Fuzzy Integral Optimization with Deep Q-Network for EEG-Based Intention Recognition

Dalin Zhang[1(✉)], Lina Yao[1], Sen Wang[2], Kaixuan Chen[1], Zheng Yang[3], and Boualem Benatallah[1]

[1] School of Computer Science and Engineering, UNSW Sydney, Sydney, Australia
{dalin.zhang,kaixuan.chen}@student.unsw.edu.au,
{lina.yao,b.benatallah}@unsw.edu.au
[2] School of Information and Communication Technology, Griffith University, Brisbane, Australia
sen.wang@griffith.edu.au
[3] School of Software, Tsinghua University, Beijing, China
hmilyyz@gmail.com

Abstract. Non-invasive brain-computer interface using electroencephalography (EEG) signals promises a convenient approach empowering humans to communicate with and even control the outside world only with intentions. Herein, we propose to analyze EEG signals using fuzzy integral with deep reinforcement learning optimization to aggregate two aspects of information contained within EEG signals, namely local spatio-temporal and global temporal information, and demonstrate its benefits in EEG-based human intention recognition tasks. The EEG signals are first transformed into a 3D format preserving both topological and temporal structures, followed by distinctive local spatio-temporal feature extraction by a 3D-CNN, as well as the global temporal feature extraction by an RNN. Next, a fuzzy integral with respect to the optimized fuzzy measures with deep reinforcement learning is utilized to integrate the two extracted information and makes a final decision. The proposed approach retains the topological and temporal structures of EEG signals and merges them in a more efficient way. Experiments on a public EEG-based movement intention dataset demonstrate the effectiveness and superior performance of our proposed method.

1 Introduction

Attempting to translate brain activities into commands for a computer or other devices always attracts great research interests due to its various potential applications. Electroencephalography (EEG) signals reflecting the fluctuations of the voltages from the scalp are one of the most widely used tools for brain activity analysis. Despite many efforts have been devoted into EEG-based brain activity analysis, traditional methods not only separate feature extraction and classification stages, but also rely on handcrafted features which need domain knowledge

D. Phung et al. (Eds.): PAKDD 2018, LNAI 10937, pp. 156–168, 2018.
https://doi.org/10.1007/978-3-319-93034-3_13

and extensive experience, for example, determining which frequency bands are related to specific brain activities. Deep learning techniques have demonstrated advantages in automatic feature learning, and have dominated in many research fields [1]. Recently, many works have reported successful applications of deep learning in EEG analysis [2–4]. However, most neural network based approaches either still involve in complex preprocess stages or lack reasonable motivations in decoding EEG signals. There is still large room for in-depth research and improvement in terms of recognition accuracy and interpretability.

Since EEG signals are acquired on top of different cortical regions of human's head over a time period (see Fig. 1), effectively fusing these spatial and temporal information is crucial to identify uncertainties introduced by both inter- and intra-subject variability. The fuzzy integral has been proven an appropriate way of aggregating information from different sources according to their correlations in the human-computer interaction areas [5–8]. Compared with the simple weighted ensemble approach, the major advantage of fuzzy integral is the flexibility of fusing information with nonlinearity. Kim et al. have conducted extensive work using the fuzzy integral for human-robot interaction [6,7]. Cavrini [5] and Shoaie [8] also apply the fuzzy integral for a brain-computer interface application. However, the fuzzy measure for each information source often heavily depends on domain experts or massive experience. This is often unreliable, time-consuming and impractical to implement. Recent advances in deep reinforcement learning especially the deep Q-network (DQN) has shown promising capability of human-level control [9]. The reinforcement method simulates the process of a human brain interacting with an external environment. This enables the artificial intelligence to conduct tasks like human beings, and even beats human experts in certain areas [10].

In this paper, we present a novel ensemble method combining DQN and fuzzy logic to take advantages of both two techniques at the same time, wherein the DQN is utilized to tune the fuzzy measures in fuzzy integral for integrating the automatically extracted local spatio-temporal and global temporal information of EEG signals. The local spatio-temporal information represents the complex dependencies of adjacent sensory nodes, while the global temporal information is for the long term dependencies of the non-adjacent ones. The proposed model has good generalization in the cross-subject, multi-class scenario for brain activity analysis. The main contributions of this study can be summarized as follows:

– We propose to utilize the local spatio-temporal features and the global temporal features extracted by a 3D convolutional neural network (3D-CNN) and a recurrent neural network (RNN) respectively to enhance the EEG-based brain activity analysis.
– We develop an ensemble system with the fuzzy integral to combine both the 3D-CNN and the RNN classifiers. Rather than assigning the fuzzy measures heuristically, the deep reinforcement learning technique is employed to optimize the fuzzy measures of each integrated classifiers in the fuzzy integral.

