UKRAINIAN CATHOLIC UNIVERSITY

BACHELOR THESIS

EEG-based mobile system for envisioned Ukrainian words recognition

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in the

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Declaration of Authorship

I, Marian DUBEI, declare that this thesis titled, "EEG-based mobile system for envisioned Ukrainian words recognition" and the work presented in it are my own. I confirm that:

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- Where I have consulted the published work of others, this is always clearly attributed.
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"When something is important enough, you do it even if the odds are not in your favor."

Elon Musk

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EEG-based mobile system for envisioned Ukrainian words recognition

by Marian DUBEI

Abstract

Nowadays brain-computer interfaces are becoming more and more popular and the number of their applications is constantly growing. Usually, they are associated with implants, that can turn a human into a cyborg, but today there is a much more necessary application of brain-computer interface - curing people with various mental diseases that prevent them from normal living. Some of the most common diseases are deafness and muteness. People with an inability to express their thoughts would have a much easier life if they had a device that can help them solve their problems. So in this work, we create the system, which recognizes envisioned Ukrainian words from the selected vocabulary. We achieve this result by making a dataset of EEG recordings with our recording device and analyzing them using neural networks.

Acknowledgements

I want to thank my supervisor Anton Popov for mentoring me during this research and helping with a lot of problems both with the theoretical and practical parts. Also, I am very grateful to Infineon Technologies for supplying me with all the necessary components, and a special thank to Leonid Sarry for helping me with building the hardware part of the project.

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List of Abbreviations

EEG	**E**lectro**e**ncephalo**g**ram
MCU	**M**icro**c**ontroller **U**nit
SPI	**S**erial **P**eriferal **I**nterface
UART	**U**niversal **A**synchronous **R**eceiver-**T**ransmitter
PCB	**P**rinted **C**ircuit **B**oard
ADC	**A**nalog-to-**D**igital **C**onverter
PCB	**P**rogrammable **G**ain **A**mplifier

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Chapter 1

Introduction

1.1 Problem

Communication is one of the most necessary aspects of the life of people who want to stay full-fledged members of society. It is vitally important to share information with other people and be able to receive it in the easiest way. Nowadays most of us don't even recognize how easily we can communicate with others. But there is a great number of people, who have big problems and who aren't properly noticed by the whole world. These are people with serious speech impediments, who struggle with expressing their opinions and ideas or are completely mute. According to World Health Organisation, 430 million people or 5% of the world population are deaf or mute, and only a little fraction of them can use sign language to properly communicate with others [4]. This number seems a bit exaggerated, but usually, we cannot recognize these people, and only after direct contact, we can notice how hard it is for them to integrate into our community.

Of course, there are a lot of solutions for this problem besides mentioned sign language, like using social networks or writing down messages on paper. But none of them is as easy as using direct speech. Even with all these ways to solve the problem, it is still very hard for disabled people all over the world to contact healthy ones. Moreover, not all deaf and mute people can use sign language as a communication tool. As the research shows [4], 90-95% of deaf children are born in families where neither mother nor father can use sign language.

All of us deserve to have equal opportunities and communicate with each other as easily as possible. And since no more efficient way to exchange messages exists, it is required to create a possibility for disabled people to talk as freely as all other people do.

1.2 Motivation

The aim of this work is to make own contribution to solving the problem of communicating using only your mind, improve existing non-invasive approaches to deciphering imagined words and create a prototype system that can be a starting point for other works on envisioned speech recognition systems.

One of the main advantages of this thesis is that it is concentrated on recognizing Ukrainian words. Since there are no analogs that can be accessed, this work will be the first one to help deaf and mute Ukrainian people, who struggle with delivering their message to the world. The major benefit of the system is that it is very mobile and consists only of a microcontroller unit, PCB, electrodes, and a headband and does not require any large machinery compared to one used in the healthcare industry. Due to the simplicity of the project and cheap components, this work also makes it more affordable for people to solve this problem.

Chapter 2

Related Works

First studies of electroencephalography took place in 1929 and considerably developed since then. But mostly it was used only to assist in curing neurological diseases. Later, biopotentials were used also for getting information that could be applied as commands that allowed to create the first BCI - brain-computer interface. The first research on BCIs was published in 1973 by Dr. Jacques Vidal at the University of California. It was intended to create a proper communication channel for paralyzed people.

Since then BCI became much more popular and more and more applications were created where it would be much more convenient to use mind-controlled input than any other, such as entertainment industry, augmented reality, emotional management, smart house control, etc.

Here are some works that have some research using EEG as a tool for mind-related tasks implementation:

2.1 Articles

2.1.1 Imagined speech recognition

Envisioned speech recognition is one of the most needed applications of EEG. With properly configured hardware and well-trained models, it is possible to reach a quite good accuracy of recognition [12].

EEG is a hard and not fully examined area and different aspects of it may seriously impact speech recognition implementation. For example, not all EEG frequency bands are required for words recognition, δ-, β- and γ -bands are most important for good accuracy of the recognition model [14].

There are also spoken words recognition articles that use real-time automated speech recognition models for continuous noisy speech recognition [8].

