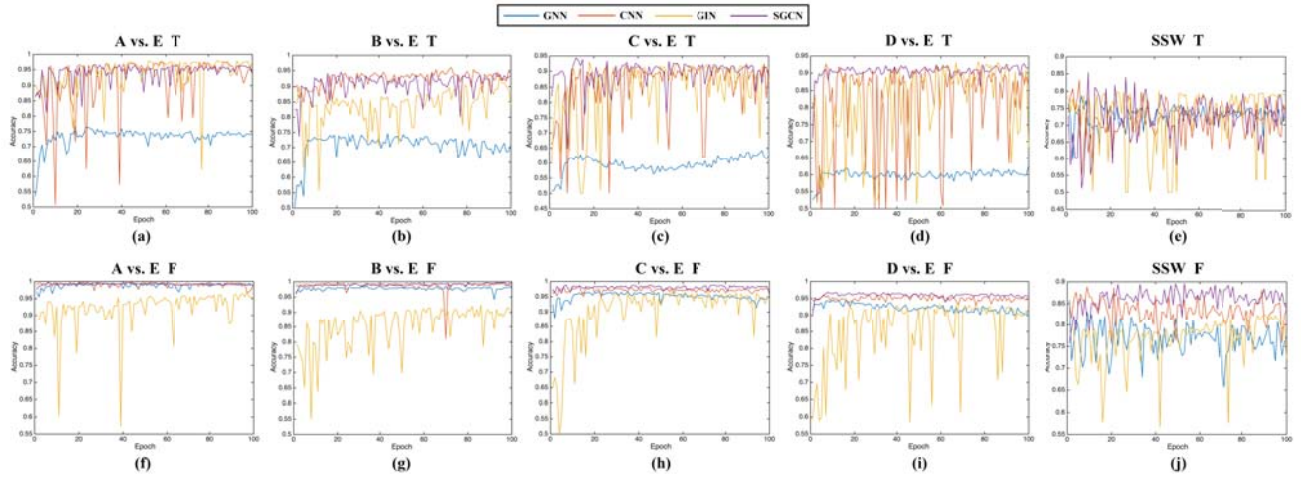

Fig. 10. Training curves of the four deep models in time/frequency (T/F) domain. The complex network used here is VG.

again verifies that the frequency domain is a better feature space.

4) Comparison of Deep Models: We now take a closer look at the four deep models we have previously considered, which are GNN, CNN, GIN, and SGCN. Concretely, we consider the training curves in Fig. 10, which shows their accuracies after each epoch. From it, we draw the following conclusions:

- For GNN, its training curves are generally stable in both time and frequency domain. In the former, it consistently yields poor results. However, its performance is greatly enhanced in the more discriminative frequency domain, albeit it is still generally inferior to our SGCN.
- For GIN, its training curves are significantly less stable than the other models. This is likely due to its inability to handle the sequential nature of the complex networks.
- For CNN and our SGCN, due to their superior design features (in particular, the ability to retain sequential information), their training curves are highly stable and can yield highly accurate results, especially in the frequency domain. Also, in the frequency domain, SGCN is generally superior to CNN, especially on the C vs. E, D vs. E, and SSW datasets.

5) Interpretability: Finally, we look into the interpretability of our method. As was previously explained, our interpretability comes from the learnable weight vector in Fig. 7 (c). Concretely, each weight corresponds to a specific frequency and can be seen as the importance of that frequency to epilepsy detection. This echos studies in the medical domain [11], [12] which suggests that certain frequencies in EEG signals are related to epilepsy.

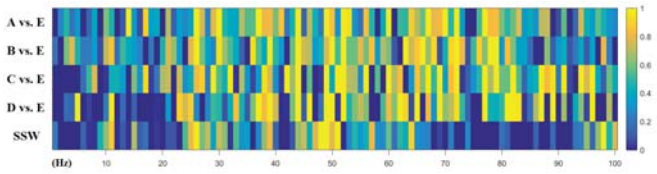

Fig. 11. Learnable weight vectors of SGCN on all datasets, which can be interpreted as the importance of each frequency to epilepsy detection.

