Automatic Identification of Brain Independent Components in Electroencephalography Data Collected while Standing in a Virtually Immersive Environment - A Deep Learning-Based Approach

Rachneet Kaur, Maxim Korolkov, Manuel E. Hernandez, Richard Sowers
Motivation

- **Real-time brain computer interface (BCI) applications**
  - Electroencephalography (EEG) is used for monitoring brain activity
  - Automating an EEG signal processing pipeline is imperative to the exploration of real-time brain computer interface (BCI) applications
  - EEG analysis demands substantial training and time for removal of distinct unwanted independent components (ICs), generated via independent component analysis, corresponding to artifacts.

- **Procedural way to identify and eliminate signal artifacts**
  - The considerable subject-wise variations across these components motivates defining a procedural way to identify and eliminate these artifacts
  - An automated approach would greatly facilitate IC selection and hence EEG-based research beyond trained individuals
• **Develop human postural control enhancement technologies**
  ○ An automated independent component (IC) categorization would not only aid speed and consistency but also assist online EEG processing for brain-computer interfaces (BCI) to facilitate neural rehabilitation.
  ○ Several studies have explored VR and EEG-based setups to provide insights into neural connectivity and adaptation [1]-[4]. VR and EEG-based setups require real-time artifact rejection to develop novel acrophobia therapies and human postural control enhancement technologies.
Artifactual IC rejection

IC32

IC32 activity (global offset 0.011)

Activity power spectrum

IC29

IC29 activity (global offset -0.005)

Activity power spectrum

ACCEPT!

REJECT
Related works

- ICLabel classifier (proposed in [5])
  - It estimates seven IC categories using DL with near-real-time classification of online-decomposed EEG data
- However, there is a need to continue exploring the application of machine learning to automate IC classification of EEG data from noisy, visually stimulating and more real-world scenarios for future BCI applications
DeepIC-virtual

- We propose **DeepIC-virtual**, a CNN deep learning classifier to automatically identify brain components in the ICs extracted from the subject's EEG data gathered while they are being immersed in a virtual environment.
- We examine the feasibility of DL techniques to provide automated IC classification on a noisy upright stance EEG data.
- Ground truth labelling of generated ICs by a trained specialist was done by looking at all the four components of the IC representation diagram whereas a CNN discriminates brain components from artifacts only by learning on one of the components, i.e. the scalp topographical map.
Experimental Setup

- Brainvision 64 Channel ActiCHamp EEG System
- EEG signal recording software
- HTC Vive virtual reality headset
- Force plate
- Python
Experimental Setup

- The protocols for this study were approved under the Institutional Review Board number 17010.
- **Data collection design:** a HTC Vive VR headset, a NeuroCom SMART Equitest Clinical Research System, a Brainvision 64-channel EEG head cap and a safety harness
- **VR assessment system:** Real-time EEG data recording setup [1], while a subject stands quietly to height and depth alterations and induced perturbations.
- Administred pseudo-randomized virtual surroundings with varying height settings and induced 10-degree toe-down perturbations while recording the subject's EEG signals in a secure setting.
EEG data collection setup:
The training and testing data for this study was accumulated from a designed system with real-time EEG recording setup while a subject stands quietly to pseudo-randomized height and depth alterations and induced perturbations.
Study participants

- 5 healthy young adults aged 20.4 ± 0.80 years (2 females) and 1 male healthy older adult aged 79 years from the local community.
- **Four trials**, individually lasting for **240 seconds** with eight pseudo-randomly ordered height settings (ground level, 2.5, 5, or 7.5 meters in height and in depth) in the virtual world during each trial.
- During two of the trials, **10-degree toe-down perturbations** were induced at all height levels.
- Subjects were instructed to **stand still** on the NeuroCom force plate while wearing the HTC Vive headset during the entire session.
Data Analysis

- IC data generation
- Types of ICs
- IC classification
IC data generation

- Real-time EEG data from scalp electrodes were **recorded at a 1000 Hz sampling rate**.
- The EEG signals, time-synched to the experiment in VR, were epoched into 1 second segments and processed via a **band pass finite impulse response (FIR) filter** to refine any noises.
- The filtered EEG, denoted by X, is a linear mix of source signals from 64 head cap electrodes, hence **ICA** is performed to determine weights matrix W and **statistically independent components (ICs)** I.
- The separating weights matrix W is computed such that the **statistical independence between the components of I = WX is maximized**, over all invertible matrices W.
IC representation diagram

- A IC representation diagram comprising of the following was used by the specialists.
  - A **scalp topographical map** depicting positive (red), negative (blue) and null (white) weights of the IC on 64 channels indicated by black dots
  - A **power spectral density (PSD)** diagram representing the power distribution of the IC's activity
  - An **event-related potential (ERP)**
  - A **time series** illustrating a section of the IC's activity
- ICs can be categorized as *good* acceptable ICs sourcing from the brain and *bad* removable ICs (further classified into 6 subtypes) that are vital to eliminate prior to performing further analysis on EEG [5].
Brain ICs

