Literature Study

Authentication Subgroup

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ELECTRICAL ENGINEERING PROGRAMME

Contents

Chapter 1

Introduction

The electroencephalogram (EEG) is a method of measuring brain activity with a high temporal resolution that has been around for quite a few years. It is often used in neuroscience and similar research areas in experimental settings. A limitation in the use in experimental settings is due to the fact that originally EEG's were measured using electrodes placed over the entire scalp, which are quite uncomfortable in daily life. To remove this limitation, a small measurement device placed in the ear containing dry electrodes is a promising alternative, because it can be just as comfortable as regular earphones. Ear-EEG measurements can be done comfortable throughout the entire day which that paves the way for novel applications of electroencephalograms, one of which is the ability to authenticate users.

Logging in to devices safely often requires two- or even three-factor authentication. These factors are who a person is, what the person has and what a person knows [33]. A wearable EEG device could be used for two- or three-factor authentication and the goal of this literature study is to collected information about how such an application could work in practise. In the case of EEG's the division between what a person knows and who a person is can be a bit vague, that is why we have come up with the following definitions:

- Possession: The user has the device needed to log in.
- Knowledge: Detection of a brain state that is based on a specific thought that the user consciously self-induced.
- Inherence: Classification based on features that are specific to the users EEG.

The literature study consists of a few chapters, which categorize the papers that were found. Some papers could fall in multiple categories, in this case the most relevant is chosen. Each paper has a section with a short summary and/or explanation of why it is relevant for us.

In the first chapter 2, literature regarding the difference between scalp EEG's, which are currently the standard, and in-ear EEG's are discussed. This comparison is important for the testing of the authentication system, for it is not clear yet when and how often the in-ear device is available for testing.

To make sure that the EEG signal can be used to authenticate users, the first step is preprocessing the received EEG signals. The literature studied for this problem is discussed in chapter 3.

The signals provided by the in-ear EEG could be used to verify that the device is indeed used by the owner, but could also be useful to authenticate a user for other devices or services. To make sure this can happen safely, it could also be useful to add a knowledge factor to the authentication process and see if this is measurable in an EEG. According to the literature in chapter 4, there are several potential ways this can be done.

Using the filtered signals that are found using after preprocessing the date, finally authentication is researched in chapter 5. The literature in this chapter contains information on conventional- or machine learning techniques to classify EEG signals. Some articles regarding the entire EEG authentication analysis process are also mentioned here.

Finally information on safety in authentication protocols is discussed in chapter 6. This is important to asses and compare how safe the different methods of authentication that we want to propose are.

Based on the information in this report, we hope to get an understanding of all elements needed to use the in-ear EEG as an authentication device.

Chapter 2

Scalp- and in-ear EEG comparison

In order to start testing as soon and often as possible, it might be useful to make use of a regular scalp EEG. In this chapter some papers are discussed that indicate the similarities and differences between the two EEG methods.

2.1 Dry-Contact Electrode Ear-EEG [1]

This paper compares in-ear EEG with normal EEG for four standard EEG paradigms. The electrode set-up was done in four ways: scalp-scalp (normal EEG), ear-scalp, between ears and within ear.
Important conclusions:

- Both auditory and visual steady-state responses are visible and statistically relevant using in-ear EEG measurement.
- For the mismatch paradigm, the in-ear electrodes did not deliver statistically significant results. The between ears set-up did provide an image of the first 2 negative and first positive potential differences that where also seen in the normal EEG.
- For the alpha band paradigm, the ear-scalp setup had a clearer result.

General conclusion: The in-ear EEG is very useful as a more convenient and friendlier method of doing measurements. For all paradigms the in-ear configuration showed a lot of similarities with the regular scalp EEG.

2.2 A Study of Evoked Potentials From Ear-EEG [2]

This paper is very similar to the paper in section 2.1 and also draws the same conclusion that for most applications the in-ear electrodes show similar results. This article concludes that in-ear EEG measurements are on par with the measurements that are done by regular EEG on the temporal lope. The in ear-EEG is very useful when a high spatial resolution is not required.

2.3 EarEEG based visual P300 Brain-Computer Interface [3]

In this study a BCI was used that was based on the oddball paradigm, which triggers an evoked response pattern (ERP) called P300 that is clearly visible in an EEG. They used this BCI with both scalp EEG and in-ear EEG.

For this specific BCI the information transfer rate of the brain to the computer was on average 6.5 percent lower for the in-ear EEG. This shows that the ear EEG works almost as good as the regular one.

This article shows that an in-ear EEG BCI can work, but the experiment was only based on one ERP.