To be specific, we visualize the weight vectors on all datasets in Fig. 11. On the Bonn data, the weights are generally higher on the frequency bands of 30-100Hz, which correspond to gamma rhythm in EEG. This is consistent with [11],

which says *...increased gamma EEG is probably a marker of the underlying ion channel or neurotransmitter receptor dysfunction in primary generalized epilepsies....* On the SSW dataset which focuses on absence epilepsy, the weights are higher on 12-60Hz, which correspond to beta and gamma rhythm. According to [12], absence epilepsy exhibits spike-wave discharges (SWDs) which *were characterized with an abrupt increase of oscillatory activity of 3-4 and 13-60Hz, peaking at 3-4 and 30-60Hz, and with a simultaneous decrease in the 8-12Hz frequency band.* This is generally consistent with our finding.

VII. Conclusions and Future Work

In this paper, we have approached the problem of EEG-based epilepsy seizure detection based on the complex network [6] representation. In the face of undesired intra-class variance introduced by the phase shift in the time domain, we have proposed to apply the complex network in the frequency domain to achieve perfect data alignment. In view of the urgency to preserve sequential information in the frequency domain, we have proposed Sequential Graph Convolutional Network (SGCN), which incorporates state-of-the-art GNN architecture with a novel sequential convolution operation to retain the original order in frequency-domain signals. Extensive experiments have demonstrated the effectiveness and interpretability of the proposed method.

In the future, we plan to expand our work to multi-channel EEG signals. We note that this is not a trivial task as existing complex networks can only characterize 1D EEG data. Despite the challenge, we believe this future direction has the potential of greatly enhancing the generality of our method.

Acknowledgment

This paper is funded by NSFC Grant No. 61672161 and Dongguan Innovative Research Team Program Grant No. 2018607201008.

References

[1] B. Aboukhalil, P. Auce, A. Avbersek, M. Bahlo, D. J. Balding, T. Bast, L. Baum, A. J. Becker, F. Becker, B. Berghuis *et al.*, "Genome-wide mega-analysis identifies 16 loci and highlights diverse biological mechanisms in the common epilepsies," *Nature Communications*, vol. 9, no. 1, p. 5269, 2018.

[2] Y. C. Liu, C. K. Lin, J. J. Tsai, and Y. Sun, "Model-based spike detection of epileptic EEG data," *Sensors*, vol. 13, no. 9, pp. 12 536–12 547, 2013.

[3] A. Subasi, "EEG signal classification using wavelet feature extraction and a mixture of expert model," *Expert Systems With Applications*, vol. 32, no. 4, pp. 1084–1093, 2007.

[4] M. T. Avcu, Z. Zhang, and D. W. S. Chan, "Seizure detection using least EEG channels by deep convolutional neural network," in *IEEE International Conference on Acoustics, Speech and Signal Processing, ICASSP*, 2019, pp. 1120–1124.

[5] D. Ahmedtaristizabal, C. Fookes, K. Nguyen, and S. Sridharan, "Deep classification of epileptic signals," *arXiv: Learning*, 2018.

[6] Y. Zou, R. V. Donner, N. Marwan, J. F. Donges, and J. Kurths, "Complex network approaches to nonlinear time series analysis," *Physics Reports*, 2018.

[7] L. Lacasa, B. Luque, F. Ballesteros, J. Luque, and J. C. Nuno, "From time series to complex networks: The visibility graph," *Proceedings of the National Academy of Sciences*, vol. 105, pp. 4972–4975, 2008.

[8] Z. K. Gao, Q. Cai, Y. X. Yang, W. D. Dang, and S. S. Zhang, "Multiscale limited penetrable horizontal visibility graph for analyzing nonlinear time series," *Scientific Reports*, vol. 6, p. 35622, 2016.

[9] B. Luque, L. Lacasa, F. Ballesteros, and J. Luque, "Horizontal visibility graphs: Exact results for random time series," *Physical Review E*, vol. 80, no. 4, p. 046103, 2009.

[10] M. G. Wang, A. L. Vilela, R. J. Du, L. F. Zhao, G. G. Dong, L. X. Tian, and H. E. Stanley, "Exact results of the limited penetrable horizontal visibility graph associated to random time series and its application," *Scientific Reports*, vol. 8, no. 1, p. 5130, 2018.

