Introduction

Eye movements reveal a lot about our perception, thought, and decision-making processes. The amount of time we fixate, the speed at which we shift our gaze and even the almost invisible micromovements all hint at our cognitive processing [1, 2, 3, 4, 5, 6].

They are valuable but non-intrusive biosignals that are useful for real-world applications such as education, healthcare, and security. [7]

However, classic computational methods to study and represent eye movements cannot exploit the dynamic nature of eye movements as a result of aggregation and feature engineering. They may also be stimuli-dependent, placing the restriction that eye movements have to come from the same stimulus.

Methods for comparing scanpaths and saliency maps: strengths and weaknesses (Le Meur and Baccino, 2013)

Hidden Markov model analysis reveals the advantage of analytic eye movement patterns in face recognition across cultures (Chia et al., 2017)

Methodology

Learn an abstract representation of eye movements that highlight and preserve both micro and macro movements — by using an autoencoder with dilated temporal convolutional networks [16].

The AE has two bottlenecks. The one at the fourth layer corresponds to the micro representations, while the one at the eighth layer is for the macro.

Data

1000 Hz data sets are downsampled to 500 Hz.

Training

Representations outperform previous works

Velocity is important for eye movement biometrics, position is important for inferring the stimuli

Augmented by taking overlapping 2s windows. Total samples after augmentation: 68,178

Results

Model generalizes to an unseen dataset

And outperforms a model trained solely on that unseen dataset (MLR)

Also robust against viewing time

Can handle 1s of data to up to 45s without loss of performance

-t-SNE plots for stimuli and biometric labels

<table>
<thead>
<tr>
<th>Classification Task</th>
<th>AE-250</th>
<th>AE-MIT</th>
<th>AE-MLR</th>
</tr>
</thead>
<tbody>
<tr>
<td>Biometrics (MIT-LowRes)</td>
<td>23.7</td>
<td>21.5</td>
<td>18.38</td>
</tr>
</tbody>
</table>

Learning Rate: 5e-4
Optimizer: Adam
Batch Size: 256 (pos), 128 (vel)
Epochs: 14 (pos), 25 (vel)
Framework: PyTorch
GPU: GTX 1070

Afterwards, the representations will be evaluated on classification tasks with a linear SVM.

<table>
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</thead>
<tbody>
<tr>
<td>Biometrics (EMVC-Train)</td>
<td>78.9</td>
<td>84.2</td>
<td>83.35</td>
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<td>Biometrics (EMVC-Test)</td>
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<td>86.6</td>
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<td>Biometrics (All)</td>
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<td>79.7</td>
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<td>59.2</td>
<td>85.4</td>
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<td>78.2</td>
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<tr>
<td>Gender</td>
<td>79.4</td>
<td>85.9</td>
<td>-</td>
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References


