A DEEP LEARNING FRAMEWORK BASED ON DYNAMIC CHANNEL SELECTION FOR EARLY CLASSIFICATION OF LEFT AND RIGHT HAND MOTOR IMAGERY TASKS

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Introduction

- Ideal **brain-computer interfaces (BCIs)** need to be efficient and accurate, demanding for classifiers that can **work across subjects** from **short** Electroencephalography (**EEG) duration**.
- More than the number of channels, **selecting the right location of channels** plays a key factor in setting the accuracy.
- In this study, we present a deep learning framework that includes **dynamic channel selection** to **early classify** left and right hand **motor imagery (MI) tasks**.

Methods

Fig. 1 illustrates an overview of the proposed deep learning framework for the classification of left and right hand MI-tasks. The proposed framework consists of three main stages: **preprocessing**, **dynamic channel selection** based on the Davies-Bouldin Index (DBI), and a **CNN-LSTM classifier**. Here, we describe the details of each stage.

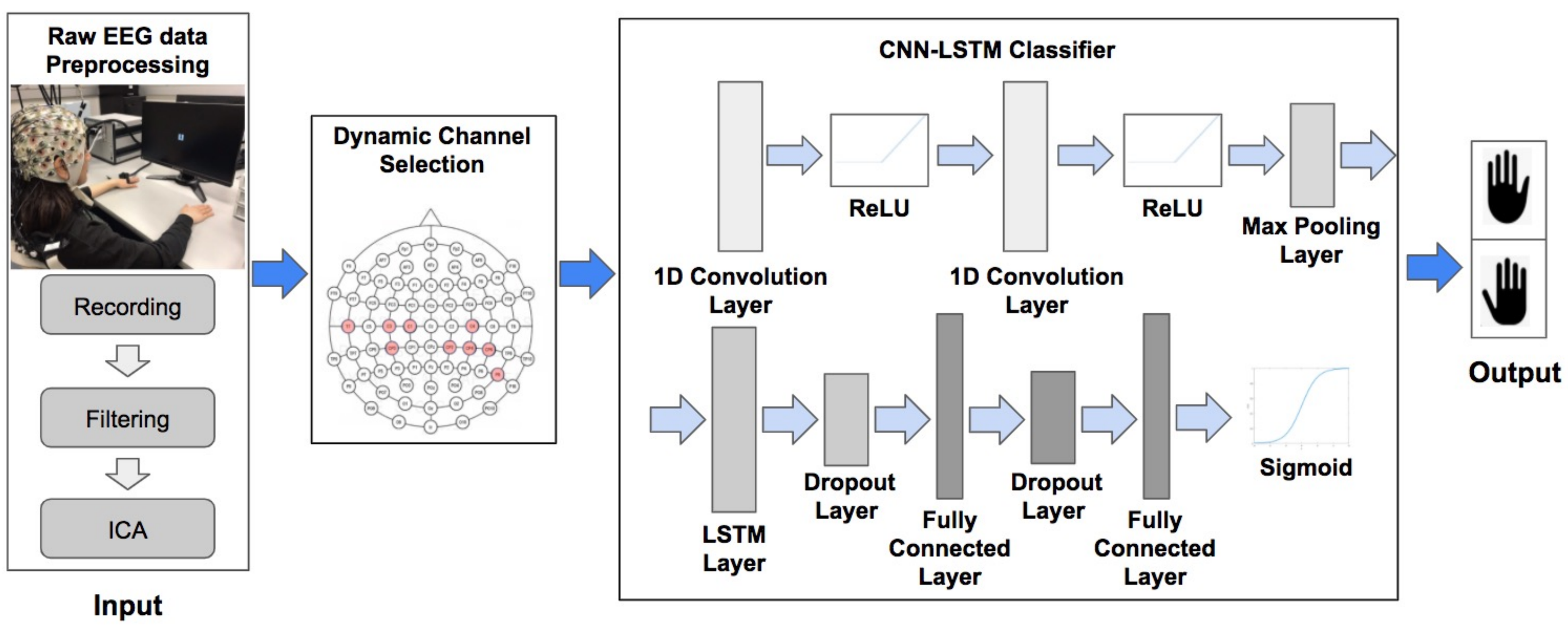

Fig. 1. Overview of the proposed deep learning framework for early classification of left and right hand MI tasks.