2.1.2 Systems with low number of electrodes

According to the aim of the work, the system that is described here is declared to be very mobile, affordable, and cheap. This requirement made an impact on the number of electrodes used in our system, so a few related works that use systems with a low number of electrodes(<=16) were reviewed.

The minimum advised number of electrodes for good results is 8 electrodes(as separate channels) not including reference electrodes [7].

Tasks for systems with a low number of electrodes may differ, e.g. vowels recognition can also be done using only 14 channels [12].

2.1.3 Emotions recognition and user identification

Besides envisioned speech recognition EEG can be used in multiple ways as a brain-computer interface. Such works include researches that may increase the quality of life of healthy people, but still have some problems that can be solved with BCI.

One major electroencephalography application is emotion recognition [6]. It is quite a big area of research and there are various branches of it, e.g. emotion recognition of older people for reminiscence therapy [3].

Another application of EEG is user identification via performing mental tasks, which can be done even by using only two electrodes [5].

2.2 Analysis

Articles described in the previous section provide various methods and solutions to solve our classification problem. Here is a short table with models used in the articles, that solve the same task:

Model	Subjects	Channels	Accuracy
Bipolar Neural Network [10]	13	19	44%
CNN+LSTM [14]	23	14	85.93%
CNN [12]	50	14	85.66%
SVM [16]	14	64	46.61%
HMM [9]	21	16	45.5%
2 GRU+TCN [7]	4	8	79.07%

TABLE 2.1: Models used for envisioned speech recognition

As we can see, the model from [14] named 1DCNN-LSTM shows the best results even for the small number of subjects and channels.

Chapter 3

Background Information

3.1 EEG

3.1.1 Local Field Potentials

EEG is a method of getting information about electrical activity forced by neurons via recording it using electrodes. EEG may be invasive, which means sticking electrodes deep into the brain itself, but in this work, we will use a non-invasive approach only which is putting electrodes on the surface of the scalp and measuring the electrical activity of millions of neurons inside the brain. It is impossible to get a signal from a single neuron without any invasive approaches, but different types of mental activity synchronously activate a large population of neurons. Because of that, superimposed electrical field can be detected by conductive electrodes put on the surface of the scalp. Such postsynaptic activity of neurons is called local field potentials.

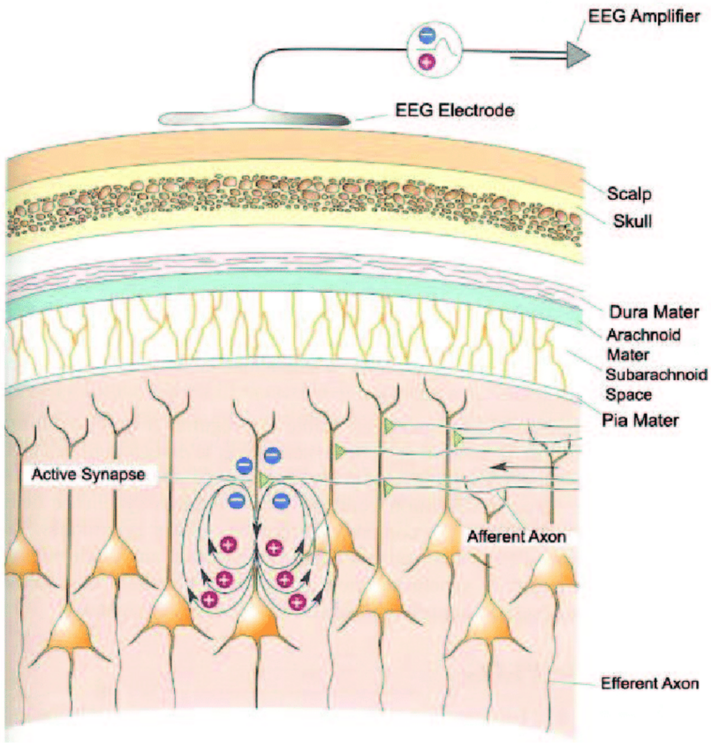

FIGURE 3.1: Electrical fields generated under cerebral cortex and collected with electrode [15]

3.1.2 EEG measurement

A system that can record electroencephalography requires:

- conductive electrodes
- filters and amplifiers
- ADC converter
- controlling unit

Electrodes are put on the scalp surface to get local field potentials from different parts of the cerebral cortex. There are two ways of electrode montage: differential montage, where every channel consists of two inputs, positive and negative, which are represented by two electrodes placed near each other to measure the difference in potentials between them and single-ended, where every needed place on the scalp surface has one electrode connected and a separate reference electrode that is used as second (negative) input for every channel. A reference electrode is usually put on the ear lobe. There are different ways to put electrodes on the scalp, but the most popular is the 10-20 electrode placement system (Fig. 3.2). Weak microvolt signals can be amplified so that they can be stored correctly for further processing.

