1 Introduction

1.1 Key idea

Real-time EEG-based biometrical identification using consumer-class recording hardware for (including, but limited to) AR and VR applications.

1.2 Key objectives

The key objective is to conduct pervasive and comprehensive study on EEG-based authentication methods including pure biometrics and PIN code input. Main goals are:

1. To collect sufficient (compared to prior work in terms of participating subjects and time period) EEG data on multiple BCI-interaction scenarios with potential authentication applications.

2. To test multiple data analysis approaches (feature extraction, classification algorithms) to optimize time and complexity of EEG biometrics.

3. To outline feasible directions of further EEG-biometrics research.

1.3 Problematic and Challenges

The major motivation for this study comes from the following:

- EEG biometrics is a promising and secure tool, yet application is limited and technology is not adopted.

- EEG-based authentication procedures require complex setup and procedures and generally are time consuming.

- Few research is conducted using consumer-class EEG signal acquisition hardware.

- AR and VR password input is reluctant and slow.

There exist reasonable requirements for biometrics systems, which are important to follow:

Universality. Every person should posses the discussed biometric characteristics. Additionally EEG based biometrics is convenient for people with disabilities (better than FaceID or TouchID which require some mechanical actions to be taken).

Uniqueness. Prior work establishes EEG signals recorded over certain time as feasible biometrics with acceptable accuracy [].

Permanence (or repeatability). Biometric trait should remain temporally constant. Very important aspect for us to follow, as far as EEG signal is a subject to change over time, even between 24-hours span. Studies which are using data samples collected in one day are not sufficient and experiments aiming at real-life biometrics should be conducted over days or even month (there are some examples for studies with 200 days between records). More precisely, that means that learning data should be collected in one day, verification – on following days. It is very important to study discussed EEG data fluctuation over time (including maturation, diet, health changes) which implies:

- Robust and complete set of samples over certain time span (e.g. 2 months)

- Data recorded from different times of the day and under various conditions (e.g. after subject consumes a cup of coffee);

- Used classifiers should be able to be re-trained each time new batch of data arrives in order to keep decision boundaries up-to-date.

Collectability. Biometrics should be easy to collect, measure and evaluate. We are going to make huge emphasis that we are using consumer-class dry EEG electrodes, and generally aim at designing seamless hardware augmentation of 2 (3,4, . . .) electrodes for AR/VR systems. Additionally we are aiming at reducing the amount of time needed to authenticate the subject.

Unobtrusiveness. Hardware part should be elegant, easy deployable and consumer friendly

Robustness. Electrodes position should be more or less the same every recording. (interesting)

User-friendliness. We propose practical, zero-efforts deployable biometric expansion suitable for VR helmets and AR headsets.

Another topic which is needed to be covered is a difference between

verification vs *identification*

identification vs *authentication*.

TODO rewrite

Person authentication aims to accept or to reject a person claiming an identity, i.e., comparing a biometric data to one template, while the goal of person identification is to match the biometric data against all the records in a database.

An authentication (or verification) system involves confirming or denying the identity claimed by a person (one-to-one matching). In contrast, an identification system attempts to establish the identity of a given person out of a closed pool of N people (one-to-N matching).

[10]

2 Plan

2.1 Data acquisition

Preliminary:

1. X Test software
2. X Collect data of 2-3 people
3. X Check feasibility of collected data by simple analysis

Main objectives:

1. X Describe used hardware (helmet, PC, electrodes configuration etc.) and software
2. X Clearly and precisely define experimental procedures
3. X List interested people
4. X Arrange timetables

Additionally:

1. X Study on relatives (heredity issue)

2.2 Data analysis

1. Filtering
2. Normalizing
3. Artifact detection
4. Feature extraction
5. Classification
6. Cosine distance and other biometrics-specific algorithms

2.3 Article

This subsection is a draft-only feature intended to track and (re)arrange article:

1. X Come up with a Title
2. X Abstract
3. X proper Introduction
4. X Related work
5. X Experiment
6. X Data Science section
7. X Results
8. X Discussion
9. X Check for consistency: AUTHENTIFICATION VS IDENTIFICATION, PIN-code etc

3 Related Work

3.1 Privacy, biometrics cancellability

3.2 Passwords in AR and VR

Consider use-case: trying to buy identified overheard music, or recently spotted advertised product without a need to get the phone out of the pocket.

3.3 EEG Principles, limitations and alternatives

As far as we target general scope conference, I believe few paragraphs on underlying technology are required.

3.4 Consumer class EEG signal acquisition hardware

What is the current market and what are the application of contemporary EEG-wearables and their coherence with AR/VR headsets.

3.5 EEG biometrics

good, yet a little out of date review is presented in [7]

3.5.1 Medical equipment and public benchmark databases

Works on non-consumer EEG hardware mentioned in [7] are worth reviewing, as far as they define a baseline for accuracy.

3.5.2 Consumer class EEG hardware biometrics

Basically these are explicit competitors for proposed solution.

3.6 BCI

It is an plausible way of entering the password, not only for healthy subjects, but for a disabled people as well. It suffers from low bit-rate and requires complex setup and steady experiment procedures. It is actually used as a password-entering technique [11] which is basically a P-300 (secret) speller.

4 The Experiment

Acknowledgement of experiment approval

Number of people participated: X

Experiment duration: X days

4.1 Experimental setup

4.1.1 Hardware

Consumer grade Open BCI [2] EEG helmet Ultracortex "Mark IV" EEG Headset [3] is used to record EEG signal.

Additionally describe:

- Dry electrodes
- Cyton board
- Sampling frequency, other recording parameters
- Configuration of electrodes
- used PC

4.1.2 Software

reference and short description of [1]

4.1.3 Data

Explain the format of the data and file names builder.