– We evaluate the proposed approach on a public EEG-based movement intention dataset for the cross-subject, multi-class scenario analysis. The results demonstrate that the proposed ensemble model is able to find the optimal fuzzy measures of classifiers automatically and enhance the EEG-based human intention recognition task.

2 Preliminaries

In this section we give a brief introduction of λ-fuzzy measure and Choquet integral, which we leverage in this study to fuse the local spatio-temporal information and the global temporal information within EEG signals for human intention recognition.

Let $X = \{x_1,\ x_2\ ...\ x_n\}$ be a finite set represents n information sources and the function $g_\lambda : 2^X \rightarrow [0,1]$ be the λ-fuzzy measure on X. The fuzzy measure satisfies the following conditions:

1. $g_\lambda(\{X\}) = 1,\ g_\lambda(\{\varnothing\}) = 0$;
2. If $A,\ B \in 2^X$ and $A \cap B = \varnothing$, then $g_\lambda(\{A \cup B\}) = g_\lambda(\{A\}) + g_\lambda(\{B\}) + \lambda g_\lambda(\{A\}) g_\lambda(\{B\})$

where $\lambda \in (-1, \infty)$ can be obtained through the following equation:

$$\lambda + 1 = \prod_{i=1}^{n} (\lambda g_\lambda(\{x_i\}) + 1). \tag{1}$$

So given the fuzzy measure density of one information set, the joint fuzzy measure of any subsets can be achieved via the above axiom 2.

The Choquet integral with respect to fuzzy measure g is defined as

$$C_g(h) = \sum_{i=1}^{n} [h(x_i) - h(x_{i-1})] g(A_i), \tag{2}$$

where $A_i = \{x_i,\ x_{i+1}\ ...\ x_n\}$ is a subset of X, and $h(x_i)$ is the data/information provided by the information source x_i. The $h(x_i)$ satisfies the monotonic property, that is $h(x_1) \leqslant h(x_2) \leqslant h(x_3) \leqslant\ ...\ \leqslant h(x_n)$, and $h(x_0) = 0$. The joint fuzzy measure of the subset A_i can be obtained by pre-defined fuzzy measure rules. The fuzzy measure density, which is the fuzzy measure of each information source $g(\{x_i\})$, is usually heuristically assigned. In this study, the $g(\{x_i\})$ is proposed to be determined via the deep reinforcement learning technology.

3 Methodology

3.1 Local Spatio-Temporal Information Extraction

To represent the spatial topological structure of the EEG acquisition system, we convert the traditional chain-like vectors to two-dimensional matrices according