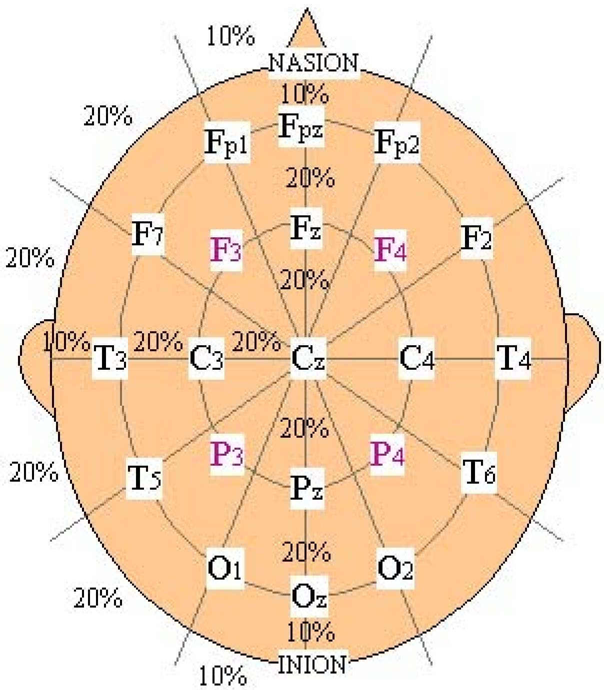

FIGURE 3.2: 10-20 eletrode placement system [13]

3.1.3 EEG frequency bands

Usually, recordings of electroencephalogram look like wavy lines, ranging from 0.5 μV to 100 μV in amplitude. After transforming raw input signal into power spectrum, we may notice that electrical activity in certain frequency ranges becomes more dominant. It allows us to classify brain waves by their frequency into four main groups:

- delta(0.5-4Hz)
- theta(4-8Hz)
- alpha(8-13Hz)
- beta(13-30Hz)

All these frequency bands show different kinds of information about our mental activity. Delta waves correspond to the depth of sleep, theta waves assess unconsciousness, creative activity, and deep meditation, alpha waves are linked to relaxation and eye movement, and beta waves are associated with active thinking, concentrating on different things, and solving tasks [11].

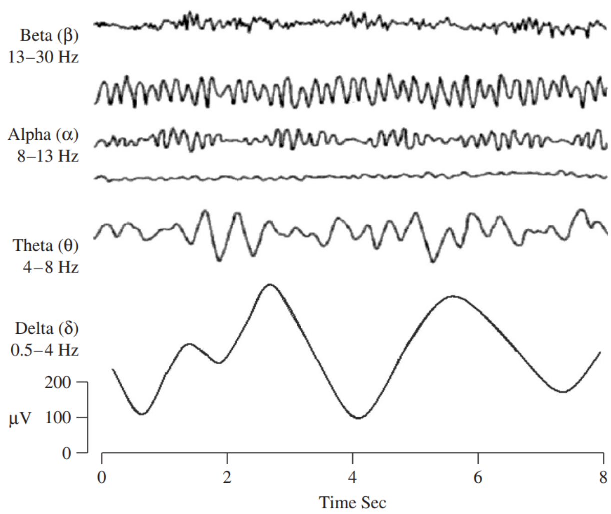

FIGURE 3.3: Brain wave samples representing various frequency bands [11]

3.2 Hardware Definitions

3.2.1 ADC

Analog-to-Digital converter is required for the EEG measurement system since it allows us to convert voltage carried by electrodes into 1s and 0s that will be ready for further processing. Every ADC has maximum reference voltage. ADC used in this system has a reference voltage of 4.5V. For every input he firstly compares it with half of the reference voltage, after that if the input voltage is higher, ADC takes half between the reference voltage and 1/2 of the reference voltage used before to compare with the input voltage, in another case half is taken between 0 and 1/2 reference voltage. These steps are repeated in a cycle in order to measure the voltage as accurately as possible. The number of repetitions depends on the resolution of the ADC (our ADC has a 24-bit resolution).

3.2.2 SPI

SPI - Serial Peripheral Interface - communication protocol that is used by microcontroller unit to configure and send commands to our PCB with ADC on how to properly amplify input signal, convert it, and send it to MCU. SPI is used by one master device and one or more slave devices and consists of 4 buses:

- CS - Chip Select, used for choosing a slave device to communicate with;
- SCLK - Serial Clock, used for sending ticks to slave device when is exchanged on data buses;
- MOSI - Master Out, Slave In - used for sending data from master to slave simultaneously with SCLK;
- MISO - Master In, Slave Out - used by a slave device to send data back on received SCLK ticks;

Chapter 4

System Overview

4.1 Hardware

Getting somebody's local field potentials in order to process them and recognize words that come up in one's head needs a proper data acquisition system. A system should comply with a list of requirements, like proper noise filtering, signal amplification, and communication that will be fast enough to match the sample rate of reading signals from the scalp surface. In our case the system consists of the following components:

- conductive electrodes
- a cap for attaching electrodes to the scalp surface
- PCB with ADCs, filters and amplifiers
- MCU
- desktop app

4.1.1 Electrodes and a cap

Proper electrodes are essential for every data acquisition system because it is necessary to make a good connection in order to receive a clear signal. Usually using EEG requires additional tools and equipment for better electrode connection like gel and paste. But it was not an option for the system since it should be as simple as possible. So because of that Dry EEG Comb Electrodes by OpenBCI were chosen as electrodes for our system. As it is stated in its name, these electrodes don't require additional liquids to attach properly to the scalp and they are good enough to make a connection through thick hair due to their construction in the form of a comb.

