Transform learning on Deep Convolution Neural Network

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Abstract

Deep learning models demonstrate incredible successes in different fields including computer vision, molecular biology, and natural language processing. As one trending track of deep learning, end-to-end learning requires less feature engineering steps compared to traditional machine learning models. It can automatically learn the internal representation of the input data and reveal latent patterns in the input data that cannot be captured by conventional data analysis techniques.

In this project, we apply end-to-end learning on the motor task classification problem based on electroencephalography (EEG) signals collected from 9 individual subjects. We compare the model performance on different modern deep learning architectures, including shallow and deep convolution neural network as well as the recurrent neural network. In addition, transfer learning technique is used to tackle the issue of the inter-subject variance of EEG signal. We observe an average 9.58% (±2.21%) improvement on the models we developed.

This study shows the deep neural network make a prediction without handcrafted features given from conventional preprocessing techniques and the capability of transfer learning and Gaussian noise to adapt the characteristic of subject-specific EEG recordings.

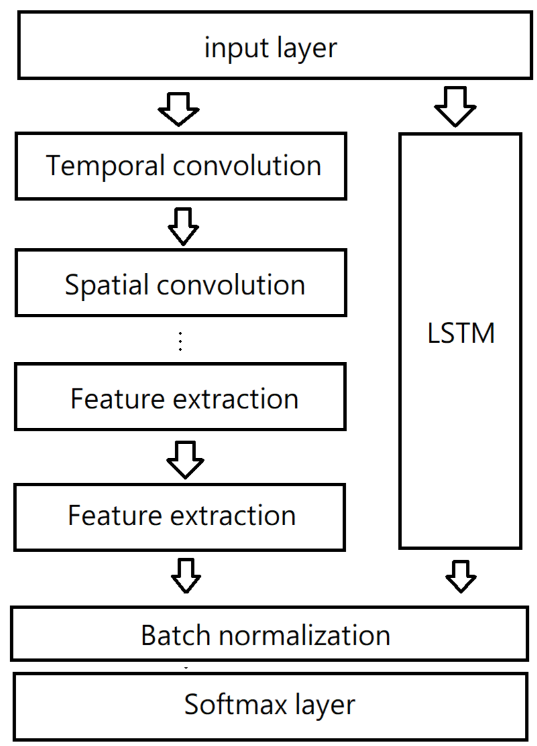

Figure 1. The LSTM-CNN architecture. The LSTM layer not only provide spatial information but serve a gradient highway that facilitate training process.

1. Introduction

One of the major challenges in analyzing human motor activity is caused by elusive human variability. Conventional signal processing techniques arm to extract frequency information such as alpha, beta, gamma frequency band by applying Fourier transform. Fourier transform assumes the transformed signals are periodic and stationary. However, due to the nature of dynamics in the human brain, the EEG signal may void the fundamental assumption of Fourier transform and could result in misconception when applying such transformation. In addition, Fourier transform is, in fact, a global transformation which cannot reflect the local information. Some time-domain operation, such as Hilbert transform and the empirical mode decomposition, are proposed to estimate the frequency components of non-stationary electrophysiological recordings, but these methods have their own limit.

1.1. End-to-end learning

Recent research evidence indicates that deep neural network has the ability to extract latent pattern and feature of data. In this study, we perform end-to-end learning which bypassing handcrafted features, such as frequency band mapping, to learn the representation of the raw EEG data covered by a holistic learning process and use it to classify various motor tasks.

1.2. Spatial and temporal convolution

Multichannel EEG recordings contain both spatial and temporal information. EEG has been classically considered to be temporal-rich with a poor spatial resolution. However, recent studies argue that the spatial information of EEG has been underestimate. For the purpose of examining this argument, convolution neural network (ConvNet) [1, 4] and recurrent neural network (RecurNet) are selected as our main architecture due the capability of integrating correlation between electrodes and the time course of scalp potentials [2]. In Figure 1, spatial convolution represent the convolution layers that integrate the data among 22 elecrodes and one single time bin while the temporal convolution serve as sliding window across time series.

1.3. Intra-subject variability

Intra-subject variability is one of the major challenges when decoding motor activity based on non-invasive EEG recordings in brain-machine interfaces. Traditionally, a time-consuming laborious procedure is performed before each new session to ensure the quality of EEG recordings and to minimize the intra-subject variability [6]. In this project, we exam the effect certain novel regularization tool including batch normalization and spatial dropout as a regulator arm to minimize the intra-subject variability and obtain stable performance within the individual subject.