- **Brain components** emerging from the cerebral mantle are identified as spatially coherent signals with broad and connected activation from numerous scalp electrodes.
- Their PSD usually include an increase in the 8-12 Hz frequency range.
An accepted IC:
The heat map demonstrates coherent signals from multiple channels with red, blue and white colors depicting positive, negative and null weights respectively.
Artifactual ICs

- The artifactual ICs can be subdivided as
  - **muscle components** originated by motion of the muscles with a substantial proportion of activity in a solitary region,
  - **eye components** depicting blinks, vertical or horizontal eye movements,
  - **cardiac components** denoting the activity of the heart,
  - **channel noise** originated via damaged or disconnected scalp electrodes with strong magnitude on only one channel,
  - **line noise** as ambient electric fields generally produced by the external sources,
  - **other artifacts** as unacceptable ICs that do not constrain to the defined subtypes.
- We define **hard to decide** class for ICs which were intricate and difficult for the specialist to assign to any one of the above mentioned categories.
A rejected muscle artifact IC: Restricted contribution in the scalp heatmap diagram can be observed.
IC distribution in our data

- 1637 labelled ICs with 285 brain, 149 muscle, 83 eye, no cardiac, no channel noise, 146 line noise, 769 other artifacts and 205 hard to decide components
- After eliminating the 205 ambiguous ICs, we retained **285 and 1147 ICs classified as good and bad components** respectively with an imbalance ratio of 1:4.
- We identified components that are acceptable for EEG analysis (**good** brain ICs) from those which are not (**bad** artifactual ICs).
Deep learning-based approach

- Given the nuances in the ICs, significant training is required for researchers to carry out visual inspection and classification.
- Advanced DL-based investigations may be an appropriate approach for automating the IC classification task.
- IC ground truth labelling by a trained specialist was done by looking at all the four components of the representation diagram whereas a CNN discriminates brain components from artifacts only by learning on the scalp topographical maps without considering the other three components.
IC classification

- 1432 scalp images were colored and 135x165 pixels in size
- Randomly stratified samples into 80% of data for training and 20% for testing
- 1145 topographical maps in the training set, with 228 good and 917 bad ICs (112 muscle, 70 eye, 118 line noise and 617 other artifacts)
- 287 maps in the test set, with 57 good and 230 bad ICs (37 muscle, 13 eye, 28 line noise and 152 other artifacts)
- A supervised CNN architecture was utilized to categorize good brain ICs and bad artifactual ICs
CNN architecture

- **8 convolutional layers** with ReLU activation, batch normalization, dropout, max polling
- **2 fully connected layers** with ReLU non-linearity.
- Network was trained using the root mean square propagation (RMSProp) optimization scheme and the cross entropy loss function.
- **Xavier initialization** assigned initial weights from a Gaussian distribution.
- **Class weights** were assigned to loss function restraining the network from always selecting the majority class to boost accuracy.
- The classifier network was trained for **100 epochs** with a mini batch size of 16 and with an adaptive learning rate initially set to 0.001.
- Prediction efficiency for the classifier was weighed via the test set **confusion matrix, accuracy, F1 score and area under curve (AUC)**.
CNN architecture
Results

- Test set binary classification accuracy of 89.20%
- F1-score of 0.783
- AUC of 0.926
- Only 1 out of the 57 brain ICs was misclassified as an artifact.

- Confusion matrix
- ROC of AUC
## Confusion matrix

<table>
<thead>
<tr>
<th>Predicted</th>
<th>Actual</th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td><em>good</em></td>
<td><em>bad</em></td>
</tr>
<tr>
<td><em>good</em></td>
<td>True positive = 56</td>
<td>False positive = 30</td>
</tr>
<tr>
<td><em>bad</em></td>
<td>False negative = 1</td>
<td>True negative = 200</td>
</tr>
</tbody>
</table>
Receiver operating characteristic

CNN (AUC = 0.93)

Majority (AUC = 0.5)
Conclusions

- Attained an accuracy and AUC of 89.20% and 0.93 respectively categorizing *good* versus *bad* IC topographical maps.
- Most of the brain ICs are known to be topologically coherent structures with connected broad cortical activities.
  - Thus, scalp topographical information may provide sufficient data for accurate automatic and objective IC classification.
  - These motivate further exploration on how spatial topology plays a role in such a classification task.
- Given the variability in artifactual ICs, these results will encourage clinicians to automate and study BCI methods to explore neural responses while in a visually immersive task.
Entire data for this study was manually classified by a researcher depicting the challenge of time and training inherent in such investigations.

With the creation of DeepIC-virtual, we hope to lower the entry bar in terms of both knowledge and equipment while performing EEG and BCI explorations.
Future works

- Verification of the examined test setups for a larger and more diverse cohort involving subjects with motion-related disorders and over multiple experiments.
- Use supervised transfer learning and multi-class classification methods to explore the efficiency of accurately discriminating the sub groups of bad ICs.
- Examining the role of spatial proximity and connectivity of EEG electrodes in the IC categorization task.
- Investigating the addition of attention or weights to the network architecture.
Acknowledgements

Illinois Geometry Lab

M+FP
University of Illinois at Urbana-Champaign
Mobility and Fall Prevention Research Laboratory

jump ARCHES

The William A. Chittenden
References


