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Brain Dynamic States Analysis based on 3D Convolutional Neural Network

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Abstract—Drowsiness driving is one major factor of traffic accident. Monitoring the changes of brain signals provides an effective and direct way for drowsiness detection. One 3D convolutional neural network (3D CNN)-based forecasting system has been proposed to monitor electroencephalography (EEG) signals and predict fatigue level during driving. The limited weight sharing and channel-wise convolution were both applied to extract the significant phenomenon in various frequency bands of brain signals and the spatial information of EEG channel location, respectively. The proposed 3D CNN with limited weight sharing and channel-wise convolution has been demonstrated to predict reaction time (RT) of driving with low root mean square error (RMSE) through the brain dynamics. This proposed approach outperforms with the state-of-the-art algorithms, such as traditional CNN, Neural Network (NN), and support vector regression (SVR). Compared with traditional CNN and Artificial Neural Network, the RMSE of 3D CNN-based RT prediction has been improved 9.5% (RMSE from 0.6322 to 0.5720) and 8% (RMSE from 0.6217 to 0.5720), respectively. We envision that this study might open a new branch between deep learning application in neuro-cognitive analysis and real world application.

Keywords — driving safety, drowsiness, deep learning, convolutional neural network, Electroencephalography.

I. Introduction

Driving safety becomes one of the major concern in our daily life, and drowsiness driving is a major factor of traffic accident due to the driver's increasing tiredness and stress levels. According to World Health Organization (WHO), there are 1.2 million people died in car accidents and 20 to 50 million people have non-fatally injured in car accidents [1]. In these kinds of accident, the lapses behavioral errors are responsible for 90% [1]. In previous studies, drowsiness has been highly connected to the behavioral lapses before an accident [2]–[4]. In drowsy driving, there are two major categories. First category is the behavioral detection, and the movement of steering wheels, the deviation of vehicle, and the car speed are all the indexes. The second category is physiological detection, and heart rates, breath, brain wave and respiratory rate are considered as the features [5], [6]. Especially, electroencephalogram (EEG) has been proved to be a reliable indicator of human cognitive states. In particular, there are rich special features in EEG data. Therefore, many EEG-based assistance systems have been proposed for monitoring the fatigue or drowsiness levels during driving [5], [6]. Some of these researches have applied the statistical models according to the previous neuroscience knowledge. The others have applied the machine learning approaches, including support vector machine (SVM) [7], Gaussian mixture model [8] and neural network (NN) [9]. All works have demonstrated that EEG is one feasible features to monitor the cognitive changes during driving.

Some behavior-based technologies have been developed to predict fatigue level of drivers. In particular, monitoring brain signals provides an effective way to predict the changes of fatigue during driving [10] [11]. Recently, many researchers leverage the deep learning algorithm to solve the image recognition and signal processing [12], [13]. Many researchers have been used deep learning methods to analyze EEG signals [10], [14], [15] and shown the improved results compared with the traditional approaches. Convolutional neural network (CNN) has very strong feature to extract spatial information in different areas, such as image recognition [12]. Although CNN is a powerful algorithm for spatial information capturing, spatial and temporal information of brain dynamics cannot be captured well [16], [17]. In video analysis, the module is designed to extract the feature between adjacent frames, since the frames of a video are a trend demonstrates a continuous movement. EEG signals have the similar characteristic because it is continuous, which brain state varies dynamically over time, and the brain states are related closely, especially in adjacent time frames.

Recently, deep learning is used into EEG signals processing [14], [15]. CNN is one of the powerful deep learning method for analysing spatial information because of its convolutional data extraction in spatial domain. Each convolutional layer extracts 2D input feature maps, and only the spatial information is considered. Compared to traditional CNN, 3D CNN has ability to analyse temporal and spatial information based on 3D filters which extract both temporal and spatial information. In other words, 3D CNN extracts both temporal and spatial information by feeding 3D input data. Therefore, 3D CNN has been widely used in analysing the data which includes spatial and temporal data, such as video [16], [17].The results in the previous studies showed that 3D CNN can reach the higher performance in video recognition [16] . The characteristics including continuous time signal in EEG signals (temporal information) are similar with that in video. In particular, the spatial information in every single time window (frame) is also one important characteristic for drowsiness detection [18]. Therefore, applying 3D CNN to multi-frame EEG signals is one potential way for drowsiness prediction. Furthermore, channel-wise convolution and limited weight sharing mechanisms were both applied to enhance the spatial relationships of EEG signals and capture the phenomenon from all EEG frequency bins, respectively [13]. The extracted features by these two mechanisms were then the inputs of 3D CNN.