2.4 EEG Recorded from the Ear: Characterizing the Ear-EEG Method [4]

The in-ear EEG is most effective in detecting ERP's from the auditory cortex. The in-ear EEG also works really well for detecting paradigms based on frequency.

Chapter 3

Preprocessing EEG Signals

An EEG measures the electrical activity of the brain. These real-world signals always contain a combination of artifacts, noise and other inconsistencies. In order to perform accurate and efficient analysis of these signals, preprocessing is required with the aim to clean up the data.

Important things to consider regarding the improvement of the signal is what types of noise and artifacts are present. Literature shows that interference from electronic devices that are present during the measurement process reduce the signal quality. Physiological noise caused by for example the cardiac system is also detectable in an EEG. There are methods available to reduce these sources of noise.

Subject	Article(s)
Environmental noise	[5], [9]
Physiological noise	[6], [7], [8], [9]
General preprocessing techniques	[10]
Independent Component Analysis	[11]
Wavelet Analysis	[12]

Table 3.1: Overview of reference topics

3.1 Artifact Removal from EEG Signals [5]

This paper discusses the fact that there are two types of artifacts, powerline noise and baseline noise, in EEG recordings that are present in every patient. Powerline noise is introduced due to the presence of electrical outlets or electrical equipment in the neighbourhood of the measurement setup. Baseline noise is introduced due to things like poor contact of the electrodes or patient perspiration, both which cause low frequency artifacts. Multiple strategies are mentioned in order to deal with these noise sources, both during the recording stage of the data, as well as in the preprocessing stage.

3.2 Real-Time Cardiac Artifact Removal from EEG Using a Hybrid Approach [6]

The presence of electrocardiac artifacts in EEG data can have an impact on the ability to reliably process the signal. The artifacts can introduce spikes in the potential that can obscure relevant information. In this paper, the occurrence and strategies for the removal of these artifacts are discussed. The removal algorithm can be executed in real-time, which is promising for embedded applications.

3.3 EMG contamination of EEG: spectral and topographical characteristics [7]

Electromyogram contamination is another artifact which is present in EEG recordings. This is especially noticable in BCI applications that rely on automated measurements. The artifacts cover a broad frequency range of 0 to over 200 Hz with peaks around the 20-30 Hz and 40-80 Hz range. This paper discusses a technique for the removal of this type of interference.

3.4 Removal of Ocular Artifacts in the EEG through Wavelet Transform without using an EOG Reference Channel [8]

Electro-oculo artifacts are caused by the movement of the eyes and can be detected in EEG recordings. These artifacts introduce spikes which should be removed. In this paper, a method using the wavelet transform and adaptive thresholding is described which can improve the quality of the data.

3.5 Dealing with Noise in EEG Recording and Data Analysis [9]

In this paper, a few general approaches are discussed in order to deal with the different sources of noise in the EEG recordings. For example, during the measurement phase electronic devices can be switched off in order to limit line noise interference. It also mentions some basic methods to filter the unclassified noise.

3.6 Artifacts and Noise Removal for Electroencephalogram (EEG): A Literature Review [10]

This literary review summarizes and discusses many noise removal methods based on different techniques which is useful for deciding on a method tailored to a specific application. The four categories of approaches mentioned are noise removal techniques based on Independent Component Analysis, Statistical Analysis methods, Wavelet based analysis, and some other specific techniques.

3.7 ICA-based EEG denoising: a comparative analysis of fifteen methods [11]

In this article, one of the most commonly used preprocessing techniques called Independent Component Analysis is explained. The main goal of this technique is to find the components making up the signal which are statistically the most independent from each other. Many implementations of the algorithm are discussed and their advantages and disadvantages are compared.

3.8 Wavelets for EEG Analysis [12]

In this chapter of the book called Wavelet Analysis, this frequency analysis technique is explained in context of EEG analysis. The technique is an alternative to Fourier Analysis and is better applicable to non-stationary signals. This chapter also compares the method to ICA techniques, helping with deciding on our implementation.

Chapter 4

Brain Stimulation

In order to verify that the user wants to authenticate his or herself at a certain time or for a specific goal, it is necessary for the user to alter the EEG signal on command. In this chapter of the literature study, papers about the brain and brain computer interfaces (BCI) are reviewed to study which thoughts are best able to induced changes which can be detected.

An overview of the methods found that might be possible to authenticate a person are given in table 4. In addition to a summary of the paper which is found in each section, there is also a short explanation of how we believe it could be used for knowledge based authorization.