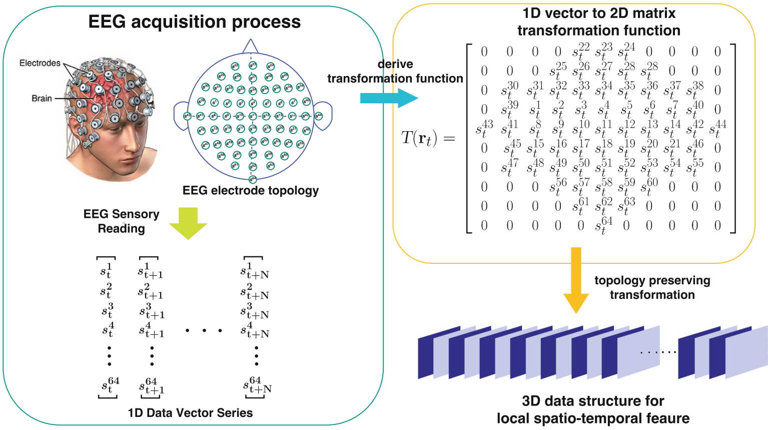


Fig. 1. EEG data acquisition and transformation process

to the EEG electrode topology. Let $\mathbf{r}_t = [s_t^1,\ s_t^2,\ s_t^i\ ...\ s_t^n]^T$ be the EEG sensory readings at time step $\mathbf{t}$, where s_t^i represents the ith electrode signal. The 1D vector to 2D matrix transformation function is defined as in Fig. 1. Through this equation each EEG reading vector $\mathbf{r}_t$ at time stamp $\mathbf{t}$ is converted to a EEG data matrix $\mathbf{m}_t$ of size 10×11. In the transformation function, the *null* electrode elements are set to zero as no effects on neural network. Some previous work has also proposed to apply topological transformation for spatial information representation [2]. However, our approach is fundamentally different from the previous conversion method by preserving both the raw data and spatial information, in contrast [2] employs complex data preprocess including frequency filter, data compression and interpolation to covert raw EEG data to images. On top of spatial representations, we use the sliding window technique to divide the converted streaming EEG matrices to individual clips for temporal information extraction. Each clip has fixed length of time slice of EEG matrices, and neighboring clips have 50% overlapping to keep the signal continuity. Overall, the raw streaming EEG readings are converted to clips with a 3D structure containing both temporal and spatial information:

$$[\mathbf{r}_t,\ \mathbf{r}_{t+1}\ ...\ ] \Rightarrow [\mathbf{C}_t,\ \mathbf{C}_{t+W}\ ...\ ],$$

where $\mathbf{C}_t = [\mathbf{m}_t,\ \mathbf{m}_{t+1}\ ...\ \mathbf{m}_{t+W-1}]$ is a 3D-structure clip with window size W starts at time step $\mathbf{t}$.

The 3D-CNNs have achieved great success in video processing applications, in which local spatio-temporal features are extracted for further analysis. Herein, we explore the 3D-CNNs for modeling the local spatio-temporal information of adjacent sensory nodes from the transformed 3D EEG data structures. The final local spatio-temporal information representation is the classification probabilities of each aimed brain intention task $\mathbf{A} = [a_1,\ a_2\ ...\ a_K]^T$ performing in the corresponding windowed period $[t,\ t+W-1]$:

$$\text{3D-CNN: } p_{tc} = C_{3D}([\mathbf{m}_t,\ \mathbf{m}_{t+1}\ \dots\ \mathbf{m}_{t+W-1}]),\ p_{tc} \in \mathbb{R}^K.$$

In the 3D-CNN, we concatenate three convolutional layers directly without pooling operations. Although a convolutional operation is often followed by a pooling layer, this is not mandated. It is primarily introduced for balancing the information integrity and data complexity, while in this situation the data dimension is much smaller that we withdraw the pooling operation and keep all the information for better feature extraction. We utilize the *exponential linear unit (elu)* function as the activation function, which performs better than the commonly used rectified linear units ($ReLUs$) function in many cases. The kernel size of all 3D-CNN layers is set to 3×3 with a stride of 1, and the number of feature maps are 32, 64 and 128 respectively. Finally, a fully-connected layer with 1024 hidden units is applied on top of the 3D-CNN architecture, followed by a five-way softmax layer for final prediction.

3.2 Global Temporal Information Extraction

Since mental activities are temporal dynamic processes, modeling the evolution through time-series sequences with RNN, which has been demonstrated powerful in processing time series data in various fields, can provide important information about the ambiguity of brain activities. Long Short-Term Memory (LSTM) model is an improved RNN model with better capabilities discovering long-term dependencies. Two LSTM layers between two fully-connected layers are adopted for the global temporal information extraction. Only the output of the last LSTM unit after observing the whole time sequence is fed into the final fully-connected layer. To keep consistent with the local spatio-temporal information representations, we use the same window size for the global temporal feature extraction and 50% overlapping sliding window technique as well. We experiment with various sizes of hidden states in LSTM cell, and adopt the best result hidden state size of 1024. The RNN model takes the raw windowed EEG signal vectors $[\mathbf{r}_t,\ \mathbf{r}_{t+1}\ \dots\ \mathbf{r}_{t+W-1}]$ as input, and makes the final prediction with a softmax layer:

$$\text{RNN: } p_{tr} = L([\mathbf{r}_t,\ \mathbf{r}_{t+1}\ \dots\ \mathbf{r}_{t+W-1}]),\ p_{tr} \in \mathbb{R}^K.$$

Different from the 3D-CNN model, which just uses receptive fields to extract the local spatio-temporal features capturing the relations of the adjacent sensory nodes, the RNN considers the long-term temporal dependencies of the whole sensory values including non-adjacent ones. Thus the global temporal features extracted by the RNN model provides another informative description of raw EEG signals.