In this study, we demonstrated a 3D CNN based monitoring system to predict reaction time (RT) during driving. The novel channel-wise convolution and limited weight sharing mechanisms also significantly improve the overall performance of prediction. Compared with traditional CNN and other machine learning algorithms including neural network (NN) and support vector regression (SVR), the proposed 3D CNN can reach the minimum root mean square error (RMSE).

II. Experimental Setup

A. *Experiment*

The experiment dataset was collected by a 360-degree virtual-reality (VR) environment with motion platform, which simulates a driving environment in reality (as shown in Figure 1A). One real car was mounted on the 6-degree-of-freedom platform to provide the kinaesthetic stimulus.

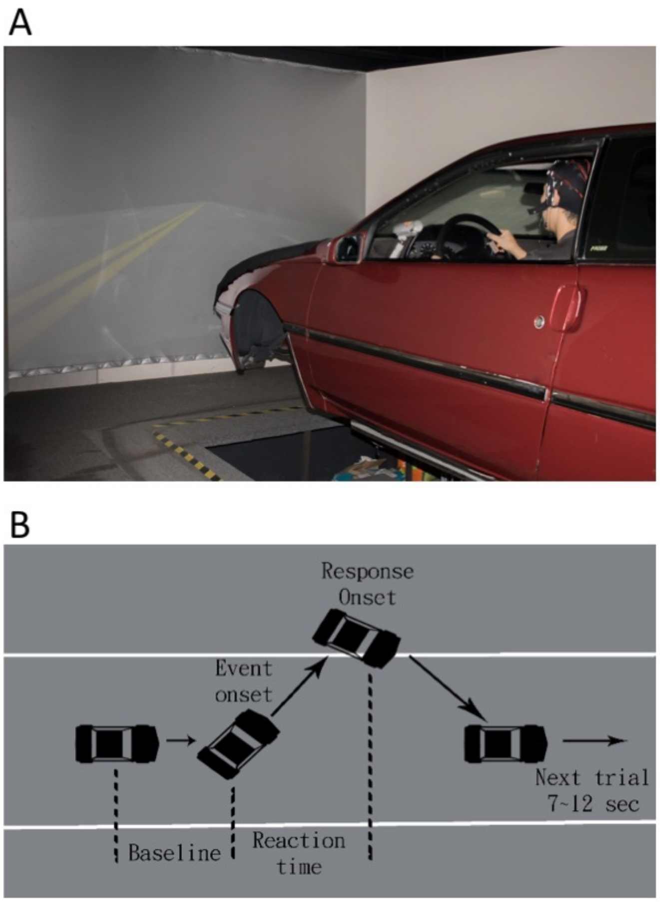

Figure 1: (A) The driving experiment is conducted in a real car which is mounted on 6 degree-of-freedom motion platform. (B) We use the signal before the event onset 6 second as baseline signal, and the time between event onset and response onset as reaction time.

There were 80 healthy subjects without any history of psychological or sleep disorders. All the subjects were collected with a 32-channel EEG equipment, which includes 30 channels and 2 reference channels. The impedances of all EEG channels were all less than 5 kΩ and the sampling rate of EEG signals were 250 Hz. We measured human's brain states during driving by land-keeping task, which can measure driver's drowsiness and alertness. In lane-keeping task, the participants were asked to drive vehicles along a lane, however, the vehicle were designed to deviate forward left or right lanes from their original lane automatically. When the participants detected the vehicles deviated from the lane, they were asked to drive the car back to the original lane through turning the steering wheel. In this study, one trial was defined as from the onset of deviation to the offset of turning the steering wheel (back to the original lane). There was a random 7-12s break between two continuous trials (as shown in Figure 1B). The whole experiment continued 90 minutes, and there were approximately 400 trials.