[11] J. O. Willoughby, S. P. Fitzgibbon, K. Pope, L. Mackenzie, A. V. Medvedev, C. R. Clark, M. P. Davey, and R. A. Wilcox, "Persistent abnormality detected in the non-ictal electroencephalogram in primary generalised epilepsy." *Journal of Neurology, Neurosurgery, and Psychiatry*, vol. 74, no. 1, pp. 51–55, 2003.

[12] K. Benedek, A. Berenyi, P. Gombkotő, H. Piilgaard, and M. Lauritzen, "Neocortical gamma oscillations in idiopathic generalized epilepsy," *Epilepsia*, vol. 57, no. 5, pp. 796–804, 2016.

[13] W. L. Hamilton, Z. Ying, and J. Leskovec, "Inductive representation learning on large graphs," pp. 1024–1034, 2017.

[14] K. Xu, W. Hu, J. Leskovec, and S. Jegelka, "How powerful are graph neural networks?" in *International Conference on Learning Representations, ICLR*, 2019.

[15] T. Kipf and M. Welling, "Semi-supervised classification with graph convolutional networks," in *International Conference on Learning Representations, ICLR*, 2017.

[16] A. Shoeb and J. V. Guttag, "Application of machine learning to epileptic seizure detection," in *International Conference on Machine Learning (ICML)*, 2010, pp. 975–982.

[17] A. Subasi, J. Kevric, and M. A. Canbaz, "Epileptic seizure detection using hybrid machine learning methods," *Neural Computing and Applications*, vol. 31, no. 1, pp. 317–325, 2019.

[18] V. Schetinin and L. Jakaite, "Classification of newborn EEG maturity with bayesian averaging over decision trees," *Expert System Application*, vol. 39, no. 10, pp. 9340–9347, 2012.

[19] L. Wang, X. Long, J. B. Arends, and R. M. Aarts, "EEG analysis of seizure patterns using visibility graphs for detection of generalized seizures," *Journal of Neuroscience Methods*, vol. 290, pp. 85–94, 2017.

[20] G. H. Zhu, Y. Li, and P. P. Wen, "Epileptic seizure detection in EEG signals using a fast weighted horizontal visibility algorithm," *Computer Methods and Programs in Biomedicine*, vol. 115, no. 2, pp. 64–75, 2014.

[21] S. Supriya, S. Siuly, H. Wang, J. L. Cao, and Y. C. Zhang, "Weighted visibility graph with complex network features in the detection of epilepsy," *IEEE Access*, vol. 4, pp. 6554–6566, 2016.

[22] M. Zeng, C. Y. Zhao, and Q. H. Meng, "Detecting seizures from EEG signals using the entropy of visibility heights of hierarchical neighbors," *IEEE Access*, vol. 7, pp. 7889–7896, 2019.

[23] X. Y. Li, B. Y. Qian, J. S. Wei, A. Li, X. Liu, and Q. H. Zheng, "Classify EEG and reveal latent graph structure with spatio-temporal graph convolutional neural network," in *International Conference on Data Mining, ICDM*, 2019, pp. 389–398.

[24] P. X. Zhong, D. Wang, and C. Y. Miao, "Eeg-based emotion recognition using regularized graph neural networks." *arXiv: Learning*, 2019.

[25] R. G. Andrzejak, K. Lehnertz, F. Mormann, C. Rieke, P. David, and C. E. Elger, "Indications of nonlinear deterministic and finite-dimensional structures in time series of brain electrical activity: Dependence on recording region and brain state," *Physical Review E*, vol. 64, no. 6, p. 061907, 2001.

[26] S. Siuly, L. Yan, and P. P. Wen, "Clustering technique-based least square support vector machine for EEG signal classification," *Computer Methods and Programs in Biomedicine*, vol. 104, no. 3, pp. 358–372, 2011.

[27] C. C. Chiang, X. L. Wei, A. K. Ananthakrishnan, R. S. Shivacharan, R. L. E. Gonzalez, M. M. Zhang, and D. M. Durand, "Slow moving neural source in the epileptic hippocampus can mimic progression of human seizures," *Scientific Reports*, vol. 8, no. 1, p. 1564, 2018.

[28] Y. Kumar, M. Dewal, and R. Anand, "Epileptic seizure detection using dwt based fuzzy approximate entropy and support vector machine," *Neurocomputing*, vol. 133, pp. 271–279, 2014.