4.2 Experimental setup

(Arms rested, electrodes placed, instructions read and understood, papers signed etc)

4.3 Experimental procedure

Data collection during the experiment is aimed at exploring plausibility of two major authentication approaches - passive and active. Passive approach is identification of a subject based solely on rested state EEG signals. It includes records of subjects with eyes closed and eyes opened. Active authentication methods are pin-code code inputs based on SSVEPS, P300 response and Motor Imagery (MI).

4.3.1 Rested state

intro to EO/EC

Procedure: Patient is asked to sit back, relax and do nothing. No sound or visual isolation is provided. Patient is supposed to keep ones eyes closed (or opened depending on the experiment) for the given amount of time without any major distractions.

4.3.2 SSVEPs based

if multiple stimuli flashing at different rates presented to the patient, the stimulus that the patient attends to (the target) will elicit a larger amplitude response than the stimuli that the user ignores[12]. Potentials evoked by attending visual stimuli are called SSVEPs - Steady State Evoked Potentials.

In paper [12]:

Frequencies: 6.2Hz, 7.7Hz, and 10Hz (Based on the previous experience and because they are less likely to elicit photo-induced seizures).

Calibration phase: 5 second trial, short pause between the trials, random shuffling of targets, 15 trials in total.

Experimental phase: 15 trials of 5 seconds. Preferable window length - 5 seconds (accuracy keeps growing).

In paper [9]:

9 Flickers of 27 Hz, 29 Hz, 31 Hz, ..., 43 Hz

Offline calibration - 9 frequencies in 60 seconds

7 Hz stimulus elicits a 7, 14, 21 Hz SSVEP !!!

In paper [6]: 8.5 Hz, 10 Hz, 12 Hz, 15 Hz and nothing about timings

TODO choose frequences.

Procedure:

1. Patient is asked to stare at the screen.
2. Flickers with frequencies *F1, F2, F3, F4* are presented consequentially for the time of T in order to collect data for training of classifiers.
3. Patient is given some rest in order to relax eyes.
4. 4-label PIN input board is presented on the screen. Four areas of the screen are flickering with four different frequencies *F1, F2, F3, F4* respectively. Numbers 1, 2, 3, 4 are associated with flickering areas. *Picture*
5. Patient is asked to look at areas in order of *2, 4, 1, 3* for T seconds each.
6. Procedure described in 5-th item is repeated N times. Between attempts patient is given time to rest.

No feedback was provided to participant at any stage of SSVEPs experiment.

4.3.3 P300 based

intro to P300

[8] 300ms after stimuli -¿ time window of 2 seconds is enough

Procedure:

A single trial is consisting of the following steps:

1. Patient is asked to stare at the screen.
2. 9-digits PIN input board is presented on the screen.
3. Each digit is flashing for *0.1* second in ascending order.
4. The process is repeated *4* times (corresponding to the total input sequence length).

Input trial is repeated *3* times.

4.3.4 Motor Imagery based PIN input

Motor imagery(MI) as authentication technique is used in [10] with two motor-related tasks in the experiment: imagination of left and right hand movement. Tasks were performed in self-paced and repetitive way about 15 seconds each.

MI experiment discussed in [5] involved two classes of tasks - imagination of touching fingers on the left and right hand. Important timings: 2 seconds before the experiment starts, 3 seconds for each MI atomic task, 5 seconds rest after the task.

Another MI dataset [4] contains records of imagination of movement of the left hand, right hand, both feet, and tongue. A cue of one of the 4 arrows (left, right, up and down) corresponding to certain activity. Important timings: 2 seconds before the single atomic MI starts, cue for 1.25 seconds on the screen, 3 seconds for the MI task itself, 2 seconds break.

Collected MI records (theoretically) can be used in two scenarios: passive as in [10] and as a PIN-code input technique - sequence of 4 symbols of arbitrary length sufficient for desired security level.

Procedure:

First, **calibration** stage is conducted. Calibration consist of 10 trials for each MI task: imagination of left hand movement with corresponding arrow to the left, right hand movement (right arrow), imagination of both feet movement (down arrow) and tongue movement (arrow to the up). Each trials is designed in a following way (according to prior experiments in MI [4] [5]):

1. Patient is asked to look at the screen.
2. Fixation cross appears on the screen for 2 seconds.
3. Arrow representing the current MI task is shown on the screen for 1.25 seconds.
4. Until 6 seconds of the current trial fixation cross will stay on the screen and patient is supposed to perform certain MI task.
5. A short break of 2 seconds is followed after each trial.

Second is PIN-code **Input** stage. The sequence itself and sequence length is chosen arbitrary: 12 input trials similar to the calibration trials. Patient is asked continuously perform MI tasks following the instructions (directional cue) on the screen. In real application the directional cue won't be shown in order to conceal the person input, creating a secret BCI-speller similar to the one discussed in 4.3.3.

No feedback was provided to participant in any phase of MI experiment.

Arguably, to test the classifier accuracy and the general applicability of MI-based input, random shuffle of the calibration phase trials can be used. But it is worth investigating how quickly and efficiently subjects can switch between different MI tasks for BCI interaction.

4.4 Experiment summary

Summarize experiments description by the following table:

Experiment	Duration (seconds)	Data label
Rested state, Eyes Opened	180	EO
Rested state, Eyes Closed	180	EC

References

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[3] Ultracortex "Mark IV" EEG Headset – OpenBCI Online Store. https://shop.openbci.com/collections/frontpage/products/ultracortex-mark-iv. Accessed: 2018-12-30.

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5 Dimitris do these:

1. https://arxiv.org/pdf/1705.03742.pdf

2. X Overview of methods of AR/VR password input