

173836 2019-03-24 16-15-lily-watch-2-2.txt

7 participants 5 tasks(read, write, browse, video, copy) rest(NULL) each lasts for 5 minutes Each task was performed twice Sampled EOG @ 1000Hz X-P-X-DI 2,871 KB

2,437 KB

2,834 KB

5,848 KB 4.550 KB

5.001 KB

KB

KB.

4.151 KB

KB. KB.

6.116 KB 2,002 KB

5,807 KB

5,769 KB

5,752 KB

6,159 KB

6,004 KB

5,858 KB

2,141 KB

文本文档

1173836_2019-03-24_16-09-19-lily-rest2-2.txt

173836_2019-03-24_16-12-32-lily-video2.txt

opensignals_001403173836_2019-03-24_16-18-15-lily-browse2.txt

opensignals_001403173836_2019-03-24_18-49-18-angela-video2.txt

opensignals_001403173836_2019-03-24_18-56-56-angela-copy2.txt

opensignals_001403173836_2019-03-24_19-03-05-angela-write.txt

opensignals_001403173836_2019-03-24_19-09-08-angela-read2.txt

opensignals_001403173836_2019-03-24_19-15-37-angela-browse2.txt

opensignals_001403173836_2019-03-24_19-22-40-angela-NULL2-slee...

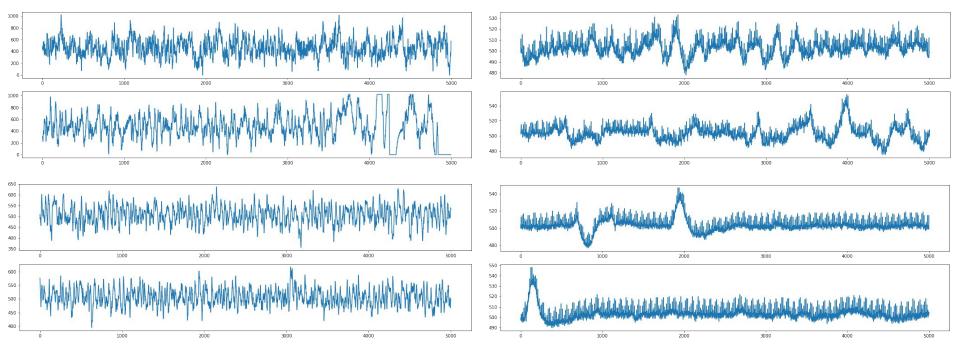
opensignals_001403173836_2019-03-24_19-30-11-angela-eyemoves.txt

EOG and EEG wave recorded, here we focus on EOG wave

Some samples: (over 5 seconds)

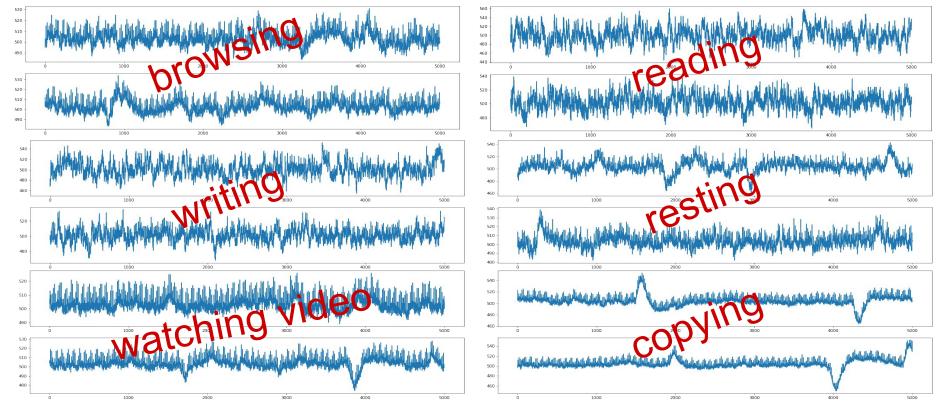
person Y copying

person E copying



Even performing the same task, the EOG wave differs from person to person

Person L: browsing, reading, writing, resting, watching video, copying



For the same person, different task could cause similar waves e.g. resting and watching video are very similar, we cannot tell difference with bare observation

