Final Report: Brain Dataset

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Overview

Dataset: WAY-EEG-GAL

Experiment recording human grasp and lift tasks[1]

- 12 participants, 9 series recorded each
- EEG: 32 brain electrodes recorded at 5kHz
- EMG: 5 muscle sensors at 4kHz
- kinetic: 36 position/force signals at 500Hz
- grasp objects with different surface friction/weight (165-660g)

Figure: EEG sensor cap

[1] Data source: [EEG-GAL, 2014]

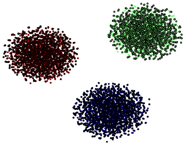
What this is all about

What are we trying to do with this dataset?
A: We want to see if one can use EEG and EMG data to get an idea about the following issues:

- Does a participant intend to grasp the object?
- Is he moving his hand **to** the object?
- Is he moving **back** to the resting position?
- Is he lifting the object?
- Is he holding an object?

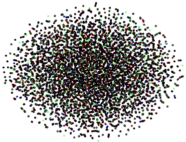
Visualizing high-dimensional EMG and EEG data using t-SNE. Why?

- Get a *feeling* for the data
- See if notion of *grasping* could possibly be captured by a Feedforward Neural Net



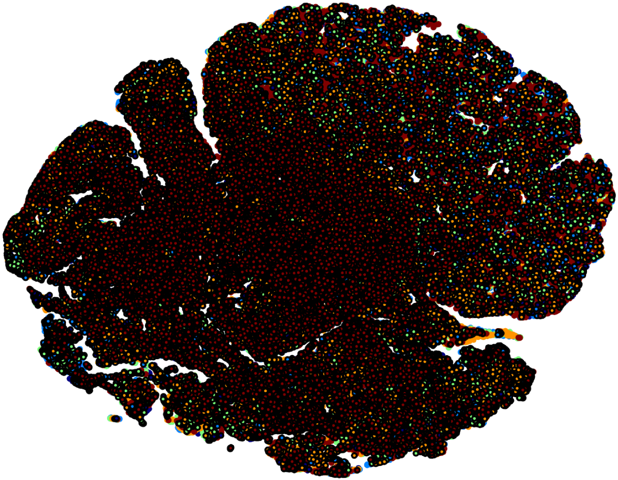
Idea

- *Grasping*-states and *Not Grasping*-states clustered respectively $\rightarrow$ Use Feedforward NN to classify *Grasping*.
- No apparent structure in the plot $\rightarrow$ Use Recurrent NN.



Analyzing the data using t-SNE

Visualizing EMG data using t-SNE



Attributes

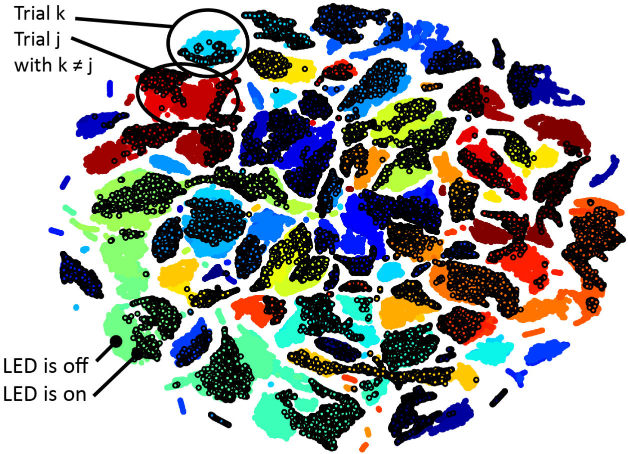
- Data of 34 trials
- Each colour stands for one trial
- Black spots mark *Grasping*-states

Conclusion

No apparent structure → Feedforward NN not sufficient, use Recurrent NN instead.

Analysing the data using t-SNE

Visualizing EEG data using t-SNE



Attributes

- Data of 34 trials
- Each colour stands for one trial
- Black spots mark *Grasping*-states

Conclusion

Trials cluster → Weird? Use Feedforward NN to classify trials?

Classifying trials using a NN

Further analysis of EEG data

Verifying correct function of implementation

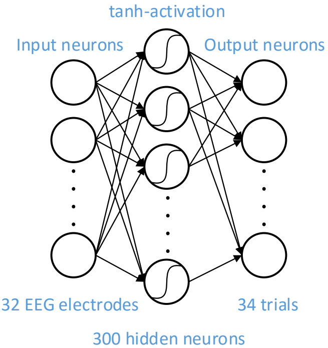
Check code over and over, use reference data sets to make sure the plot is indeed correct $\rightarrow$ Everything seems fine

If there is some truth to the t-SNE plot, classification of trials should be possible

Classify trials using a Feedforward NN

Feedforward NN with:

- 32 EEG electrodes as input
- 300 tanh-activated hidden neurons
- 34 trials as output classes



Results of the data analysis

Results of trial classification

Depending on participant and series nearly perfect classification with up to just about 0.01% error on test set.
Even when classifying all participant 1's 296 trials still a good test error of about 15% was achieved.

Conclusion

We conclude that there indeed has to be some kind structure encoding the time of measurement within the EEG data. Also, this structure is not bound by single series but seems to be of global nature.

Furthermore...

Also somewhat possible to classify the *intention to grasp* (LED on states).
Using the NN a test error of about 9% was achieved.

