A 1D-CNN Approach to Comparing Real and Imagined Activities

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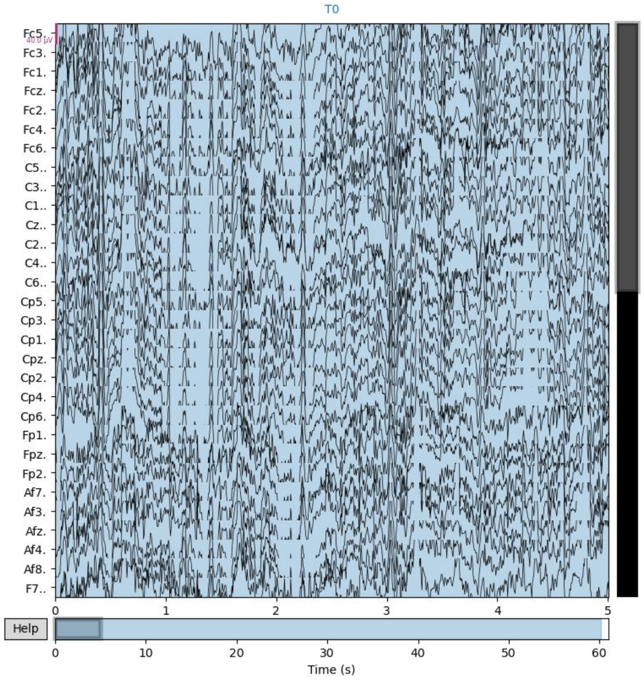
ICS 691D - 06 May 2024

Motor Movement/Imagery Dataset - Recap

- Subjects perform different motor/imagery tasks
- 64-channel EEG (160 samples/sec) + annotation channel
- International 10-10 naming convention
- Used BCI2000 system (http://www.bci2000.org)
- 109 volunteer subjects
- Each subject performed 14 experimental runs
  - 2 baseline recordings (1 mins) [eyes open and closed]
  - 3 repetitions of four tasks (2 mins)
- Low pass data with 80 Hz
- Data in EDF+ format



Motor Movement/Imagery Dataset - Recap (ctd ...)

- Four tasks performed
  1. A target appears on one side ⇒ subject clenches the matching fist until it's gone ⇒ relax
  2. A target appears on one side ⇒ subject imagines clenching the corresponding fist until it's gone ⇒ relax
  3. A target appears at the top or bottom ⇒ subject clenches both fists (top) or both feet (bottom) until it's gone ⇒ relax
  4. A target appears at the top or bottom ⇒ subject imagines clenching both fists (top) or both feet (bottom) until it's gone ⇒ relax

Motor Movement/Imagery Dataset - Recap (ctd ...)

- Each task repeated 3 times + 2 baseline runs
- In summary, the experimental runs were:
    1. Baseline, eyes open
    2. Baseline, eyes closed
    3. **Task 1 (open and close left or right fist)**
    4. **Task 2 (imagine opening and closing left or right fist)**
    5. Task 3 (open and close both fists or both feet)
    6. Task 4 (imagine opening and closing both fists or both feet)
    7. **Task 1**
    8. **Task 2**
    9. Task 3
    10. Task 4
    11. **Task 1**
    12. **Task 2**
    13. Task 3
    14. Task 4

Related Work

Motor Imagery Decoding Using Ensemble Curriculum Learning and Collaborative Training
Georgios Zoumpourlis, Ioannis Patras
Queen Mary University of London

- Address challenges caused by individual differences.
- Introduce a two-stage model ensemble architecture with multiple feature extractors and a shared classifier. Train with novel loss terms including curriculum learning and intra-ensemble distillation.
- Surpasses existing techniques on large motor imagery datasets. Demonstrates high learning capacity and robust performance with fewer parameters. Addresses domain shift challenges in multi-subject EEG datasets.

Multi-Class Classification of Motor Imagery EEG Signals Using Image-Based Deep Recurrent Convolutional Neural Network
Ward Fadel, Csaba Kollod, Moutz Wahdow, Yahya Ibrahim, Istvan Ulbert
Pazmany Peter Catholic University, Budapest, Hungary

- Explore EEG signal classification for Motor-Imagery (MI) based Brain-Computer Interface (BCI) systems.
- Transform EEG signals into images for classification.
- Model comprises a Deep Convolutional Neural Network (DCNN) for spatial and frequency feature extraction, followed by Long Short-Term Memory (LSTM) for temporal feature extraction.
- Achieve promising average accuracy of 70.64%. Outperform Support Vector Machine (SVM) by 5%.
- Evaluate various imaginary tasks for classification.

Related Work (Cont.)

