Progressive Fusion of Multi-rate Motor Imagery Classification for Brain Computer Interfaces

Tim Maloney, Golnar Kalantar, and Arash Mohammadi
Concordia Institute for Information System Engineering, Montreal, QC, Canada

Motivations/Objectives

Motivation

- Practical Implementations of Brain-Computer Interfaces: Requiring rapidly-trained classifiers.
- Cost of Rapidly-training the classifier: Limited number of available training data (epochs), less validation accuracy.

Objectives

- Propose a novel multi-rate EEG-based Motor Imagery framework, consisting of two filters, Active and Progressive, which is initialized by a limited number of training trials, and adaptively improves itself over time.

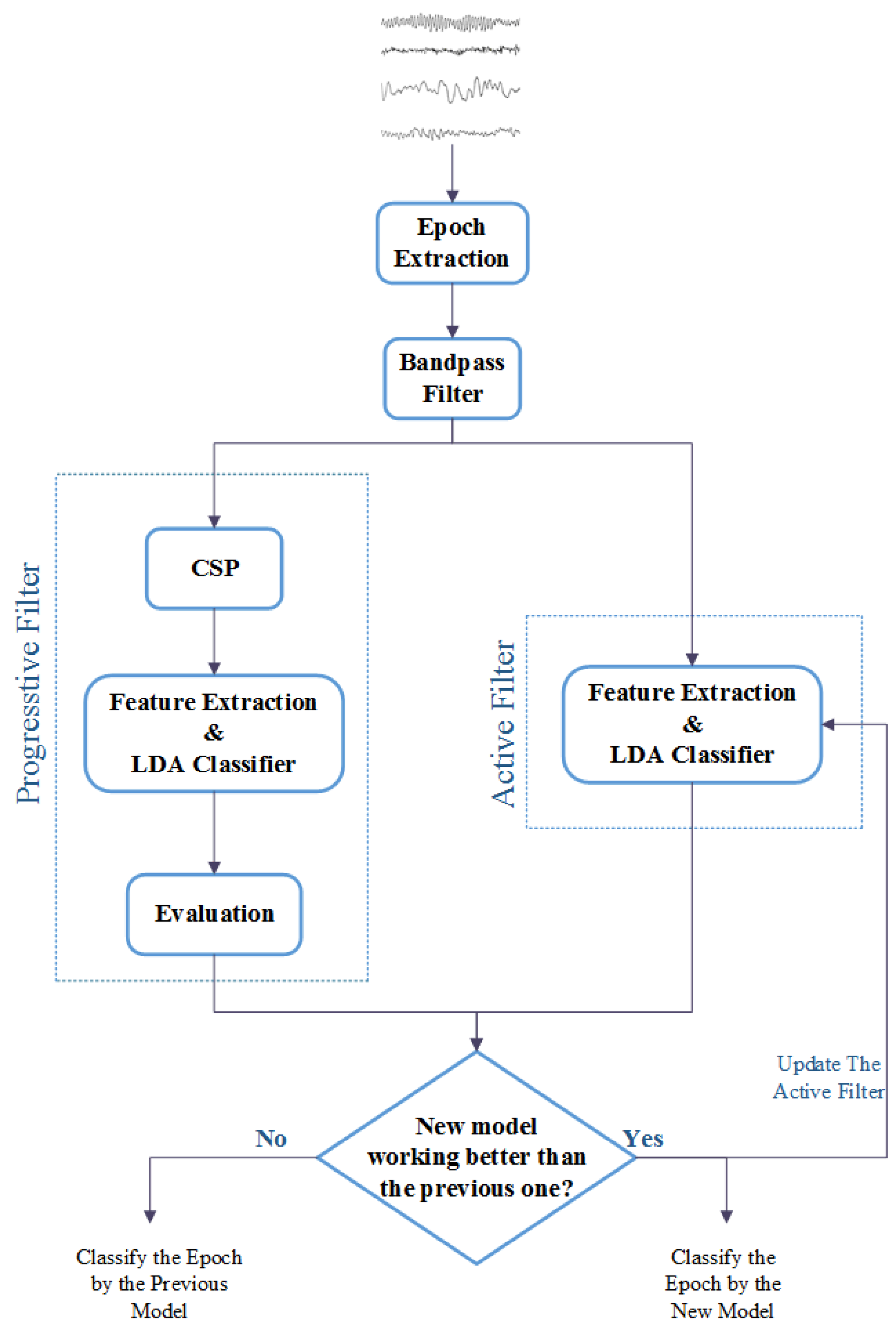
Filter Descriptions

Progressive Filter

Takes several epochs for re-training. Once the computation of the Progressive Filter is complete, the two filters are coupled to improve the real-time performance of the overall system.