Preprocessing

- The EEG data from each trial first is filtered using a band-pass finite impulse response (FIR) filter with the pass-band of [1-50] Hz.
- Artifacts are removed using independent component analysis (ICA).

Dynamic Channel Selection

- DBI is a measure of distinctiveness between two classes of data, and considers both the distance between their centers, and the spreadness of data in each class.
- The smaller the $R_{i,j}$, the more significant the contribution of the channel would be in separating the two classes **(Fig. 2).**

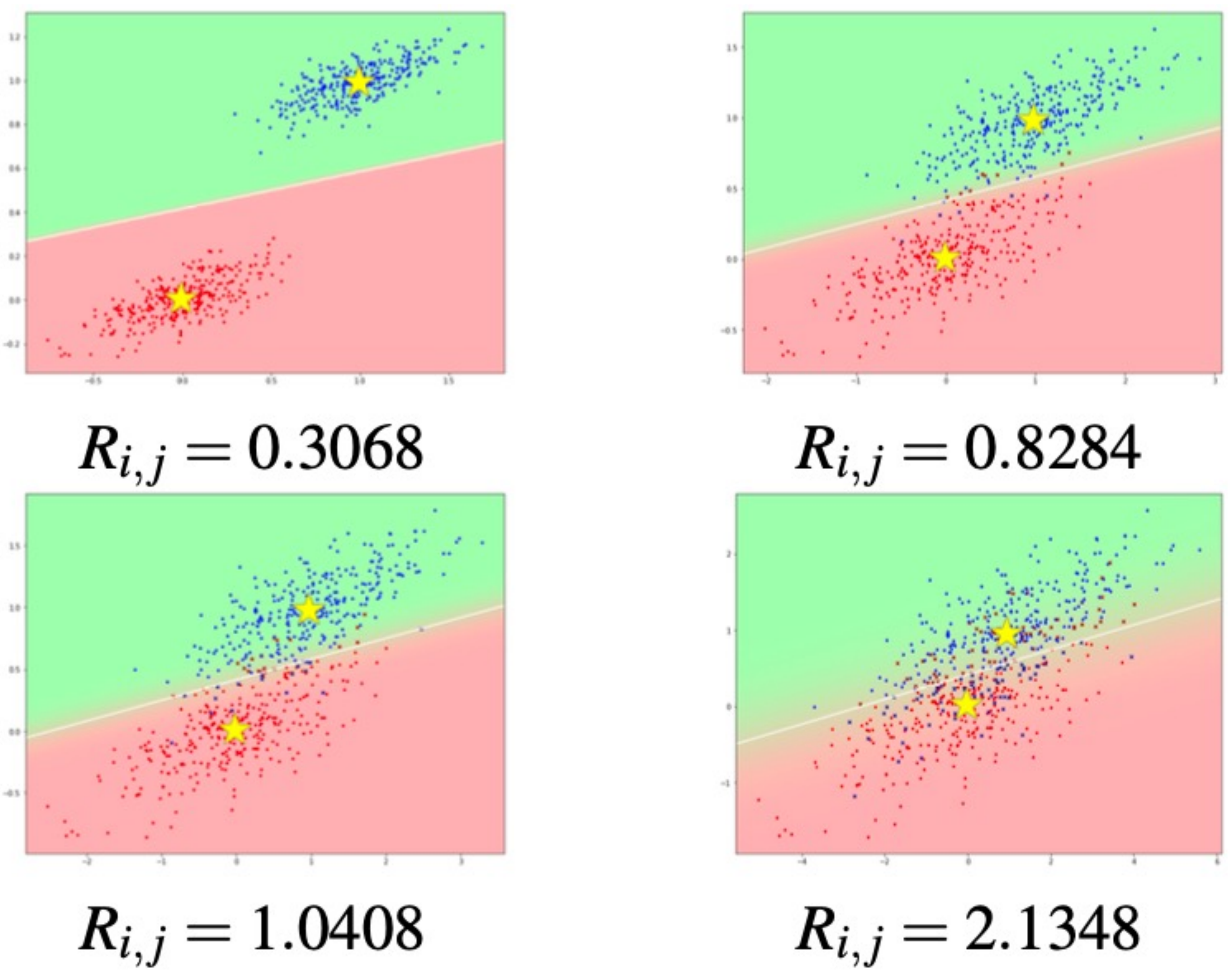

Fig. 2. The overlap degree between two classes, for four scenarios of various overlaps between classes.