3.3 Choquet Integral with Deep Q-Network

The above local spatio-temporal and global temporal information extraction describes the EEG signals from different angels, thus aggregating the two aspects

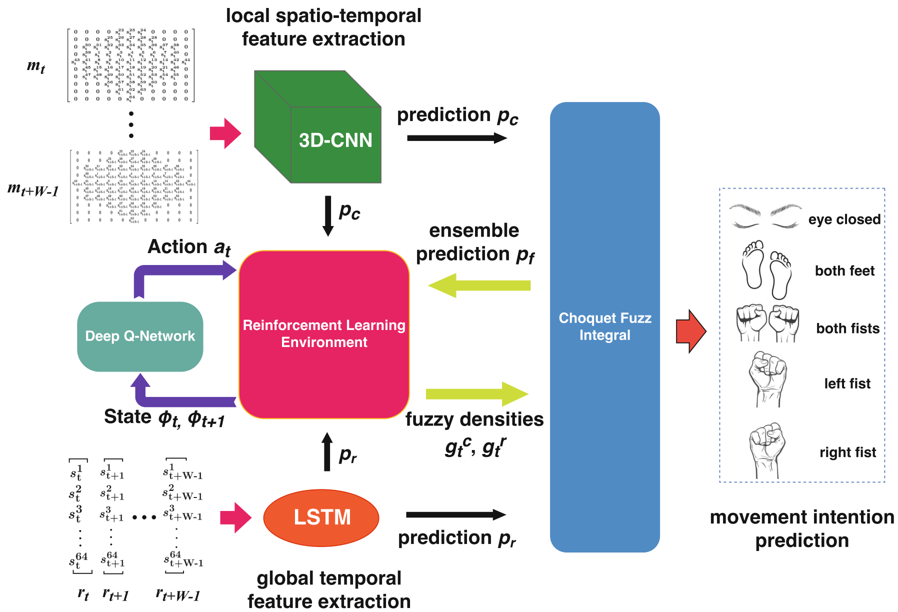


Fig. 2. Overall flowchart of the proposed approach

of data may enhance the EEG analysis tasks. The overall flowchart of the proposed approach is illustrated in Fig. 2. The two schools of information are integrated with respected to the λ-fuzzy measure by the Choquet integral to make final predictions. DQN is utilized to optimize the fuzzy measures of the 3D-CNN and the RNN instead of being selected heuristically in previous study.

Concretely, Algorithm 1 presents the pseudo-code of Choquet integral of 3D-CNN and RNN ensemble. The input is the probability predictions from the 3D-CNN and the RNN models, and the output is the aggregated results by Choquet integral. For the probability of a windowed instance belonging to one class, $p_c^{k,m}$ and $p_r^{k,m}$, the Choquet integral is applied to aggregate the two probabilities regarding their fuzzy measures, and calculate a final probability for this class. All the predictions from the 3D-CNN share the same fuzzy measure during the fuzzy fusion process and so do the predictions of the RNN model.

The overall procedure of fuzzy integral optimization with DQN is that an agent takes actions a_t tuning the fuzzy measures in a specific environment characterizing the fuzzy integral ensemble result and gets reward according to the tuning result. There are totally five candidate actions, namely, keeping unchanged, ascending or descending 3D-CNN fuzzy measure, and ascending or descending RNN fuzzy measure. The reward for one action is determined by the difference between the fusion accuracy before and after executing the action: $r_t = \delta \times (A_{t+1} - A_t)$, where $\delta = 10^5$ is the reward coefficient and A_t is the fusion accuracy at tuning step t. Thus the agent gets positive rewards when boosting the ensemble accuracy, negative rewards when descending the accuracy and zero

Algorithm 1. Ensemble 3D-CNN and RNN with Choquet fuzzy integral

Input: p_c and $p_r \in \mathbb{R}^{n\times K}$, are the classification probabilities of the 3D-CNN and the RNN, where n is the number of windowed instances in one dataset and K is the number of classes; g_c and g_r are their corresponding fuzzy measures.
Output: p_f is the classification probabilities after fuzzy fusion.

```
function ChoquetIntegral(p_c, p_r, g_c, g_r)
    Calculate all the joint fuzzy measures w.r.t fuzzy measure density
    for the prediction of each windowed time clip p_c^k ∈ p_c and p_r^k ∈ p_r do
        for the probability of each class p_c^{k,m} ∈ p_c^k and p_r^{k,m} ∈ p_r^k do
            // perform Choquet integral
            if p_c^{k,m} ⩽ p_r^{k,m} then
                p_f^{k,m} = (p_c^{k,m} − 0) × g_λ({cnn, rnn}) + (p_r^{k,m} − p_c^{k,m}) × g_λ({rnn})
            else
                p_f^{k,m} = (p_r^{k,m} − 0) × g_λ({cnn, rnn}) + (p_c^{k,m} − p_r^{k,m}) × g_λ({cnn})
    return p_f
```