Active Filter

Simplified feature extraction approach running online based on pre-trained classifiers. The Active Filter produces classification results at the end of each epoch.



IEEE International Midwest Symposium on Circuits and Systems (MWSCAS), Boston, MA, USA, 2017.

EEG Headset Experiments

Design I

1. MI during trials lasting 3-5 seconds with 1-3 seconds break between trials.
2. Two MI classes.
3. 200 trials per subject.
4. The headset tilted back to approximately cover C3 and C4 motor cortex area.

Feedbacks: Too long, and uncomfortable.

Design II

Some improvements to Design I:

1. Two sessions of 30 trials with an intermission.
2. Headset worn normally.
3. Improved test area with reduced sources of noise .

Design III

More improvements to previous designs:

1. More intuitive stimuli.
2. Stimuli changed to black and white images of hands.

Multi-rate Algorithms

Pre-processing Algorithm

This algorithm is applied to every new trial and consists of the following two tasks:

1. Epoch extraction.
2. Bandpass filtering.

Progressive Filter Algorithm

This algorithm, running in parallel to the Active Filter, cycles for every span of a fixed number of trials.

1. Re-evaluate CSP filter
2. Re-evaluate LDA classifier.
3. Evaluate the last model produced by the progressive filter algorithm.
4. Fusion: Compare the classification results of the two filters and replace the active filter with the better of the two models.

Active Filter Algorithm

This faster algorithm is applied following every trial giving immediate feedback:

1. Feature extraction.
2. LDA classification.

Fusion of Filters & Implementation

	Model 1	Model 2	Model 3	Model 4	Model 5
CSP(2d) LDA	52.00%	62.50%	66.67%	50.00%	20.00%
CSP(2d) QDA	54.00%	60.00%	70.00%	55.00%	30.00%
CSP(4d) LDA	48.00%	47.50%	50.00%	60.00%	80.00%

Table 1: Performance of different models based on real experimental data sets.

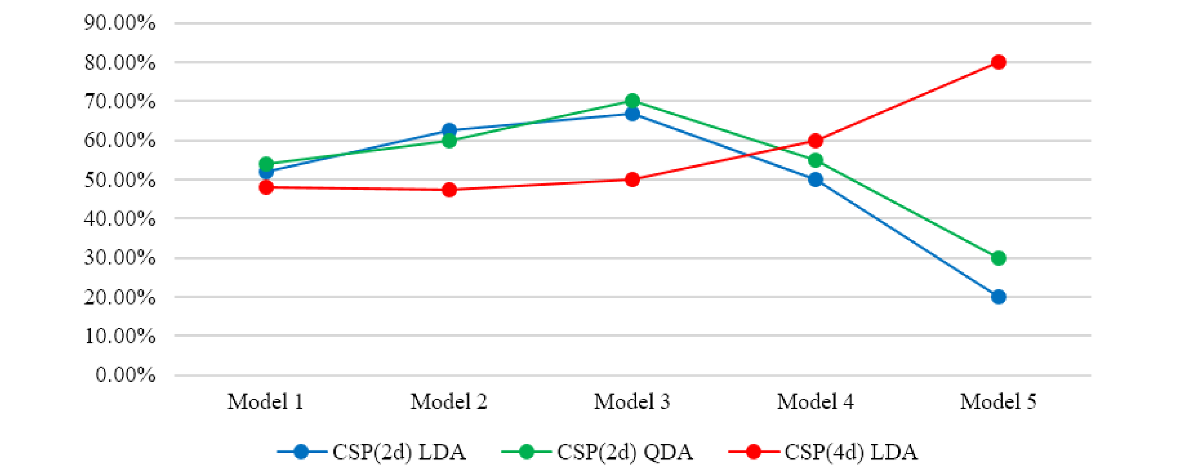


Figure 1: Classification results obtained from implementation of the proposed progressive and multi-rate framework based on data collected via Emotiv headset.