B. *Data pre-proccessing*

Reaction time (RT) is the duration between the onset of deviation and the time that participants started to drive the vehicle back to the original lane. To evaluate driver's brain states, RT represents driver's drowsiness and alertness during driving (Figure 1B). Divers might be drowsy while the RT was high. In contrast, drivers might be alert while the RT was short. The brain dynamics in the baseline was then extracted, and 6s-data was extracted. Eighty subjects involved in this drowsiness driving. There were nine subjects abandoned because some EEG channels of these subjects were broken. Additionally, some trials with noise or high RT (> 10s) were removed manually. There are total 24,203 trials from 71 subjected. For normalization, all RTs was divided by the baseline (the shortest 10% RT). In particular, the maximum normalized RTs were set to three. The flowchart of data processing is list in Figure 2.

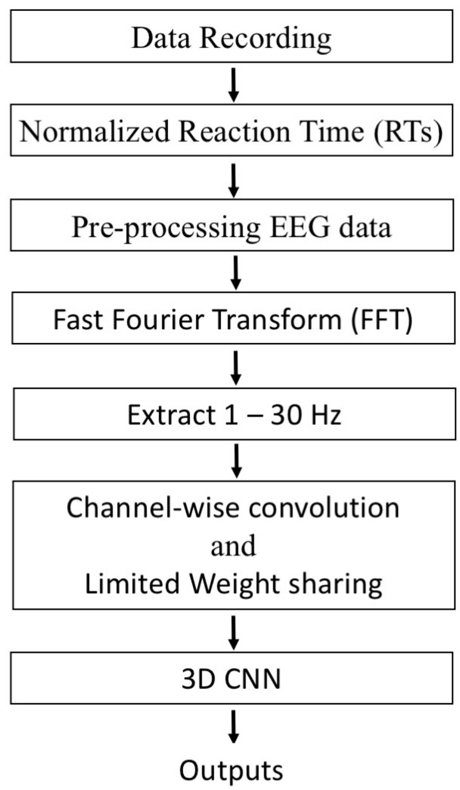

Figure 2: The flowchart of data processing

III. Method

A. *Algorithm*

In this research, 3D convolution neural network was majorly applied to analyse the recorded brain activities during driving. To extract the spatial features and frequency features from EEG signals efficiently, two algorithms including channel-wise convolution and limited weight sharing were both applied to reach higher performance.

Firstly, the structure of 3D convolutional layers and traditional (2D) convolutional layers are listed in Figure 3. Briefly, traditional CNN equips 2D filters, comprised of 2D weights, to convolute 2D input feature maps or input data at 2 axis (usually spatial axis), and produce 2D output feature maps too. The feature maps also are compressed by 2D pooling layers. Finally, the feature maps are flattened to 1D vectors and connected to fully connected layers. In 3D CNN, input data and input feature maps are 3D, and the filters are 3D cubes comprised of $N * N * N$ weights, which can convolute input data or input feature maps at 3 axis (usually spatial and temporal axis). Following, each output feature maps of 3D convolutional layers are compressed by 3D pooling layers. Finally, the 3D feature maps are flattened to 1D vectors and connected to fully connected layers.

In terms of the function of 3D CNN,

$$v_{ij}^{xyz} = relu\left(b_{ij} + \sum_{m}\sum_{p=0}^{P_i-1}\sum_{q=0}^{Q_i-1}\sum_{r=0}^{R_i-1} w_{i_{ijm}}^{pqr} v_{(i-1)m}^{(x+p)(y+q)(z+r)}\right)$$

which v_{ij}^{xyz} is the unit at x, y and z position at feature map between i^{th} and j^{th} layers, b_{ij} is the bias between the two layers, m is the m^{th} filter in convolutional layer, P, Q and R are the kernel size of filters, $w_{i_{ijm}}^{pqr}$ is the weight at pqr position of m^{th} filter, and *relu* is an activation function.