In order to hold them to the head conveniently, a cap was used to stick electrodes into it. The choice was Unicorn EEG Cap. It is able to hold 8 electrodes and is tight enough to keep them close to the skin.

4.1.2 Sigma-delta ADC

Local field potentials should be transformed into digital format, saved, and transferred to the processing unit. It requires a bunch of components such as ADC, filters, and amplifiers for every channel. Especially for this aim dedicated PCB was used. It is ADS1299EEG-FE, a board that is able to process eight channels simultaneously with a sigma-delta analog-to-digital converter, a programmable gain amplifier, low-pass analog, and digital filter and high-pass digital filter for every one of them. This board is designed especially for performing electroencephalography with all minimum requirements for proper EEG recordings.

Board Features

However analog filters, communication outputs, and power supply are located on the board [2], most of the necessary features are located on the chip, ADS1299, that performs digital filtering, amplifying, and the analog-to-digital conversion on eight channels via eight converters simultaneously. These and other features have a wide range of customization, e.g. sampling rate(250 Hz to 16 kHz), programmable gain(up to 24 x), internal or external voltage reference, oscillator(including internal clock output), and test signals [1].

EEG Specific Features

Besides general features for analog-to-digital conversion, ADS1299EEG-FE has some EEG-oriented features in order to have a better output signal.

In addition to common electrodes used by EEG systems that measure local field potentials using a pair of electrodes for one channel, there is an option to use a dedicated reference electrode that will be attached to the ear lobe and used as a negative input for all channels, decreasing the number of electrodes almost in half.

Another useful option provided by ADS1299 is a bias electrode, that is also attached to the head in order to settle common mode for reference voltage range. It becomes useful when the input voltage is negative and cannot be processed by a device with a unipolar power supply.

Also, ADS1299 provides an option to implement lead-off detection, that allows users to check whether electrodes are properly attached and get a notification when one or more are disconnected. Lead-off can be either DC or AC, depending on if the input signal is dc-coupled or ac-coupled.

4.1.3 MCU

One of the most necessary components for the system is a controlling unit that is able to communicate both with the PCB to configure it and receive EEG recordings, and with a processing device that will have enough power to recognize words based on the recordings using ML methods. The MCU that fulfilled all these requirements is PSoC 6 CY8CPROTO-063-BLE. A large list of features available on this kit is enough for creating a proper EEG acquisition system: dual-core MCU with Arm Cortex M4 and Arm Cortex M0+, programmable analog and digital block that can perform various tasks such as UART communication, SPI communication, BLE communication, clock generation and a large range of GPIO pins for full control of used PCB. Pin connections are shown in Fig. 4.1.

4.2 Software

4.2.1 Firmware

The firmware starts with the PSoC Creator environment, which allows configuring all pins, analog, and digital blocks, that are responsible for the communication and writing the functions that will be uploaded to the PSoC 6 CY8CPROTO-063-BLE. The current version uses only one, more efficient core Arm Cortex M4, but in the future second core is planned to be used for BLE implementation.

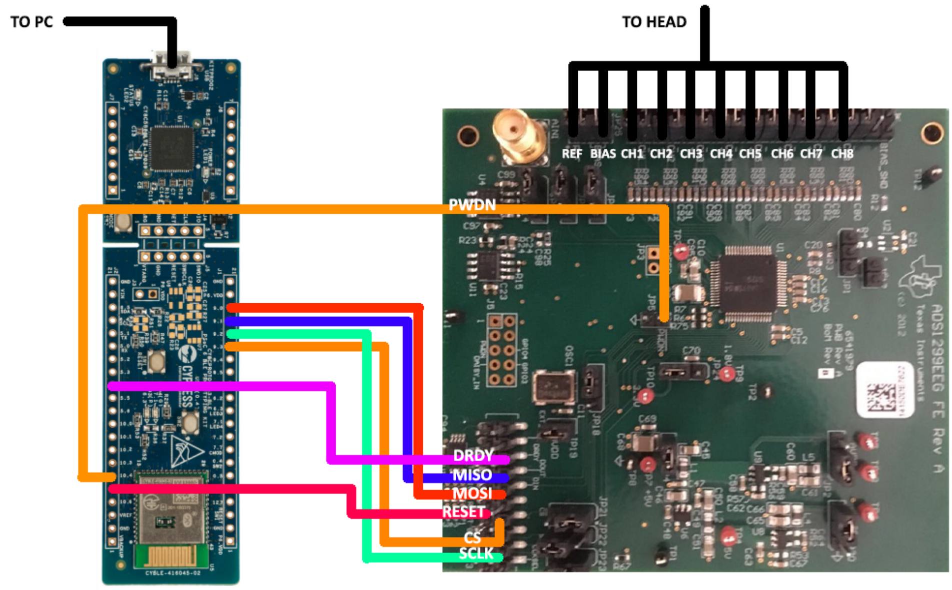

FIGURE 4.1: System diagram with pin connections

Communication

The firmware project allows creating two communication blocks for UART and SPI, for PC and PCB communication respectively. UART uses default communication settings, such as baud rate 115200, 1 stop bit, 8 data bits, and no parity bit. SPI communication has a protocol defined by ADS1299. The clock was configured at 1 MHz, which is enough for the system to receive the latest channel data as soon as possible. SPI can be used for several options: writing to registers, reading them, sending commands, such as WAKEUP, STANDBY, etc., and receiving data from channels. Sending data to PCB requires pulling the CS pin low for the whole communication period and sending one or more bytes of data via the next clock ticks. While reading data from registers, PCB will send back data after proper command RREG <register address> on the next 16 clock ticks. Data conversion should be stopped before working with registers.