CNN-LSTM Classifier

- The **CNN** contains two 1D convolutional layers, one with 16 filters of size 15 and another with 64 filters of size 64. The second convolutional layer is followed by a max-pooling layer of factor 3.
- The **LSTM** models the temporal dynamics of the extracted by the CNN, in order to avoid the long-term dependency issue that exists in traditional recurrent neural networks.
- Two **fully connected layers** with an output sizes of 64 and 32, activate the abstract features using a sigmoid activation function. A 0.5 dropout layer follows each fully-connected layer.
- Binary cross-entropy is used as loss function. Adam is used as the optimizer.

Results

Channel Selection Strategies

- 22-chan: All available channels
- 16-chan: 16 channels close to MI-tasks activities regions [1] **(Fig. 3).**
- 10-chan: Top 10 significant channels identified by DBI (fixed number of channels).
- Dynamic-chan: Top significant channels identified by DBI and with $R_{i,j}$ greater than the set threshold. TH=11.5 in our setting.

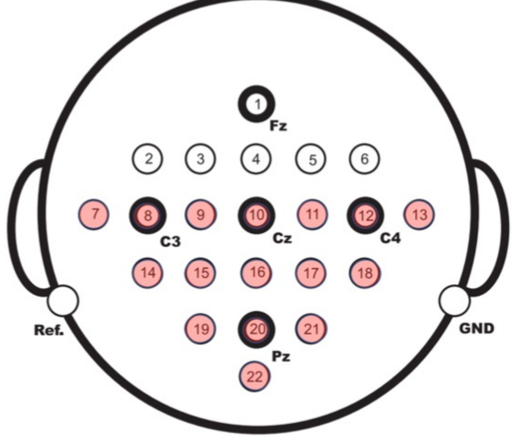

Fig. 3. Location of the electrodes for 22-chan case (shown in black circles) and 16-chan case (shown in red).

Comparison Result

- Comparison of strategies. **Dynamic-chan** reported the best result **(Table 1).**

Table 1. Classification accuracy (%) of left and right hand MI tasks for different channel selection methods using 800 ms EEG recording.

Subject \ Strategies	22-chan	16-chan	10-chan	Dynamic-chan
A01	49.36	47.27	54.09	55.91
A02	59.09	58.36	59.82	62.73
A03	69.09	70.36	70.91	75.09
A04	64.82	65.18	63.55	67.09
A05	67.09	68.00	70.91	69.09
A06	57.45	62.55	63.18	63.73
A07	62.91	62.00	65.18	65.09
A08	77.27	79.64	71.45	84.73
A09	85.36	86.27	89.73	88.09
Average	65.83	66.74	67.65	70.17

- Comparison of EEG duration. **1500 ms** reported the best result **(Table 2).**

Table 2. Classification accuracy (%) of left and right hand MI tasks considering dynamic channel selection for various duration after task onset.

Subject \ Duration	500 (ms)	1000 (ms)	1500 (ms)	2000 (ms)	2500 (ms)	3000 (ms)
A01	41.09	54.82	58.82	52.09	53.73	56.45
A02	60.27	76.82	71.00	62.91	60.27	58.00
A03	54.82	74.27	82.55	79.36	76.27	68.00
A04	63.09	69.64	72.55	72.64	66.45	64.82
A05	59.18	66.18	73.64	67.18	64.00	66.18
A06	60.91	69.64	78.64	64.91	54.64	57.45
A07	57.45	65.82	64.82	66.36	57.36	58.45
A08	78.64	85.45	90.91	84.91	82.36	72.09
A09	74.18	86.27	92.18	89.55	79.73	77.82
Average	61.07	72.10	76.12	71.10	66.09	64.36

- Comparison of **related works.** Our framework reported the best result **(Table 3).**

Table 3. Performance comparison with existing works.

Subject \ Duration	Ref.	Duration (ms)	Feature	Classifier	Accuracy(%)
2016	[2]	3000	Channel-based	SVM	74.92
2017	[3]	3000	Channel-based	RBM	64.60
2019	[4]	2000	Functional Connectivity	LS	71.00
2021	[5]	800	Functional Connectivity	LSTM	66.27
This paper		800	Dynamic Channel	CNN-LSTM	70.17
This paper		1500	Dynamic Channel	CNN-LSTM	76.18

- Compared to static channel selection approaches. It can be concluded that the proposed method is an efficient method for improving the accuracy and efficiency of BCIs for early classification.

References

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