reward when no accuracy changes. We have also tried a fixed reward system with constant reward regardless of the accuracy fluctuation extent, and this method would easily lead the ensemble result to a local optimal value. We use how much the predictions deviate from the ground truth to characterize the state of the environment. Concretely, we define the state of a model ϕ as the class-wise summation of the absolute difference between the predicted probabilities and the ground truth:

$$\phi = |p[1] - T[1]| + |p[i] - T[i]| + \ \ ... \ \ + |p[n] - T[n]|; \ \ p, \ \ T \in \mathbb{R}^{n\times K}, \phi \in \mathbb{R}^K$$

where $p[i]$ and $T[i]$ are the prediction and ground truth of the ith sample, respectively, and there are totally n samples over K classes. The states of 3D-CNN ϕ_t^c, RNN ϕ_t^r and the fuzzy integral ensemble model ϕ_t^f are stacked horizontally and normalized using the Z-score method to form a final representation of the environment: $\phi_t = [\phi_t^c, \ \phi_t^r, \ \phi_t^f]$, where $\phi_t \in \mathbb{R}^{3K}$.

The DQN based fuzzy measure optimization is presented in Algorithm 2. This procedure allows us to select optimal actions tuning the fuzzy measure for each information resource to achieve an optimized ensemble result. We first initialize the fuzzy measures g_1^c and g_1^r arbitrarily, and keep the same initialization for every episode. In one episode, there are total $T = 2000$ tuning steps updating the fuzzy measures 2000 times with an interval of 10^{-3}. The agent selects and executes actions according to an ϵ-greedy policy with ϵ annealed linearly from 1 to 0.01 over first 72 episodes, and fixed at 0.01 thereafter. It selects a random action with probability ϵ, otherwise select the action a_t with maximum Q value. Formally the action-value function:

$$Q^*(s,a) = \max_{\pi}\mathbb{E}[r_t + \gamma r_{t+1} + \gamma^2 r_{t+2} + ...|s_t = s, a_t = a, \pi] \tag{3}$$

is approximated using a neural network called Q-network in DQN. $Q^*(s,a)$ is the maximum sum of rewards r_t with discounted factor γ at each tuning step.

Algorithm 2. Fuzzy measure optimized with deep Q-network

Input: predictions from the 3D-CNN p_c and RNN p_r; ground truth prediction T
Output: action-value network Q for action selection policy

1: Initialize replay memory D
2: Initialize action-value network Q with random weights θ
3: Initialize target action-value network $\hat{Q}$ with weights $\theta^- = \theta$
4: Initialize fuzzy measure density g_1^c and $g_1^r \in [0, 1]$ arbitrarily
5: **for** episode = 1 to MaxEpisode **do**
6: Observe the initial state of the environment $\phi_1(g_1^c,\, g_1^r)$
7: **for** t = 1 to MaxStep **do**
8: Select action $a_t = \begin{cases} \text{a random action} & \text{with probability } \epsilon \\ argmax_a \mathrm{Q}(\phi_t, a; \theta) & \text{otherwise} \end{cases}$
9: Execute action a_t
10: Observe reward r_t, fuzzy measures g_{t+1}^c, g_{t+1}^r and next state ϕ_{t+1}
11: Store transition $(\phi_t, a_t, r_t, \phi_{t+1})$ in replay memory D
// **experience replay**
12: Sample random minibatch of transitions $(\phi_j, a_j, r_j, \phi_{j+1})$ from D
13: Set $y_i = \begin{cases} r_j & \text{if episode terminates at step } j+1 \\ r_j + \gamma max_{a'} \hat{Q}(\phi_{j+1}, a'; \theta^-) & \text{otherwise} \end{cases}$
14: Perform gradient descent on $(y_j - Q(\phi_j, a_j; \theta))^2$ w.r.t Q-network parameter
15: Every C steps reset $\hat{Q} = Q$. i.e. set $\theta^- = \theta$// **target Q-network update**