A 1D CNN for high accuracy classification and transfer learning in motor imagery EEG-based brain-computer interface
F Mattioli, C Porcaro and G Baldassarre
Institute of Cognitive Sciences and Technologies (ISTC), National Research Council (CNR), Rome, Italy

- Utilize a 10-layer one-dimensional convolutional neural network (1D-CNN).
- Incorporate data augmentation and a limited number of EEG channels.
- Employ transfer learning to customize the model to individual subjects with minimal training data.
- Achieve a high accuracy of 99.38% at the group level on the EEG Motor Movement/Imagery Dataset.
- Attain an average accuracy of 99.46% with transfer learning.

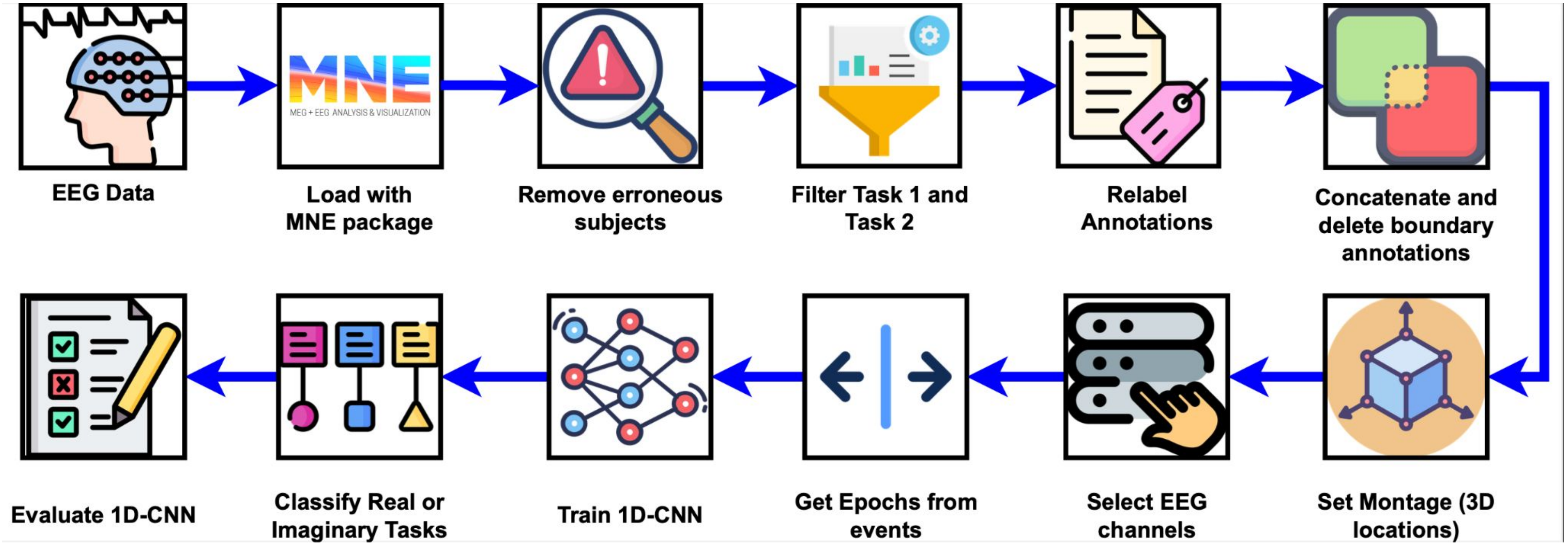
Research Contribution

- **Novel Exploration:** Investigate the potential of the Physionet Dataset to differentiate between tasks performed in reality versus imagination.
- **Machine Learning Techniques:** Employ deep learning techniques to analyze EEG data and discern between real and imaginary tasks.
- **Potential Implications:** Pave the way for understanding mental disorders associated with hallucinations and imagination.
- **Future Research Direction:** Open avenues for further exploration into the role of EEG data in differentiating between real and imagined tasks, contributing to advancements in brain-computer interface technology and mental health research.

Hypotheses

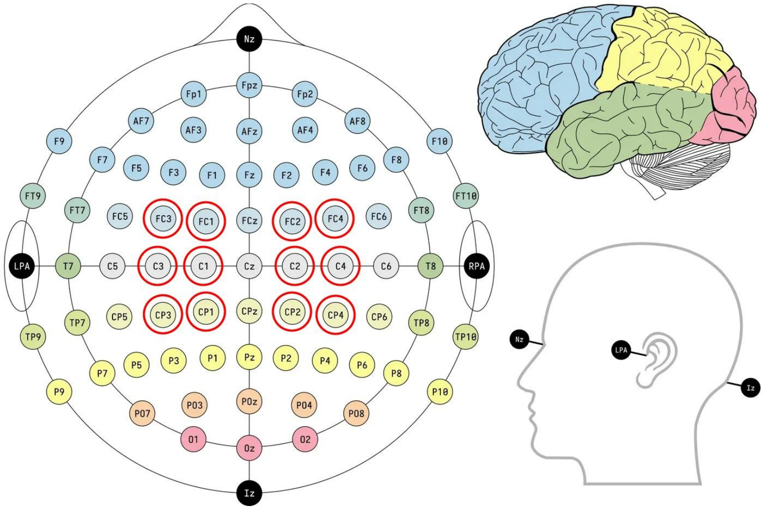
- **Hypothesis 1:** The EEG signals for Real and Imaginary motions of Right and Left fists can be distinguished using 1D CNNs with minimal preprocessing and alteration of the data.
- **Hypothesis 2:** The EEG signals for Real and Imaginary motions of both fists and both feet can be distinguished using 1D CNNs with minimal preprocessing and alteration of the data.
- **Hypothesis 3:** Preprocessing EEG data and adding filters will improve the accuracy significantly.