SPI communication while getting channel data is different. PCB has pin DRDY, which is pulled low when data is ready for transmission. After that, if the device is in continuous reading data mode, channel data will be sent back on the next 216 SCLK ticks. The data packet consists of 27 bytes, the first three bytes are the status of data, next eight series of three bytes are data from every channel. All timings can be found in the datasheet [1].

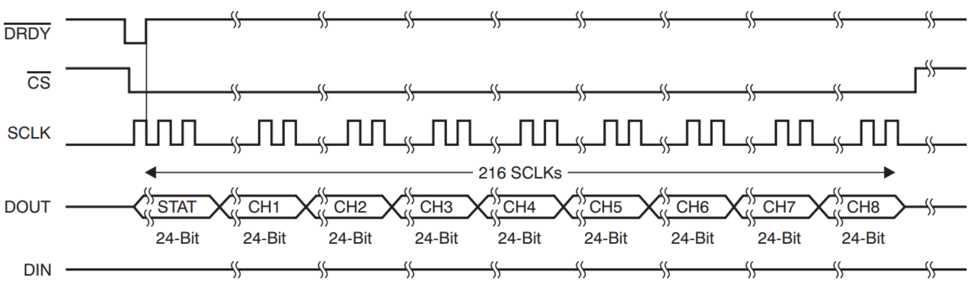

FIGURE 4.2: SPI Bus Data Output [1]

Board Configuration

Besides providing a power supply to the board, and connecting all pins and electrodes, ADS1299 also requires configuring clock output, waiting for oscillator start-up, and setting internal or external voltage reference as shown in Fig. 4.3. After that configuring internal settings via writing necessary parameters into configuration registers is required. ADS1299 has 4 configuration registers, 8 registers for setting PGA and mode parameters for every channel, and registers for configuring bias and lead-off for every channel.

The system uses an internal 2.048-MHz clock from ADS1299. A dedicated bias electrode is used, but there is an option to use internal bias via setting bias as an average between selected channels' voltage. Also, the dedicated reference electrode is used. In order to get a minimum input-referred noise configuration of 250 samples per second and 24x gain for programmable amplifiers was chosen.

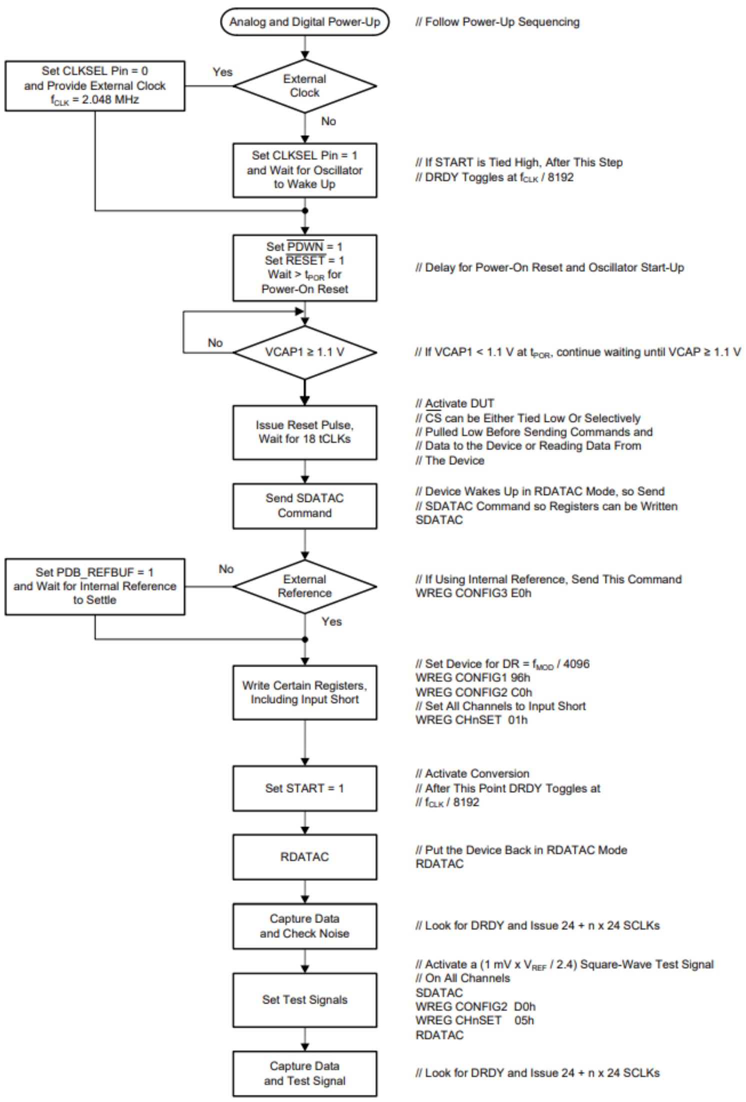

FIGURE 4.3: Initial Flow at Power-Up [1]