The reward at each tuning step t is obtained by executing an action a selected according to state observation s and policy $\pi(a|s)$. This optimal action-value function obeys the following Bellman equation:

$$Q^*(s, a) = \mathbb{E}_{s'}[r + \gamma \max_{a'} Q^*(s', a')|s, a], \tag{4}$$

where $Q^*(s', a')$ is the optimal value of the state at the next tuning step. Then the optimal strategy is to select the action a' maximizing the optimal value at the next tuning step. A feedforward neural network with two hidden layers with 32 and 64 neurons respectively is used to approximate the optimal action-value function. We employ the experience replay and separate target Q-network techniques [9] to stabilize the Q-network training process. To perform experience replay, the transitions $(\phi_t, a_t, r_t, \phi_{t+1})$ are stored in a memory pool. During training process, stored transitions are randomly sampled using minibatches to feed the Q-network. The network is updated with the following loss function :

$$L_i(\theta_i) = [(r + \gamma \max_{a'} Q^*(s', a'; \theta_i^-) - Q(s, a; \theta_i)]^2, \tag{5}$$

as illustrated in Algorithm 2 line 14. A separate network with parameters θ_i^- is used to generate the target Q value and only updated with the Q-network parameters (θ_i) every C steps. Through the whole process, optimal fuzzy measures g^c and g^r are obtained for optimizing fuzzy integral based ensemble.

4 Experiments

4.1 Dataset and Model Implementation

To evaluate the proposed approach, we adopt the widely used EEG dataset *eeg-mmidb* from PhysioNet[1] for EEG-based movement intention recognition. The EEG data is collected using BCI2000 instrumentation system[2] [11] with 64 electrode channels and 160 Hz sampling rate. During the data acquisition process, one subject sits in front of a screen with prompts indicating the subject performing different movement intention tasks: imagine opening and closing left fist, right fist, both fists and both feet, and think nothing with eye closed. We select 20 subjects with 5 tasks to construct a cross-subject multi-task dataset.

During the preprocess stage, we carry out experiment with different sliding window size, namely 10, 20, 40 and 80 recordings per time window. The results show that 10 recordings in one time window gives the best performance. Thus we adopt the window size of 10 for all experimental setup. The 3D-CNN and RNN model are trained with Adam algorithm with a learning rate of 10^{-4} to minimize the cross-entropy loss function. Due to the large amount of parameters in the neural networks, we utilize dropout technique with 50% probabilities after the final fully connected layer in both models and L2 regularization in the 3D-CNN model to address the overfitting issue.

4.2 Compared Algorithms

All the methods are based on the same dataset with our model.

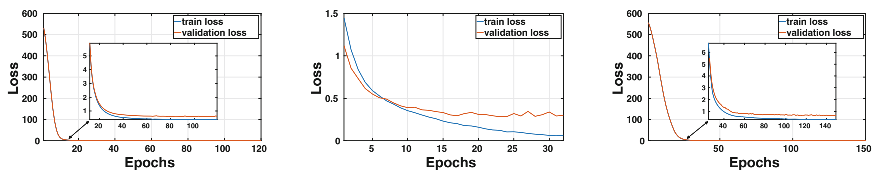
- **SR-FBCSP** [12]. The Shrinkage Regularized Filter Bank Common Spatial Patterns(SR-FBCSP) algorithm, which is based on the widely used FBCSP algorithm, outperforms FBCSP in classifying motor imagery tasks.
- **ICA+QDA** [13]. The independent component analysis (ICA) is for the feature extraction followed by quadratic discriminant analysis (QDA) for final classification.
- **Autoencoder+XGboost** [3]. The autoencoder is used for automatic EEG feature extraction. XGboost, which has been demonstrated competitive performance in many competitions, is used for final classification.
- **1D-CNN** [4]. The 1D-CNN is the traditional neural network based spatial filter for EEG signal analysis, and we apply it in our dataset.
- **3D-CNN**. The 3D-CNN is the model used in this study for classification based on the local spatio-temporal information of EEG signals.
- **RNN**. The RNN model is the model used in this study for classification based on the global temporal information of EEG signals.
- **Neural network ensemble**. We ensemble the 3D-CNN and RNN with a neural network based method. In this model, the 3D-CNN part and the RNN

[1] https://www.physionet.org/pn4/eegmmidb/.
[2] www.bci2000.org.

part have the same settings with the above described models. Their representations from the last fully-connected layer are concatenated together and fed into a softmax layer for final prediction. The training process and implementation tricks are also the same with the individual models.
- **Fuzzy Integral Ensemble**. We ensemble the 3D-CNN and RNN with Choquet integral with randomly selected fuzzy measure density, $g_c = 0.924$ and $g_r = 0.158$.
- **Fuzzy Integral Ensemble with DQN**. The proposed method in this study. The initial fuzzy measures are the same with the **Fuzzy Integral Ensemble** method, and the final measures are $g_c = 0.203$ and $g_r = 0.19$.