1.4. Inter-subject variability

It is crucial to understand that the EEG decoding highly depends on the specific source subject. It is a well-known issue when developing a reliable and sustainable brain-computer interface. Having large amount of training data can certainly helps us build a beter decoding machine. However, in medical applications, it is unpractical to acquire a large number of subject-specific labeled data in the laboratory.

Inspired by the success of transfer learning on object detection [3, 5], we first train our deep learning model among all the 9 subjects to capture the generalized representations and underlying structures of EEG signals. Then we fine-tuning the model with each subject-specific EEG recordings to "fuse" the characteristics of specific user into our pre-trained model.

2. Result

The experiments are mainly done on the DeepCNN model due to the limitation of computational resources since recurrent layers take significantly longer (4 hr) to train compared to the DeepCNN architecture (1 hr). On the other hand, by applying data augmentation technique, DeepCNN certainly almost always outperform shallowCNN (shown in Table 3) because of the increased training data size and higher model complexity.

Model	generic	BN and noise
DeepCNN (train)	77.48%	76.36%
DeepCNN (val)	56.74%	57.68%
DeepCNN (test)	57.34%	59.59%

Table 1. Mean accuracies of the Deep train with and without applying batch normalization (BN) and Gaussian noise layer .

Method	generic	augmentation
DeepCNN (val)	49.66%	66.82%
DeepCNN (test)	49.66%	64.22%
ShallowCNN (val)	51.06%	42.12%
ShallowCNN (test)	47.86%	41.38%
CNN-LSTM* (val)	–	65.09%
CNN-LSTM* (test)	–	63.47%

Table 2. The accuracies of different model train with and without data augmentation.

Training the DeepCNN with batch normalization and Gaussian noise layer does improve the classification accuracy by 2.24% (shown in Table 2. Batch normalization constrain the distribution of each convolution output and offset the non-stationary (bias term) and the Gaussian noise layer generalized the intra-subject variability (variance term).

In order to answer the question whether optimizing one classification accuracy for a specific subject help to train across all subjects. We train the DeepCNN on each subject for 200 epochs. Figure 2 shows that the knowledge learned from subject does not generalize to other subject. It is conceivable since the DeepCNN model does not identify the current subject and adapt parameters when making the prediction.

The transfer learning arm to overcome the issue of inter-Subject variability. Figure 2 displays the effect of transfer learning among the users. We can see a general improvement of the classification accuracies except for subject 07. The more epochs we train, the better predicting power it has. However, if we over-train the deep network, it may suffer from overfitting and "forget" the generalized internal representation and underlying structure we learned in the pre-trained model.

3. Discussion

The EEG time series modeling is synonymous with recurrent networks. However, our results indicate that temporal constitutional architectures can at least reach the same

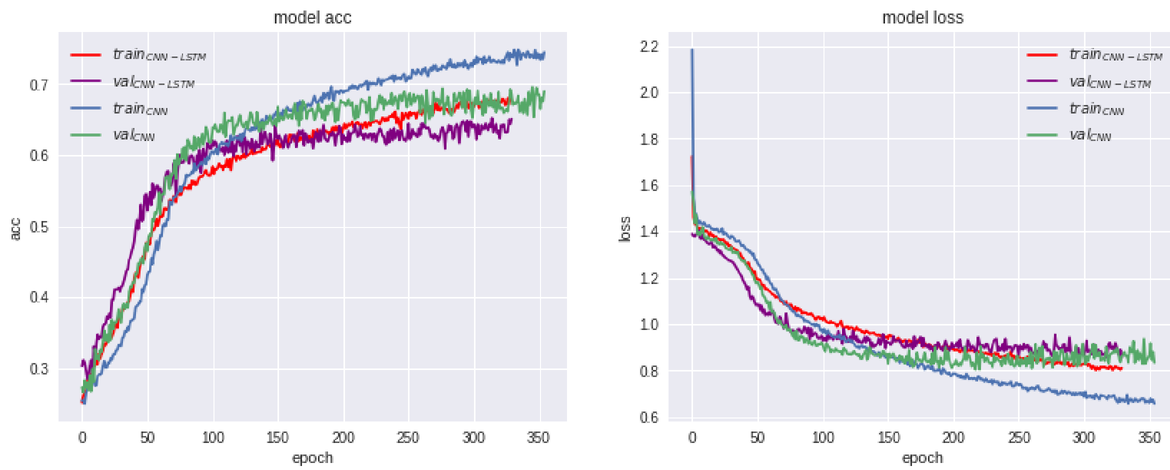

Figure 3. The traing process of DeepCNN v.s. LSTM-CNN. The LSTM-CNN converge earlier compared to DeepCNN. However, DeepCNN achieve better performance after 400 epochs