Our model

Mission:

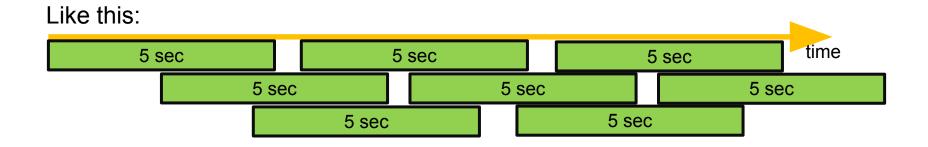
to predict the type of activity using EOG wave

Assumptions:

- It is possible (at least theoretically) to distinguish a person's activity within 5 seconds of observation
- EOG waves share the same distinguishable features among different people, as long as they are doing the same activity
- When a person claims to be doing one task, they are doing that task 100% percent of the time without distraction(because otherwise the wave will look like this person is resting)

Data augmentation

- Since each file contains ~400000 data points, we chop then into episodes of 5 seconds, with 5000 data points in them each.
- Prediction is invariant over a sliding window of time, which means we can get data from any sliding window of 5000 from our dataset:



Scaling

 We scale each of the 5000-length data to mean~0, std~1, facilitating NN training

Train-test split

 We extracted 13565 episodes in total, stratified by activity, getting 12280 training samples and 1357 test samples

Training

- Optimizer: Adam
- Loss function: categorical cross entropy
- Batch size: 32
- •50 epochs (taking around 2 hours on GPU)

Deep Neural network Architecture

Layer (type)	Output Shape	Param #
conv1d_1 (Conv1D)	 (None, 999, 32)	352
conv1d_2 (Conv1D)	(None, 997, 32)	3104
max_pooling1d_1 (MaxPooling1 (None, 332, 32)		0
conv1d_3 (Conv1D)	(None, 330, 32)	3104
conv1d_4 (Conv1D)	(None, 328, 32)	3104
max_pooling1d_2 (MaxPooling1 (None, 109, 32)		0
Istm_1 (LSTM)	(None, 109, 32)	8320
lstm_2 (LSTM)	(None, 16)	3136
dense_1 (Dense)	(None, 6)	102
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CNN, for feature extraction

Deep LSTM classifier, for time-series predictions

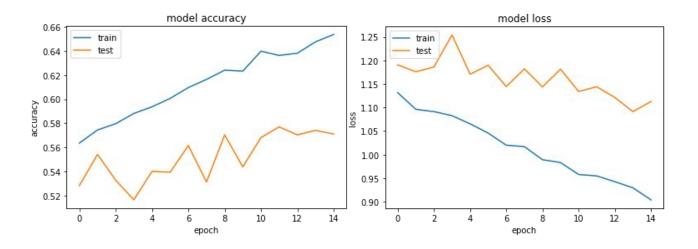
Total params: 21,222

Trainable params: 21,222 Non-trainable params: 0

Result: accuracy~60%

training history

Last 15 epochs

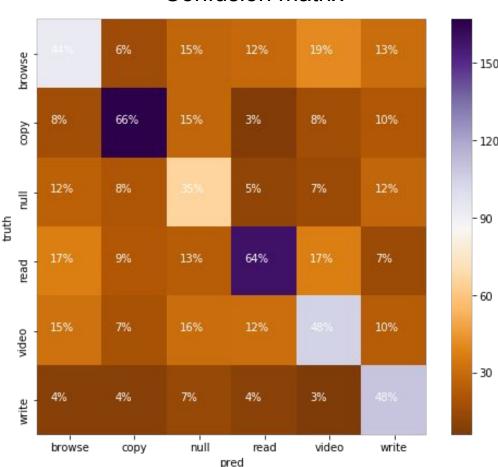


Detailed analysis of result

- Overall our model achieved
 58% accuracy on the test set.
- Our model does relatively well in predicting read and copy activities
- 3. null activity is the most confusing, hard to spot
- Video-browsing, reading

 browsing, null-browsing are
 three pairs of activities that
 often confuse with each other

Confusion matrix



Deep LSTM architecture

Total params: 7,590

Trainable params: 7,590

Non-trainable params: 0

Result training history