4.3 Experimental Result

Figure 3 gives the training information of the neural networks in this work. We stop model training at minimum validation loss. The performance of our proposed approach and the comparison models are summarized in Table 1. It is observed that the simple 1D-CNN spatial filter model outperforms the previous studies even without frequency band filter. This result is consistent with [14], in which it is shown the CNN can act as frequency band filters itself and achieves competitive performance. What's more, the 3D-CNN or RNN model performs better than the traditional 1D-CNN filter approach, demonstrating optimal data representation is capable of enhancing neural network performance and the local spatio-temporal and the global temporal information is favourable for successful EEG signal analysis. However, it is interesting to find that ensemble of the 3D-CNN and the RNN with neural network does not performs better performance. Although much evidence reveals that deeper network or combination of different kinds of neural network benefits the feature representation capabilities for final model performance, it is required careful parameter tuning or diverse implementation tricks. Complex models derived from suitable simple models may even suffer performance degradation problem [15]. It is not easy to optimize a complex neural network system.



(a) 3D-CNN (b) RNN (c) Neural Network Ensemble

Fig. 3. Train and validation loss with training epochs

Thus in this work we adopt a traditional but widely used fusion approach, fuzzy integral, to aggregate the local spatio-temporal information and the global

Table 1. Comparison with previous studies and baseline models

Method	Multi-class	Validation	Accuracy
SR-FBCSP [12]	Binary	Intra-Sub	0.8206
Autoencoder+XGboost [3]	Multi(5)	Cross-Sub(20)	0.794
ICA+QDA [13]	Multi(3)	Cross-Sub(30)	0.8724
1D-CNN [4]	Multi(5)	Cross-Sub(20)	0.8909
3D-CNN	Multi(5)	Cross-Sub(20)	0.9006
RNN	Multi(5)	Cross-Sub(20)	0.9110
Neural network ensemble	Multi(5)	Cross-Sub(20)	0.9108
Fuzzy Integral Ensemble	Multi(5)	Cross-Sub(20)	0.9082
Fuzzy Integral Ensemble with DQN	**Multi(5)**	**Cross-Sub(20)**	**0.9302**

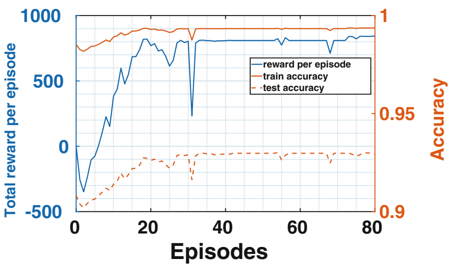


Fig. 4. Training curves tracking the total reward and accuracy

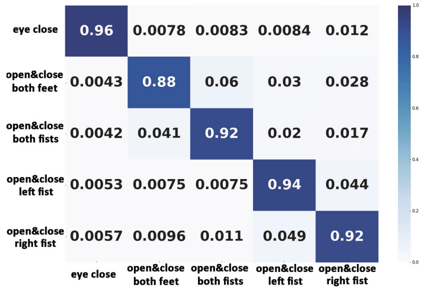


Fig. 5. Confusion matrix

temporal information from the 3D-CNN and the RNN models. Furthermore we propose to use the DQN to optimize the fuzzy measures instead of relying on domain knowledge or empirical selection. The results surpass both the single neural network methods and the neural network ensemble method. It is illustrated in the Table 1 that the fuzzy integral ensemble with randomly selected fuzzy measures does not provide an effective fusion scheme, thus can not enhance the overall performance. We also randomly select other fuzzy densities, and only a few sets aggregate information effectively. The Fig. 4 shows the process of the DQN optimization. It is observed that at the initial stage, the agent chooses actions according to the Q-network with little training, and large random probability ϵ, thus gets negative total rewards. As the training process proceeds, the total rewards increases and saturates. The test and train accuracy fluctuate in the same way as the total reward. In the final confusion matrix (Fig. 5), the model exhibits equally good performance for each class, with little imbalance.