Method	Article(s)
Mental tasks	4.1, 4.2
Frequency tagging	4.3, 4.4, 4.5
Familiar music	4.6
Pseudowords	4.7
Emotions	4.8, 4.9

Table 4.1: Overview of methods that are explored and corresponding articles

4.1 Increase Information Transfer Rates in BCI by CSP Extension to Multi-class [13]

The paper is quite old, so the techniques are no longer state-of-the-art, but it provides some useful general information about the information transfer rate (ITR) that can be achieved. The main findings that are relevant to this literature study are that the maximum number of tasks is around 3 or 4 for most people, customizing the array of tasks for each individual can increase the ITR and training can help improve the ITR, but this can take up to 300 hours and is therefore not user-friendly.

The ITR is relevant for us, because it provides us with a sense of the amount of information that can be transmitted using a BCI. This information transfer can be used to transmit a password consisting of one or a series of mental tasks.

4.2 EEG-Based Synchronized Brain-Computer Interfaces: A Model for Optimizing the Number of Mental Tasks [14]

This paper is slightly more modern than the paper described in section 4.1 and provides some more information on the ITR for a BCI based on EEG.

An interesting conclusion of this paper is that different signal processing methods work best for different individuals. For three of the four subjects the highest ITR was achieved using SVM and for the fourth LDI worked best.

The optimal number of tasks to differentiate according to this paper is around 3 or 4, but this does vary a lot between individuals.

The optimal ITR that was achieved using the methods in this paper was 0.19 bit/s, which is quite low. Having a mental password that is more than 1 bit will therefore take to much time. It is however interesting to see if the distinction between any of these tasks and no tasks is clear in the EEG.

4.3 Rapid Memory Reactivation Revealed by Oscillatory Entrainment [15]

The experiment described in this article uses frequency tagging of memories. The tagging is done by showing words to subjects with a flickering the background at a certain frequency. The perception of the flickering at a certain frequency can be seen in brain activity using EEG. When the word is later shown to the subject, but without the flickering the same activity in the EEG can be seen that was elicited by the flickering background.

This could provide an interesting way of authenticating a user. First the user is shown one or more words with this flickering background (this is like setting up a password). When this password is set up, our hope is that the same frequency response will be detectable in the EEG recording when the user remembers this word.

4.4 Assessing the utility of frequency tagging for tracking memory-based reactivation of word representation [16]

This paper provides more information about frequency tagging, so it is an addition to the paper of section 4.3.

4.5 Probing cortical excitability using rapid frequency tagging [17]

There is evidence that frequency tagging, which was described in 4.3, can also work at higher frequencies, so up to around 60 hertz instead of around 10 hertz. This could be useful, because some modern devices with screens operate at frequencies up to 60 hertz and a broader bandwidth of frequencies can create a clearer distinction in the EEG results.

This could be useful to give a user different passwords for different services.

4.6 Rapid Brain Responses to Familiar vs. Unfamiliar Music – an EEG and Pupillometry study [18]

When participants were presented a 750 ms soundbite of a song that they know very well, there was a clear distinction in EEG response from an unfamiliar soundbite. This response was seen after just 350 ms, which is really fast and very useful when trying to log in fast.

This technique could prove very useful if thinking about the song is also detectable this quick.

4.7 Words and pseudowords elicit distinct patterns of 30-Hz EEG responses in humans [19]

Using EEG's, it can be clearly detected whether a word has some meaning to a person.

If a user thinks of a series of words and pseudowords, our hope is that the pattern can be detected using an EEG and act like a password.

4.8 Individual Classification of Emotions Using EEG [20]

It is concluded in this paper that 4 different emotions can be classified using EEG with an accuracy of 97 percent.

Therefore, letting people think about emotional stimuli could work as a authentication method, it is however not the most convenient way for users.

4.9 Experimental Methods for Inducing Basic Emotions: A Qualitative Review [21]

As stated in section 4.8, emotions can be recognized using EEG. This paper provides prove that emotions can be induced with statistically relevance using autobiographical recall and imagery. These induced emotions are self-reported, but also measured by physiological changes.

It might be possible to use emotions as a way of authentication, without an external stimulus.

Chapter 5

Identification

After an EEG signal has been recorded and preprocessed, classification of the signal is needed to actually differentiate between subjects and thus be able to identify them and henceforth perform the target application of authentication. In this chapter of the literature study, methods used for accurate classification of the EEG signals are explored.

The literature below both includes the methodology for classification and its performance results, as well as literature that explores the end use application of authentication for in-ear EEG.

5.1 One-Step, Three-Factor Passthought Authentication With Custom-Fit, In-Ear EEG [22]

This paper forms a proof of concept for the fact that EEG can be used for authentication, by achieving an accuracy of 99.82% with a False Acceptance Rate (FAR) of 0. However, it does so by using custom fit earpods with wet electrodes, so it does not provide any guarantees on the dry electrode, general population in-ear EEG that is our base product. Furthermore it provides useful insight into the end use application of three-factor authentication (which is the future) in one step.