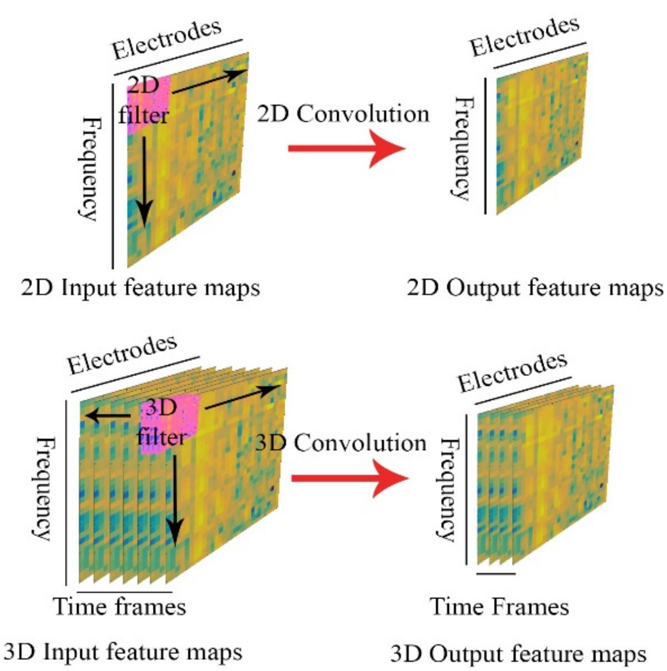

Figure 3: 3D convolutional layer and 2D convolutional layer, 3D convolutional layer extract 3D input feature maps with 3D filter, 2D convolutional layer extract 2D input feature maps with 2D filter

B. *Architecture*

The 3D conv layers extract 3D input feature maps at first and the max-pooling layers compress input feature maps to reduce the data dimension. After three convolutional and max-pooling layers, the output feature maps are flattened and feed into a 512-node fully-connected layer, which followed by an output layer. In every convolutional layer, we adopted “padding”, which pad zeros at input feature maps to make sure the input size and output size are equal. All configurations for 3D CNN are listed in Table 1. The dimension of input layer is 18 (frequency power,1-18 Hz) * 30 (EEG channel numbers) X 26 (6s frames) X one input feature map. We adopted a 3 (EEG channel) * 3 (frequency) * 3 (time frame) filter in all three convolutional layers, in which there were 32, 64 and 128 filters, respectively. We also adopted one 2 (EEG channel) * 2 (frequency) * 2 (time frame) max-pooling in all three pooling layers. Therefore, the structure of the proposed 3D CNN included Input-layer (18-30-26-1) - Conv1 (3-3-3-32) - Maxpool1 (2-2-2) - Conv2 (3-3-3-64) - Maxpool2 (2-2-2) - Conv3 (3-3-3-64) - Maxpool1 (2-2-2) - Conv3 (3-3-3-128) - Maxpool1 (2-2-2) - Fully Connected Layer (512) – Output-layer (1).

Table 1 configuration of 3D CNN and 2D CNN

Layer	3D CNN	CNN
Input layer	18-30-26-1	18-30-1
Conv1	3-3-3-32	3-3-32
Maxpool1	2-2-2	2-2
Conv2	3-3-3-64	3-3-64
Maxpool2	2-2-2	2-2
Conv3	3-3-3-128	3-3-128
Maxpool3	2-2-2	2-2
Fully connected	512	512
Output layer	1	1

We then adopted one 3 (EEG channel) * 3 (frequency) filter in all three convolutional layers, in which there were 32, 64 and 128 filters, respectively. We also adopted 2 (EEG channel) * 2 (frequency) max-pooling in all three pooling layers. The input data of CNN are 2D and the conv layers and max-pooling layers are also two dimension. The structure of CNN is Input-layer (18-30-1) - Conv1 (3-3-32) - Maxpool1 (2-2) - Conv2 (3-3-64) - Maxpool2 (2-2) - Conv3 (3-3-128) – Maxpool3 (2-2) - Fully Connected Layer (512) – Output-layer (1). The configuration of neural network is listed below. Input-layer (18-30-1) - Fully Connected Layer (512) – Output-layer (1).

Furthermore, we proposed a novel approach, channel-wise convolution. Compared to other dataset, images and videos analysed with CNN modules, EEG data signals have some unique attributes should be considered into CNN modules, for example EEG signals demonstrate different phenomenon according to the position of EEG channels. Therefore, the position of EEG channels should be considered into the CNN module to extract the full spatial information.