Signal Conversion

After performing the initial configuration, the main loop for the system performs reading data out of the board and transmitting it via UART. The function that keeps running consistently starts from checking the DRDY pin status, when it is pulled low, SPI communication starts immediately. After sending dummy bytes, receiving all channel data, and confirming successful data transfer, the data is sent over UART to the connected PC, where it will be processed. After that communication period is finished and MCU starts again by polling the DRDY pin.

4.2.2 Signal Processing

All the data sent via UART is saved into a file and gets ready for further filtering and processing with neural networks, that will recognize words, said during the recording.

Chapter 5

Methodology

5.1 Dataset Overview

To prove the system feasibility it was necessary to record the own dataset which will be used for the experiment.

Our Ukrainian word pool consists of four words that either have or do not have some emotional inflection:

- "перемога"(victory) - emotionally positive word
- "поразка"(defeat) - emotionally negative word
- "таємниця"(mystery) - neither positive nor negative, but still emotional word
- "слово"(word) - fully neutral word

Emotional words were chosen as parts of the vocabulary for dataset because they are more likely to be recognized by the system.

5.1.1 Data Recording

The data is recorded by putting electrodes on the person's scalp surface and running code programmed into MCU. Since we have only 8 electrodes, we had to choose the most necessary ones, that will match our cap holes, which are F_{pz}, F_z, P_z, O_z, F_3, F_4, P_3, P_4. The dataset consists of 20 samples of each word and additional 20 samples without any word being concentrated on. Every sample lasts 5 seconds, the word is imaginably spoken 3 times during one sample. After a person put a headset on, a Python script is launched, that starts recording data from MCU into a file and simultaneously showing the word in the console every time it should be imagined.

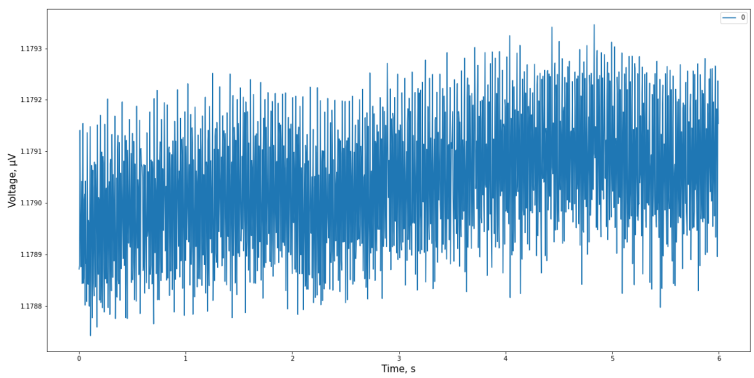

FIGURE 5.1: Raw EEG signal from one channel

5.1.2 Pre-processing

After saving data into the file, it should be filtered properly. Firstly, all artifacts that stay out of the common-mode range are corrected to the average value between two adjacent values. After that band-pass filter ranging from 0.5 Hz to 30 Hz is applied in order to fully get rid of any high-frequency noise caused by devices and mobile or wireless internet networks.

Also, before performing any further signal processing, we provide ground truth data for every sample with a word that represents one that was imagined during recording the sample and then use this data for training our model and testing it.

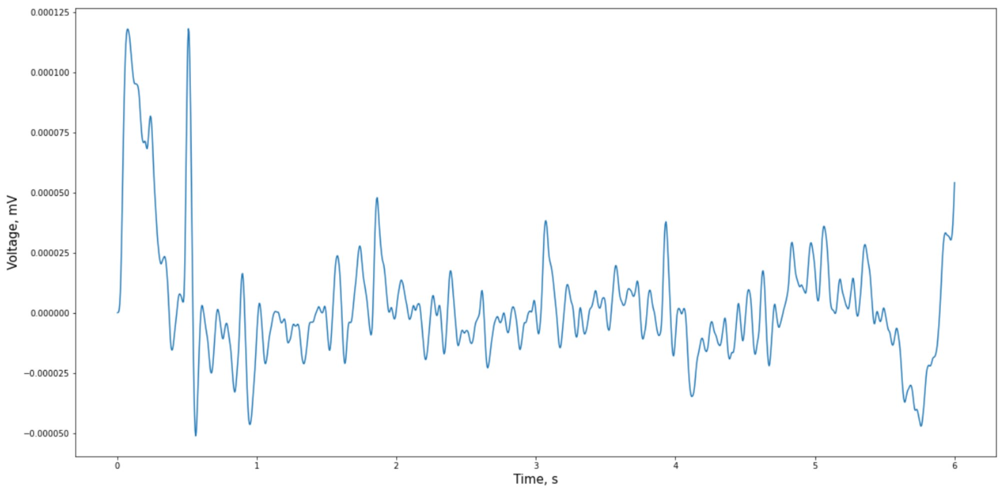

FIGURE 5.2: Filtered EEG signal from one channel

5.1.3 Words distinguishing

Our neural network will recognize words by extracting common features in its signal, that is different for each word. Here is an example of how recorded words look in form of an EEG signal taken from P_4 electrode, placed on the right part of the occipital lobe.