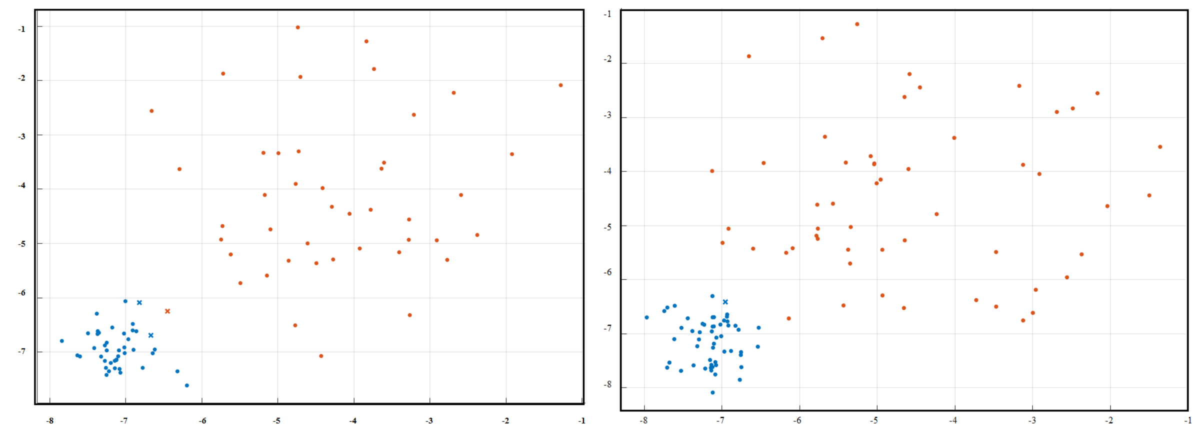


Figure 2: Scatter plots obtained from two Progressive Filters trained based on 90 and 110 epochs, respectively.

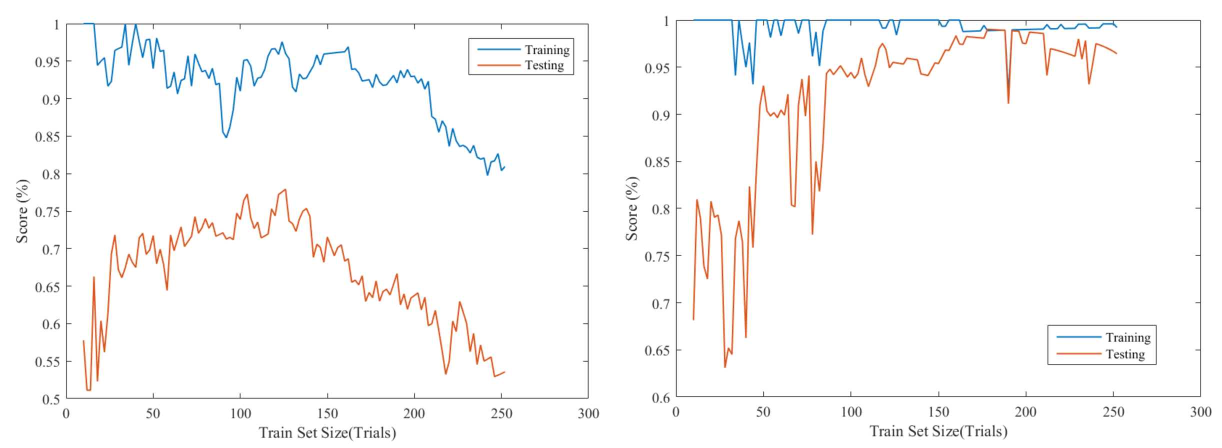


Figure 3: Training and testing scores vs. training set size for BCI competition subjects "aa" (left) and "aw" (right).

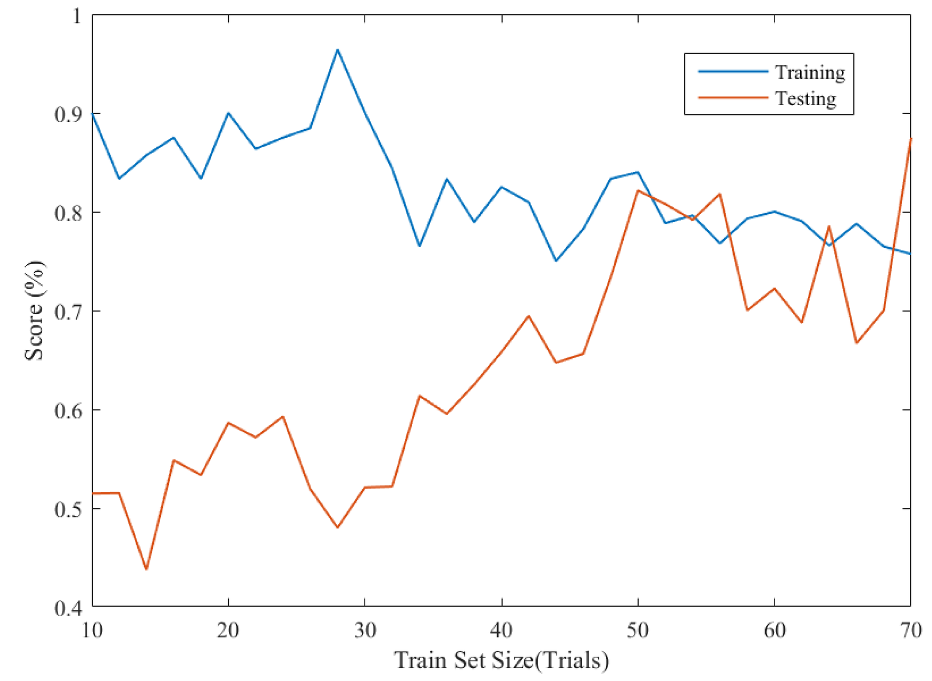


Figure 4: Training and testing scores vs. training set size for subject using EMOTIV headset.

