Adaptive Interactive Learning for Training BCI Systems

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The Core Concept

Consider a real-time setup with a user sending brain signals into the system:



The signal is transformed to a high-dimensional space (multiple features per channel in a multichannel recording) and is used by a machine learning model.

What if the user could see the signal after the transformation — the way the machine sees it? He would be able to observe whether his signal for thinking "left" is different from the "right", explore if "happiness" is closer to "money" or "children" and even compare those relative distances to other peoples' distances.

The **problem** is that the brain signal, which is a proxy to our mental activity, resides in a high-dimensional space, which we humans cannot browse intuitively.

A solution is to project this data into 2D space, while preserving the topology and then visualize user's *mental state space* on a computer screen.

Practical Application

In a BCI experiment you could hear a user asking "How exactly should I think *left*?". Indeed, the request to think *left* is quite ambiguous — should the user concentrate on the abstract notion of "left", engage in an imagery motor activity or think about an unrelated concept?

Visualization of a user's mental state space could facilitate a "*dialog*" between the learning algorithm and the user. By exploring his mental state space the user can find such mental activity for each of the stimuli, that he can produce consistently over time and that is distinguishable by the algorithm.

Self-Organising Map (SOM) [1] is one of the topologypreserving dimensionality reduction techniques. We extend it to act as a predictive model.



Once a new signal is assigned to a unit, vector **p** of that unit is used to classify user's intended action.

On the right you - - - an example - - - - - see 19 19 19 - - - - - of a SOM with ØØØØ 🔶 🔶 🔶 ØØØØ 625 units trained ØØØØ - (- (- (-↓ ↓ ↓ ↓ ↓ to classify *facial* **▲ | ★ | ★ | ★** | ★ 13 13 | 🛧 | 🛧 | 🛧 | 🛧 | 1 muscular activity. 8 stimuli were - 💶 💵 presented to the | ↓ | ↓ user: LEFT, RIGHT UP, DOWN, RELAX, 🕈 🕈 🖉 🖉 🗢 ØØØ<u>0000</u>0 ROTATE, GRAB and 000000 000000 RELEASE. Training 0000000 00000 is performed in ⇒|↑|↑ 0000 1 1 real time — after each new data sample the map is updated and the visualization is redrawn. A performance estimate (F1 score) is used to *adaptively* change the parameters of the learning algorithm. The user is observing how his efforts affect the map and is able to deduce which actions overlap and which ones are not stable.

Implementation with SOM

A cluster with centroid \mathbf{w}_a in the original feature space is represented by a SOM unit (*a*) on a 2D map. Any signal \mathbf{x} that is closer to \mathbf{w}_a than to any other centroid will be assigned to unit a. Each unit has an additional vector

 $\mathbf{p}(\mathbf{a}) = (\Pr[s_1|a], \dots, \Pr[s_n|a])$ where n is the total number of different stimuli.

Experiment

We compare the performance a user can achieve using a traditional [2] training pipeline vs. the adaptive *interactive* pipeline.

Baseline



The stimuli without any feedback.

of the pictograms each stimulus stimuli. is described with a word.

Mental activity 3 actions 5 subjects e.50-Ε 0.25 0.00-

Future Work • Perform a larger study with mental actions using a better EEG device. • Compare SOM with other topology-preserving dimensionality reduction techniques (t-SNE) converted into a predictive model.





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the error bars SOM-based above the

visualization as feedback.

after the baseline experiment.

The experiments were run with an Emotiv EPOC device.