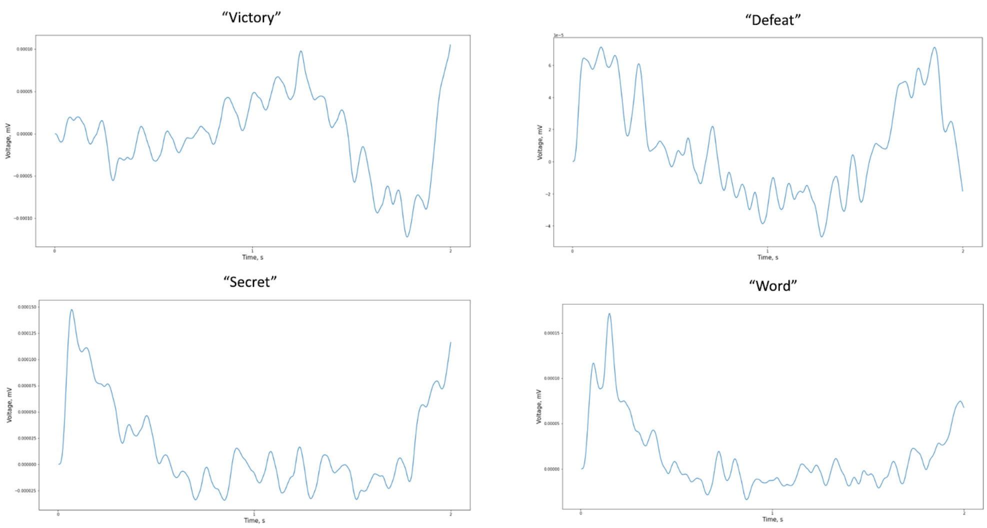

FIGURE 5.3: Signals recorded during different words being spoken

5.2 Metrics

In order to continuously improve results of our system, we need to choose the proper metric that will be applied to results so that classification could be as precise as possible. Since we have a classification problem to solve and our dataset is balanced, it will be the right decision to use the accuracy metric.

5.3 Architecture

As shown in the chapter 2, one of the best solutions for our task is the model architecture named 1DCNN-LSTM [14]. We will implement it in order to train it on our dataset and use it for predicting imagined words.

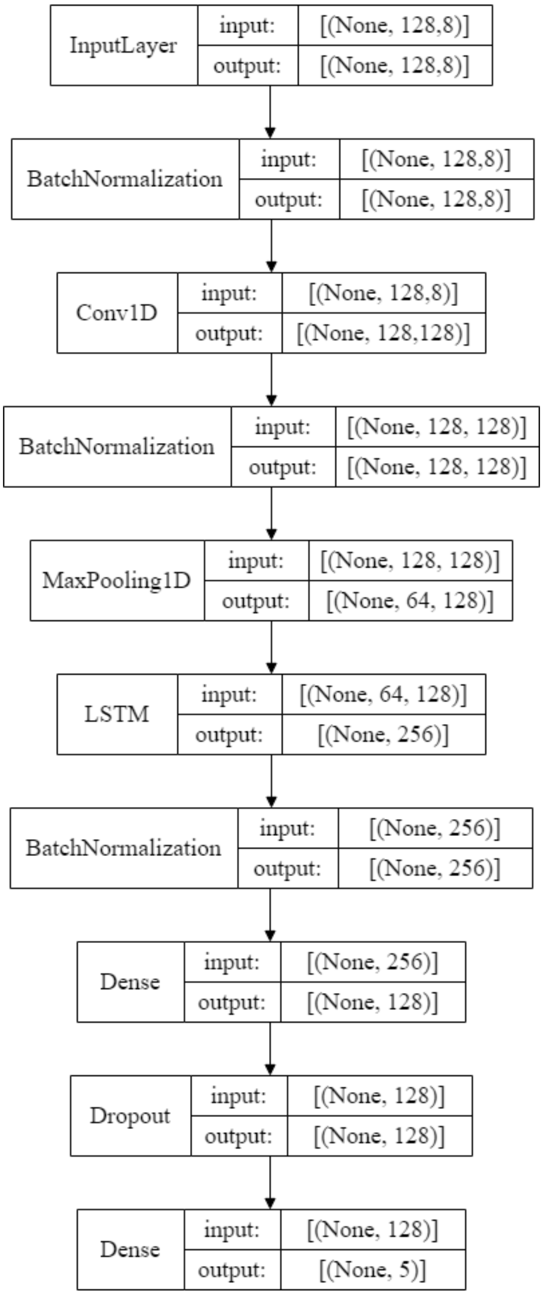

FIGURE 5.4: 1DCNN-LSTM model architecture

The model architecture is shown in Fig. 5.4. The input is the matrix 128x8, where 8 is the number of channels and 128 is the time window, which is half a second that is enough to process one imagined word at once. After that data is forwarded to the 1DCNN layer with 128 filters of size 10 with a stride of 1 and the ReLU activation function which detects features in our data. In the next step, we perform max-pooling by 2. Subsequently, we fed features to the LSTM block of 256 units. The next layer is a dense layer of 128 neurons activated by the ReLU function. After performing a dropout of 50% to prevent overfitting, the final layer is another dense layer with 5 neurons that are activated by the softmax function and make output, which corresponds to 4 words and no word being imagined.