Proposed Method Overview



Data Preprocessing

- Erroneous subjects: 38, 88, 89, 92, 100, 104
- Hypothesis 1: Filter (Task 1 + Task 2)
- Hypothesis 2: Filter (Task 3 + Task 4)



Selected EEG channels

TABLE I
CLASSES USED IN THE TESTS OF THE MODEL. (FIRST HYPOTHESIS)

Class label	Description of the class
LI	motor imagination of opening and closing the left fist
RI	motor imagination of opening and closing the right fist
LR	actual motor movement of opening and closing the left fist
RR	actual motor movement of opening and closing the right fist
B	resting state (baseline)

TABLE II
CLASSES USED IN THE TESTS OF THE MODEL. (SECOND HYPOTHESIS)

Class label	Description of the class
BI	motor imagination of opening and closing both fists
BR	actual motor movement of opening and closing the right fist
FI	motor imagination of opening and closing both feet
FR	actual motor movement of opening and closing both feet
B	Baseline

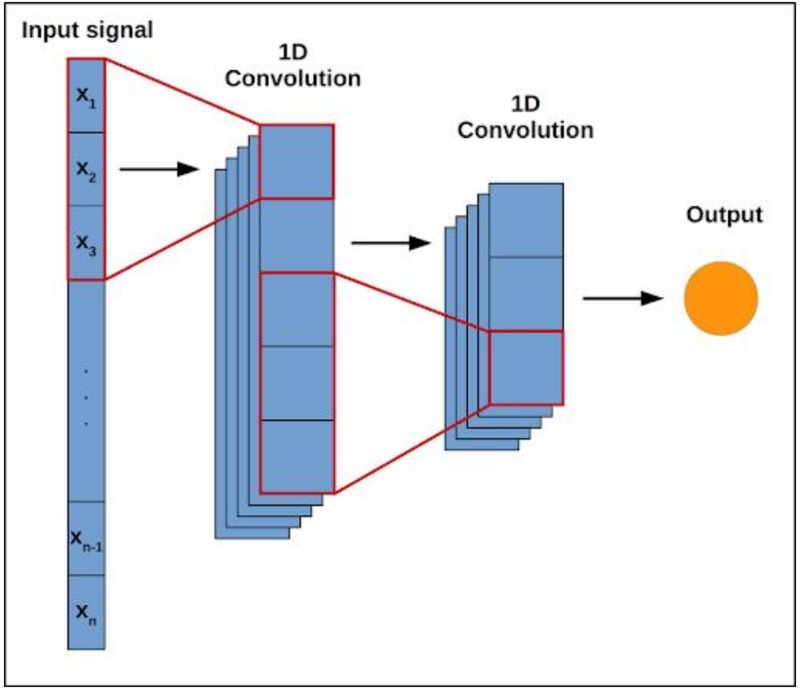
1D-CNN

TABLE III
HopefullNet architecture.

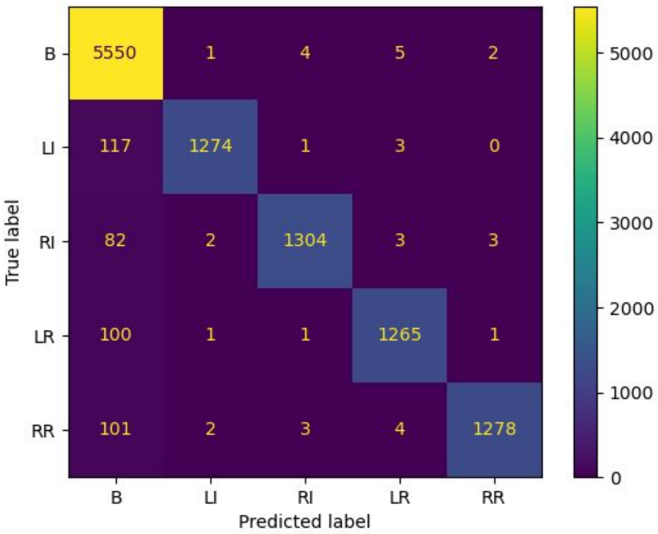
Layer	Features	Type	Input size	Filters	Kernel size	Activation
L1	Conv1D, BN	1DConvolution	(640, 2)	32	20	relu
L2	Conv1D, BN, SD	1DConvolution	(640, 32)	32	20	relu
L3	Conv1D, AP	1DConvolution	(621, 32)	32	6	relu
L4	Conv1D, SD	1DConvolution	(308, 32)	32	6	relu
L5	Flatten	Flatten	(303, 32)	-	-	-
L6	Dense, Dropout	Fully-conn.	(9696)	-	-	relu
L7	Dense, Dropout	Fully-conn.	(296)	-	-	relu
L8	Dense, Dropout	Fully-conn.	(148)	-	-	relu
L9	Dense, Dropout	Fully-conn.	(74)	-	-	relu
L10	Dense	Fully-conn.	(74)	5	-	softmax