5.2 Classifying EEG Signals in Single-Channel SSVEP-based BCIs through Support Vector Machine [23]

This paper makes a case for using Support Vector Machine (SVM) algorithm, optimised with an evolutionary algorithm for the classification of EEG signals. It explains in detail the entire process of this Machine Learning part. It also makes a comparison between other state-of-the-art approaches that use other algorithms and optimisation techniques. The fact that this paper is quite recent (2020) and outperforms state-of-the-art implementations of that time, make it a very relevant methodology to look into.

5.3 In-Ear EEG Biometrics for Feasible and Readily Collectable Real-World Person Authentication [24]

This paper provides proof-of-concept for feasible, collectable and reproducible EEG biometrics. It explores dry-electrode in-ear and scalp EEG. It explores several manners of classification, by both parametrised and non-parametrised ML models.

5.4 Adversarial Deep Learning in EEG Biometrics [25]

This paper describes a method using deep learning method that can further improve person identification using EEG biometrics.

5.5 Individual Identification Based on Code-Modulated Visual-Evoked Potentials [26]

A method to identify individuals more quickly than using the regular EEG signals is using signals after a visual stimulus. Using this technique an accuracy of 99.43% was achieved in a 10.5 second interval.
In our case we plan on having the device on the user for longer amounts of time, so other identification techniques also work. This might however be an interesting way to add a feature that allows users to share the device and be quickly recognized.

5.6 Error Correction Regression Framework for Enhancing the Decoding Accuracies of Ear-EEG Brain–Computer Interfaces [27]

Signals from parts of the brain further away from the ear are more distorted. This paper describes a method to classify ear-EEG signals that are comming from the occipital area of the brain with a higher accuracy.

5.7 Motor Imagery EEG Signals Classification Based on Mode Amplitude and Frequency Components Using Empirical Wavelet Transform [28]

This paper compares 7 classification methods for EEG signals used for an BCI based on motor imagery.

The accuracy for these methods is quite high for motor signals. might be useful to look into using these classification methods also on other types of signals that can be used for an BCI.

5.8 Classification of Mental Task From EEG Signals Using Immune Feature Weighted Support Vector Machines [29]

This paper describes an addition to regular a regular Support Vector Machine. The idea is to determine weights for each feature using something called the immune algorithm. This concept is called immune feature weight SVM or IFWSVM.

This method is especially useful on EEG signals due to the nonstationary and nonlinear features found in these signals.

To conclude, IFWSVM works better for EEG signals than regular SVM. The paper is over 10 years old, so the technique might not be state-of-the-art anymore.

5.9 Mental Task Recognition by EEG Signals: A Novel Approach with ROC Analysis [30]

This paper describes a different way of feature extraction for building the EEG classifier. They refer to and make use of benchmarked datasets from Colorado State University, which might be good data for us to resort to in case collecting data ourselves goes sideways. They also report on the entire process of building this classifier, which might prove useful for us as well.

5.10 Decoding Event-related Potential from Ear-EEG Signals based on Ensemble Convolutional Neural Networks in Ambulatory Environment [31]

The signals from an ear-EEG become more distorted when the user is walking in a real life setting. This paper tests the usefulness of the EEG in this setting and concludes that there is a reduction in performance in comparison to lab settings. The performance is however still quite robust with the method proposed in this paper.

Chapter 6

Safety

In order to ensure the success of a hypothetical authentication system based EEG signals, some thought needs to be put into its safety. Not only is a well thought out protocol of concern, the possibility of a successful attack also needs to be evaluated.

Subject	Article(s)
Password attacks	[32]
Authentication protocol construction	[33]
Protocol evaluation	[34]

Table 6.1: Overview of reference topics

6.1 Secure Authentication Mechanism for Resistance to Password Attacks [32]

This paper discusses different types of attacks possible on conventional authentication protocols. It also proposes a scheme which is protected against these attacks. The paper can be used to evaluate EEG oriented authentication methods compared to their conventional counterparts.

6.2 A Generic Framework for Three-Factor Authentication: Preserving Security and Privacy in Distributed Systems [33]

In this paper, fundamental concepts of authentication methods are discussed, as well as how they are implemented in existing systems. Using the examples, these concepts can be applied to a scheme using EEG signals.

6.3 A Semantic Model for Authentication Protocols [34]

This paper proposes a semantic framework for evaluating authentication protocols. It could be used to formalize the process and decide on its safety.

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