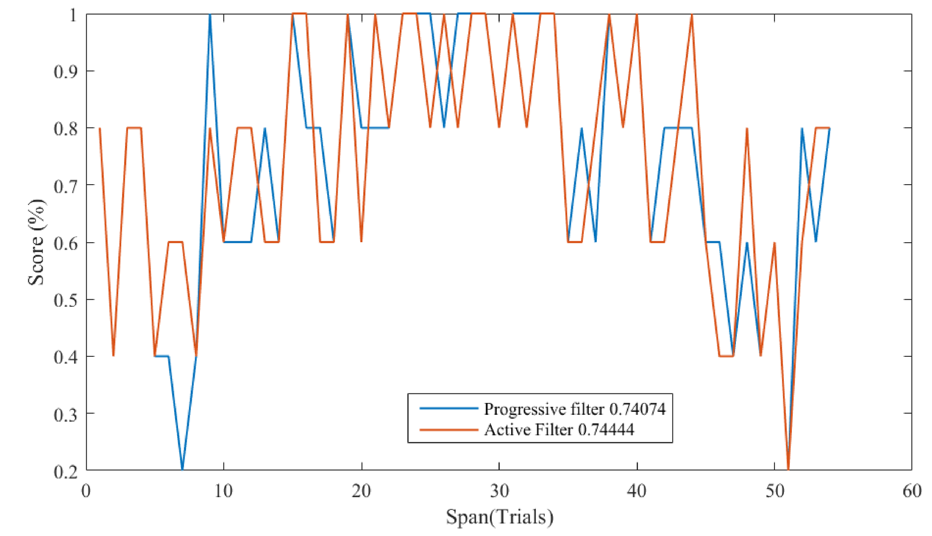


Figure 5: Active and progressive filter scores vs. number of trials for subject "aa".

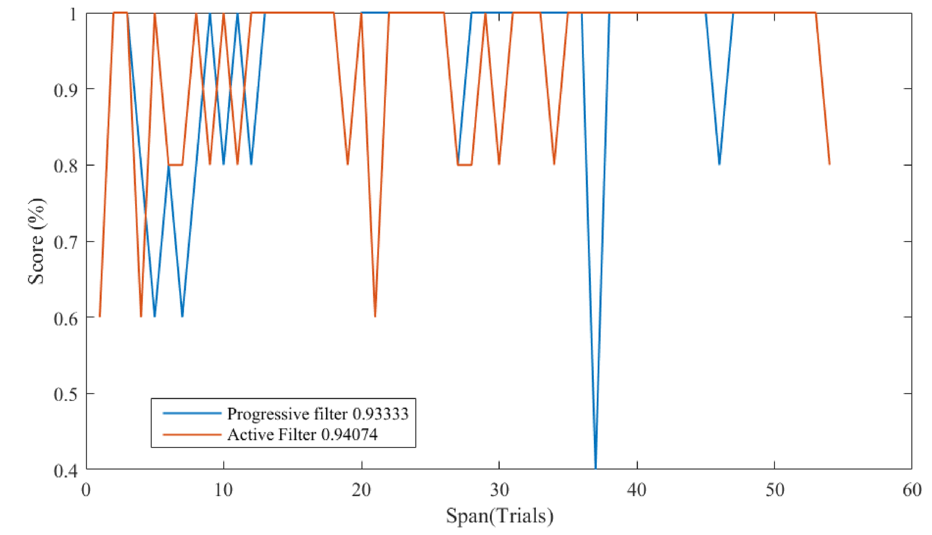


Figure 6: Active and progressive filter scores vs. number of trials for subject "aw".

Conclusion

- Active and Progressive filters are partially coupled at the consensus epochs based on the individual classification results, i.e., the Active Filter produces results at the end of each epoch while the Progressive Filter uses several epochs to re-train.
- The experimental implementations of the proposed framework indicate its potential for improving the performance of real-time MI classification.

References

[1] H. Lu, H.-L. Eng, C. Guan, K. N. Plataniotis, and A. N. Venetsanopoulos, "Regularized common spatial pattern with aggregation for eeg classification in small-sample setting," *IEEE Transactions on Biomedical Engineering*, vol. 57, no. 12, pp. 2936–2946, 2010.

[2] S. Shahtalebi and A. Mohammadi, "Error Correction Output Codding Coupled with the CSP for Motor Imagery BCI," *European Signal Processing conference (EURASIP)* 2017.