TABLE IV
Summary of parameters used in the model

Parameter	Used Value
Loss function	Categorical cross-entropy loss function
Optimizer	Adam optimizer
Regularization	Batch normalization and Dropout layers
Learning rate	1×10^{-4}
Training epochs	100
Batch size	10
Early stopping patience	10
Early stopping tolerance	1×10^{-3}



Results



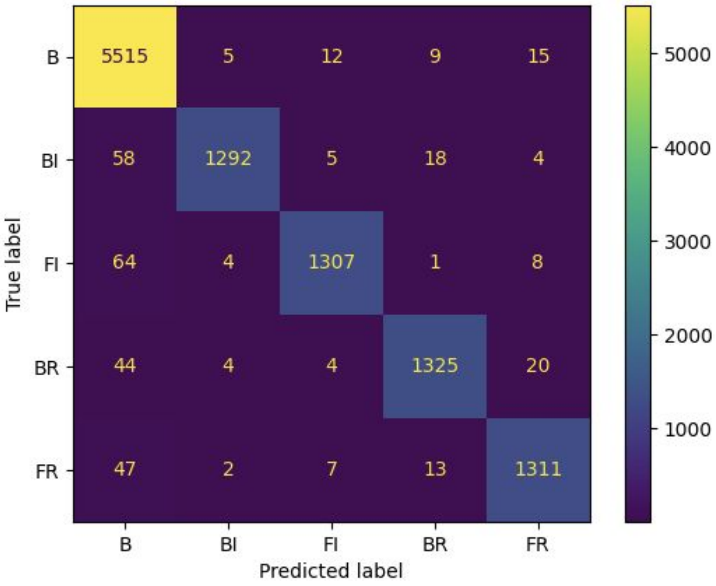
Hypothesis 1:

- Accuracy: 96.07%

Classification report

	precision	recall	f1-score
B	0.95	1.00	0.97
LI	0.99	0.94	0.97
RI	1.00	0.93	0.96
LR	0.98	0.95	0.97
RR	0.99	0.93	0.96
accuracy			0.97
macro avg	0.98	0.95	0.97
weighted avg	0.97	0.97	0.97

Results (ctd ...)



Hypothesis 2:

- Accuracy: 96.90%

Classification report

	precision	recall	f1-score
B	0.96	0.99	0.98
BI	0.99	0.94	0.96
FI	0.98	0.94	0.96
BR	0.97	0.95	0.96
FR	0.97	0.95	0.96
accuracy			0.97
macro avg	0.97	0.95	0.96
weighted avg	0.97	0.97	0.97

Discussion

- **Achieved High Accuracy** in Fist/Feet Motion Classification (96.07% & 96.70%)
- Strong Performance **Across Classes** (9 different classes across Hypothesis)
- Balanced Accuracy with **Positive (Real) Cases** (Around 95% Recall Values)
- Remaining 4% to perfect accuracy are mostly for **misclassifying baseline classes.**
- Confusion Matrix shows **mostly correct** predictions even though more **data belongs to baseline class**.

Future Research Directions

1. **Incorporating event-related potentials (ERPs)** for additional discriminative features to improve accuracy or do a comparative analysis
2. **Utilizing data augmentation methods** like SMOTE to address class imbalance and enhance model generalization
3. **Conducting extensive hyperparameter** tuning (i.e. Using Bayesian optimization) to optimize model performance.
4. **Simplifying the classification task** by focusing exclusively on distinguishing between active motor imagery tasks, potentially improving accuracy by excluding the resting state class.
5. **Exploring other configurations of 1D CNNs** like Wavenet, Temporal Convolutional Network, Convolutional Attention Networks can improve the accuracy further.

Conclusion

- Demonstrated Effectiveness of 1D CNNs on EEG data
- Demonstrated the possibility of EEG signal classification even with minimal preprocessing
- Broad Potential and Future Applications