There are high spatial relationships among the EEG signals from the adjacent EEG channels. Therefore, special filters are able to capture the information from the different EEG channels. A channel-wised convolution was applied to extract the spatial information according to the channel location of EEG equipment as shown in Figure 4.

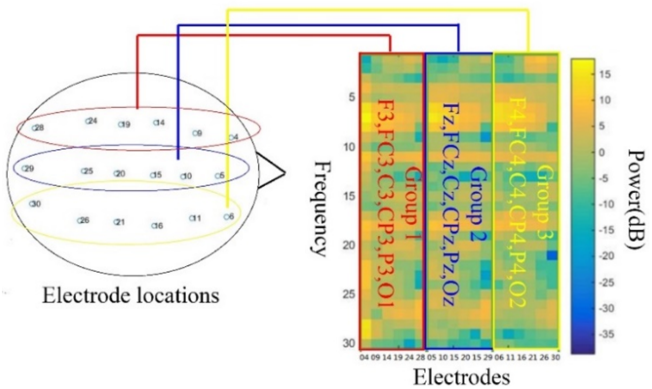

Figure 4: Channel-wise convolution. The EEG channels are divided into three groups and sorted from the frontal region to posterior region. After grouping the EEG channels by spatial location (channel location), the designed filters only convolute the information in each group.

Firstly, the EEG channels are divided into three groups (as shown in Figure 4) according to their physical locations. Furthermore, the EEG channels in each group were sorted from the front of a scalp to the behind of a scalp sequentially. After doing that, a channel-wise convolutional layer scan frequency power with adjacent EEG channels together, group by group. In other words, those groups share the same filter, however, the filters do not convolute the frequency power across different groups. Therefore, the filters can extract the information between each EEG channel according to their physical locations. Moreover, the reason why we just used 18 EEG channels in channel-wise convolution here, instead of 30, is that these three groups of EEG channels have more regular phenomenon in power spectrum here, compared to the rest of the EEG channels.

In addition, we adopt a mechanism – limited weight sharing which is widely applied in deep learning methods from speech processing. Since the phenomenon of frequency power between different frequency bands are related to distinct cognitive functions, the weight of each band is supposed to be shared in the specific bands. The extracted features should also be trained individually. It means there is a specific filter for each frequency band to extract the features form the frequency information. The idea is from speech processing [10]. In speech processing, the bandwidth is quite wide and the attributes in different frequency bands are different. Therefore, each frequency band were trained individually to extract meaningful features. Since there are the same attributes between EEG signals and speech information, the limited weight sharing was also applied for EEG processing in the current study. There are frequencies bands (Delta band: 1-4 Hz, Theta band: 4-7 Hz, Alpha band: 8-15 Hz, Beta band: 16-30 Hz) in EEG analysis. Therefore, we adopt limited weight sharing in these four bands in the first convolutional layer as shown in Figure 5. In other words, the weights (filters) of one specific band are only shared inside this band. After applying the limited weight sharing, the band-based filters can majorly extract the features in each frequency band.

In this study, the channel-wise convolution and the limited weight sharing were applied in the conv1 layer and all three conv layers, respectively. In particular, these two mechanisms were both applied in 3D CNN and traditional CNN. In the limited weight sharing mechanism, the frequency in conv1 layer were grouped into four bands (band 1:1-4 Hz, band 2: 5-7 Hz, band 3: 8-15 Hz, band 4: 16-30 Hz), and three bands in conv2 layer (band 1: 1-5 Hz, band 2: 6-10 Hz, band 3: 11-15 Hz) and two bands (band 1: 1-5 Hz, band 2: 6-10 Hz) in conv3 layer. Similarly, the channel-wise convolution mechanism was applied at conv1 layer, which could avoid the over restricting convolution in single EEG channel group (as shown in Figure 5).