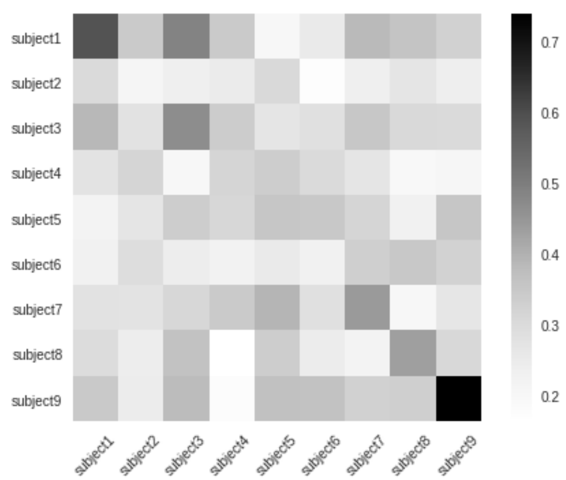

Figure 2. inter-subject variability addressed by deepCNN

performance of recurrent networks. In addition, by fusing the fully connected CNN with recurrent unit, we observe the fused model could overfit the training data rapidly if the architecture and regularization is not design properly. This result indicates that LSTM architecture does provide additional insight of EEG recordings and can potentially speed up the training process. Although the features captured by the LSTM layer could somehow overwhelm the latent structure extracted by CNN, our experiment shows that applying some novel regularization techniques such as batch normalization and Gaussian noise ensuring neuron responses at concatenating layer have similar distribution can certainly address this concern and overcome intra-subject variability.

We also shows that, by applying transfer learning technique, we can utilize the large scale public-available dataset.

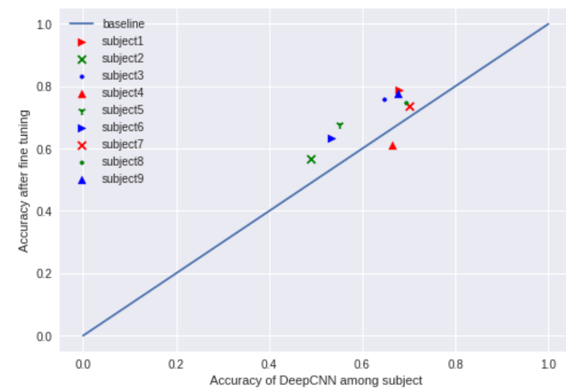

Figure 4. The effect of transfer learning on deepCNN after fine-tuning the model for 30 epochs

It is well-known that the deep learning is a data-hungry algorithm hence size of the training data play an important rule on developing a complex deep architectures.

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Configuration	Setting and parameter
Optimizer	ADAM
Callback	Early stop with 15
Train-validation split	0.2
Data argumentation	Window = 750
	sliding = 50
Dropout	0.6
Activation function	ELU or ReLU

Table 3. Optimizing one single subject and test on all other EEG subject.

Method	generic	augmentation	transfer learning
DeepCNN (val)	49.66%	66.82%	–
DeepCNN (test)	49.66%	64.22%	73.26%
ShallowCNN (val)	51.06%	42.12%	–
ShallowCNN (test)	47.86%	41.38%	52.43%
CNN-LSTM* (val)	–	65.09%	–
CNN-LSTM* (test)	–	63.47%	70.21&
Spectrum-CNN (val)	45.21%	47.29%	–
Spectrum-CNN (test)	42.15%	44.47%	–

Table 4. The accuracies of different model train with and without data augmentation.

	subject1	subject2	subject3	subject4	subject5	subject6	subject7	subject8	subject9
subject1	0.590	0.343	0.487	0.343	0.202	0.252	0.383	0.360	0.326
subject2	0.303	0.210	0.237	0.250	0.305	0.173	0.237	0.267	0.241
subject3	0.387	0.277	0.467	0.340	0.270	0.282	0.353	0.307	0.301
subject4	0.273	0.317	0.200	0.317	0.337	0.303	0.267	0.193	0.206
subject5	0.220	0.267	0.337	0.313	0.355	0.350	0.317	0.230	0.355
subject6	0.230	0.293	0.243	0.223	0.252	0.228	0.330	0.350	0.323
subject7	0.277	0.273	0.310	0.343	0.394	0.282	0.443	0.203	0.266
subject8	0.297	0.243	0.363	0.163	0.337	0.248	0.220	0.433	0.309
subject8	0.347	0.247	0.38	0.177	0.365	0.364	0.327	0.333	0.738

Table 5. Optimizing one single subject and test on all other EEG subject.