5 Conclusion

In this study, we propose to employ the fuzzy integral, which is optimized by the deep reinforcement learning, to aggregate both the local spatio-temporal and the global temporal information within EEG signals for human intention recognition. To effectively select the fuzzy measures for each information sources, the DQN is utilized to search the optimal fuzzy measures. The developed model is further evaluated on movement intention recognition tasks in the cross-subject, multi-class scenario. The experimental results demonstrate the effectiveness of neural network ensemble using the fuzzy integral with respect to the optimized fuzzy measures with the deep Q-network technique.

References

1. LeCun, Y., Bengio, Y., Hinton, G.: Deep learning. Nature **521**(7553), 436–444 (2015)
2. Bashivan, P., Rish, I., Yeasin, M., Codella, N.: Learning representations from EEG with deep recurrent-convolutional neural networks. In: International Conference on Learning Representations (2016)
3. Zhang, X., Yao, L., Zhang, D., Wang, X., Sheng, Q., Gu, T.: Multi-person brain activity recognition via comprehensive EEG signal analysis. In: 14th International Conference on Mobile and Ubiquitous Systems: Computing, Networking and Services (2017)
4. Cecotti, H., Graser, A.: Convolutional neural networks for P300 detection with application to brain-computer interfaces. IEEE Trans. Pattern Anal. Mach. Intell. **33**(3), 433–445 (2011)
5. Cavrini, F., Bianchi, L., Quitadamo, L.R., Saggio, G.: A fuzzy integral ensemble method in visual P300 brain-computer interface. Comput. Intell. Neurosci. **2016**, 49 (2016)
6. Yoo, B.S., Kim, J.H.: Fuzzy integral-based gaze control of a robotic head for human robot interaction. IEEE Trans. Cybern. **45**(9), 1769–1783 (2015)
7. Yoo, J.K., Kim, J.H.: Fuzzy integral-based gaze control architecture incorporated with modified-univector field-based navigation for humanoid robots. IEEE Trans. Syst. Man Cybern. Part B (Cybern.) **42**(1), 125–139 (2012)
8. Shoaie, Z., Esmaeeli, M., Shouraki, S.B.: Combination of multiple classifiers with fuzzy integral method for classifying the EEG signals in brain-computer interface. In: International Conference on Biomedical and Pharmaceutical Engineering, ICBPE 2006, pp. 157–161. IEEE (2006)
9. Mnih, V., Kavukcuoglu, K., Silver, D., Rusu, A.A., Veness, J., Bellemare, M.G., Graves, A., Riedmiller, M., Fidjeland, A.K., Ostrovski, G., et al.: Human-level control through deep reinforcement learning. Nature **518**(7540), 529–533 (2015)
10. Silver, D., Huang, A., Maddison, C.J., Guez, A., Sifre, L., Van Den Driessche, G., Schrittwieser, J., Antonoglou, I., Panneershelvam, V., Lanctot, M., et al.: Mastering the game of go with deep neural networks and tree search. Nature **529**(7587), 484–489 (2016)
11. Schalk, G., McFarland, D.J., Hinterberger, T., Birbaumer, N., Wolpaw, J.R.: BCI 2000: a general-purpose brain-computer interface (BCI) system. IEEE Trans. Biomed. Eng. **51**(6), 1034–1043 (2004)

12. Shenoy, H.V., Vinod, A.P., Guan, C.: Shrinkage estimator based regularization for EEG motor imagery classification. In: 2015 10th International Conference on Information, Communications and Signal Processing (ICICS), pp. 1–5. IEEE (2015)
13. Sita, J., Nair, G.: Feature extraction and classification of EEG signals for mapping motor area of the brain. In: 2013 International Conference on Control Communication and Computing (ICCC), pp. 463–468. IEEE (2013)
14. Schirrmeister, R.T., Springenberg, J.T., Fiederer, L.D.J., Glasstetter, M., Eggensperger, K., Tangermann, M., Hutter, F., Burgard, W., Ball, T.: Deep learning with convolutional neural networks for EEG decoding and visualization. Hum. Brain Mapp. **38**(11), 5391–5420 (2017)
15. He, K., Zhang, X., Ren, S., Sun, J.: Deep residual learning for image recognition. In: Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition, pp. 770–778 (2016)