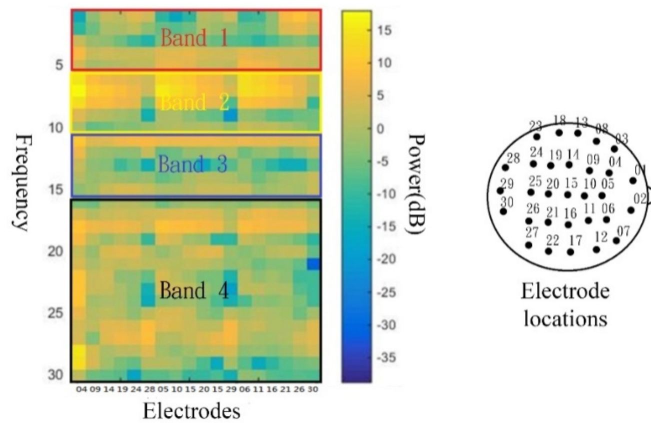

Figure 5: Limited Weight sharing in first convolutional layer. The color in power spectrum represents power (dB) in each frequency bin. The frequencies are divided into 4 bands. The weights (filters) are only shared inside a single band. In other words, the filters are trained individually inside their band without overlapping the other bands.

IV. Results and Discussion

Comparing with the result (as shown in Table 2) of 3D CNN and CNN, the average RMSE is improved 9.5% (from 0.6322 to 0.5720). The reason is 3D CNN is able to extract the temporal information by convoluting multi frames of EEG signals. Comparing with the results of 3D CNN, NN and SVR, 3D CNN still achieves the better performance. Compared with the results of SVR, the average and standard deviation RMSE of 3D CNN are improving 4.2% (from 0.5973 to 0.5720) and 10% (from 0.1636 to 0.1488), respectively.

Table 2: Results of 3D CNN, CNN, NN and SVR

RMSE	3D CNN	CNN	NN	SVR
Mean	0.5720	0.6322	0.6217	0.5973
STD	0.1488	0.1752	0.1428	0.1636

The performance of 3D CNN with channel-wise convolution and limited weight sharing is shown in Table 3. These two mechanisms both achieve higher performance. In this study, we adopt channel-wise convolution and limited weight sharing at conv1 layer and all three conv layers, respectively. These two mechanism can decrease the average RMSE by 1.9% (from 0.5834 to 0.5720) as comparing with the performance of 3D CNN. According to our results, these two mechanisms should be applied simultaneously to achieve the best performance. Otherwise, the performance is worse than that trained by original 3D CNN.

Table 3: Results of 3D CNN with & without channel-wise convolution and limited weight sharing

3D CNN	With limited weight sharing	Without limited weight sharing
With channel-wise convolution	**0.5720 ±0.1488**	0.5924±0.1464
Without channel-wise convolution	0.5909±0.1441	0.5834 ±0.1449

We also set two different structures of 3D CNN as shown in Table 4. The configurations of seven-layer 3D CNN are the same as those of three-layer 3D CNN. The structure of three-layer 3D CNN is Input-layer (18-30-26-1) - Conv1 (3-3-3-32) - Maxpool1 (2-2-2) -) - Maxpool1 (2-2-2) - Fully Connected Layer (512) – Output-layer (1). In particular, the channel-wise convolution and limited weight sharing at conv1 layer in three-layer 3D CNN. The results show that seven-layer 3D CNN reaches better performance than three-layer 3D CNN by decreasing average RMSE 7.7% (from 0.5729 to 0.6210).

Table 4: Results of different structures of 3D CNN

	seven-layer 3D CNN	three-layer 3D CNN
RMSE	0.5720±0.1488	0.6210±0.1382

V. Conclusions

The frequency information of EEG signal is continuous data. Therefore, traditional CNN did not get a good result in this study compared to the other algorithms since traditional CNN might not be able to capture brain dynamic state. In this study, 3D CNN has ability to extract multi-frame data, which content temporal information among different time frame, and the extracted features from various time frame are essential for analyzing the brain signals. The phenomenon in different EEG frequency bands are supposed to be convoluted with different filters by limited weight sharing. Furthermore, channel-wise convolution can extract more spatial information of EEG signals, compared to the normal convolution. In conclusion, 3D CNN actually captures brain dynamic state better than traditional CNN by decreasing RMSE from 0.6322 to 0.5834. Moreover, 3D CNN adopted channel-wise convolution and limited weight sharing together can also reach better performance in EEG signals, compared to original 3D CNN, by decreasing RMSE from 0.5834 to 0.5720. Based on the completive performance, we envision that deep learning might open a new branch between translation neuroscience and real world application.

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