Methodology

Development environment

- Python, Theano, Climin, Breze, Matlab, C

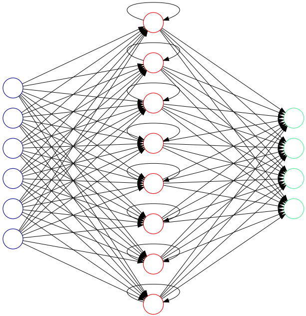
Data preprocessing

- Input normalization to -1/1 range
- Separation into sets of 300 data point records length
- EMG data subsampling at 10Hz
- Cross validation split: train/valid/test $\rightarrow$ 0.8/0.1/0.1

Methodology

Recurrent Neural Network

- deep network with recurrent connected neurons
- suitable for sequential data
- vanishing gradient exponentially worse
- decay information over time



Methodology

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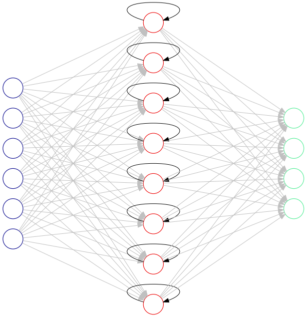

Methodology

Problem process assumption

Predictability in human planning $\rightarrow$ history matters

Recurrent Neural Network

- Network design:
  - 100 tanh neurons
  - 1 hidden layer
  - 50 samples per batch
  - optimizer: Adadelta, RmsProp
- parameter weight initialization by random uniform distribution
- Important weights: some samples are more important than others
- Bernoulli cross entropy loss

Methodology

Learning Targets

- one dim multi class vector vs. mult dim one-hot-encoding
- Selection of 16 predefined events
  1. LEDOn/LEDOff: study participant command
  2. tHandStart/tHandStop: hand moving
  3. trial_DurReach: time needed to move hand to object
  4. tLiftOff: start lift object
- Targets - defined over (multiple) intervals in between events
  1. move hand to target
  2. lift object
  3. hold object phase
  4. replace object

Training with data of one participant

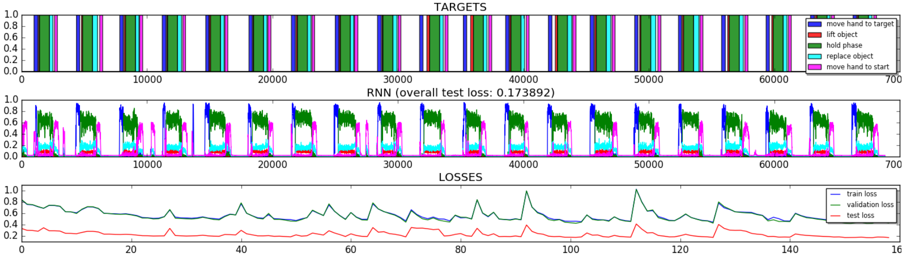

Figure: Results of RNN trained with data of participant 1, series 1-6

Results of RNN: EMG data

Training with data of more than one participant

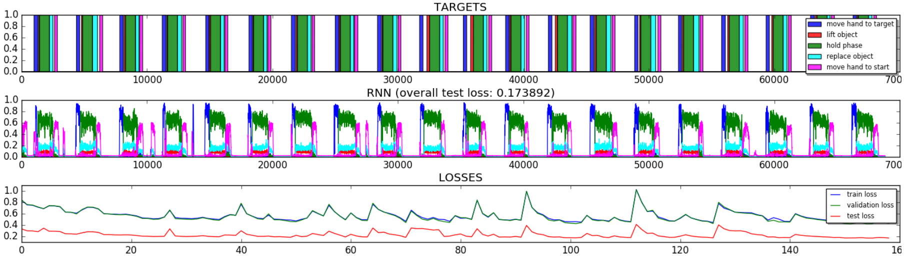

Figure: Results of RNN trained with data of participants 1-4, series 1-2

Pitfalls

- Prediction do not fit to the target borders exactly
- Limitations through Hardware
- Targets "lift object" and "replace object" cannot be predicted properly
- Different recording frequencies
- Equalization of different length records
  - zero padding → learning in danger of being misguided
  - tail cut → targets fall of, fails to learn sometimes
- Test loss by constant factor smaller than train and validation loss

Blocks of Highlighted Text

Block 1

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Multiple Columns

Heading

1. Statement
2. Explanation
3. Example

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Table

Treatments	Response 1	Response 2
Treatment 1	0.0003262	0.562
Treatment 2	0.0015681	0.910
Treatment 3	0.0009271	0.296

Table: Table caption

Theorem

Theorem (Mass–energy equivalence)

$E = mc^2$

Verbatim

Example (Theorem Slide Code)

```
\begin{frame}
\frametitle{Theorem}
\begin{theorem}[Mass--energy equivalence]
$E = mc^2$
\end{theorem}
\end{frame}
```

Figure

Uncomment the code on this slide to include your own image from the same directory as the template .TeX file.

Citation

An example of the `\cite` command to cite within the presentation:

This statement requires citation [**?**].

References

Matthew D Luciw, Ewa Jarocka & Benoni B Edin

Multi-channel EEG recordings during 3,936 grasp and lift trials with varying weight and friction

*h*ttp://www.nature.com/articles/sdata201447, requested at: July 26th 2016

Luciw, M. D., Jarocka, E. & Edin, B. B. (2014)

Data set: WAY-EEG-GAL

*F*igShare http://dx.doi.org/10.6084/m9.figshare.988376, requested at: July 26th 2016