The test set is 20% of the whole dataset, being chosen at random, while another part is used for training. Also, early stopping is applied with monitoring the validation accuracy so that the model wouldn't overfit.

5.4 Results

After recording, pre-processing, and filtering our dataset, after implementing our 1DCNN-LSTM model, testing it, and tuning its parameters so that we could get the highest possible accuracy we finally managed to get fine results of predicting imagined words in samples which is equal to 81.14%. This result is a bit lower than the accuracy values in the chapter 2, but considering the fact, that our system has only 8 channels, we achieved the best result with such configuration, channel number, and non-laboratory equipment.

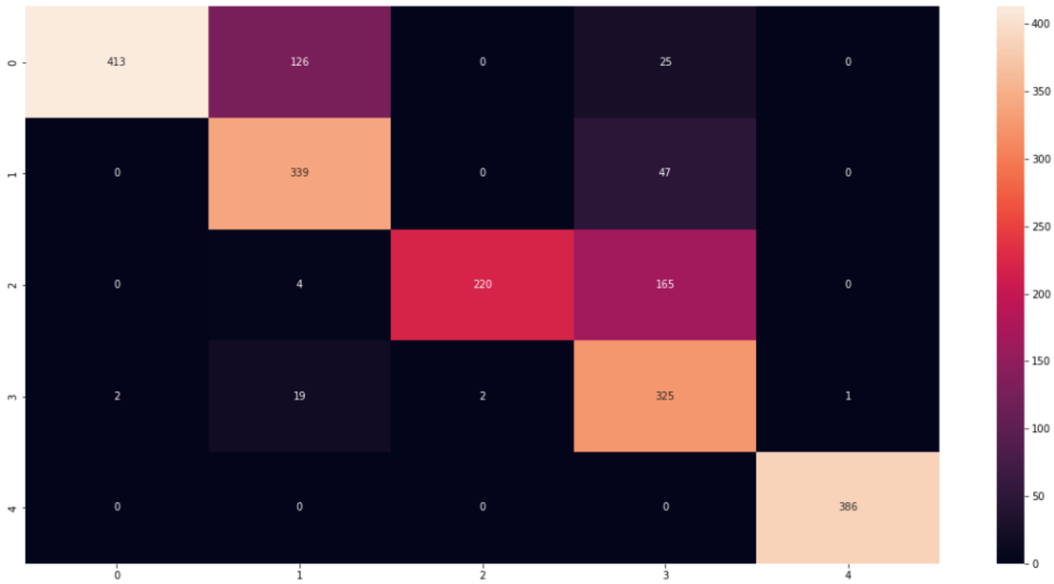

FIGURE 5.5: Confusion matrix(0-4 represent words "victory","defeat", "secret", "word" and no word in that order)

Chapter 6

Conclusion

6.1 Summary

As a result of this thesis, the first-ever EEG-based system for recognizing Ukrainian envisioned speech was created. All the goals that were set in chapter 1 were met. The system is complete, all hardware components were configured and used for creating own balanced dataset with EEG recordings, software was tested and the system produces correct results while still being very affordable. The best model for the task was chosen from analyzed related articles, implemented, trained, and successfully recognizes Ukrainian words with good accuracy of 81.14%.

6.2 Future work

However, the system is working correctly there is still a lot of space for further improvement which is necessary. One way is increasing model accuracy. It can be achieved by enlarging the dataset with EEG recordings of a lot of people of different ages and sex. Also, since MCU used in the system supports Bluetooth Low-Energy, it is planned to add Bluetooth communication support and develop a Bluetooth app to make the system more mobile. One of the main and most necessary improvements is to enlarge the used words dictionary in order to come closer to the final goal, to develop an ideal system that will be able to recognize most Ukrainian words and give a great possibility for disabled people to talk as easy as all other people do and feel like full-fledged members of the community.

Bibliography

[1] *ADS1299-x Low-Noise, 4-, 6-, 8-Channel, 24-Bit, Analog-to-Digital Converter for EEG and Biopotential Measurements*. 2017. URL: https://www.ti.com/lit/gpn/ads1299.

[2] *ADS1299EEG-FE EEG front-end performance demonstration kit (rev. B)*. 2016. URL: https://www.ti.com/lit/ug/slau443b/slau443b.pdf.

[3] Andrea Apicella et al. "EEG-based detection of emotional valence towards a reproducible measurement of emotions". In: *Scientific Reports* 11.1 (2021). DOI: 10.1038/s41598-021-00812-7.

[4] Shelly Chadha, Kaloyan Kamenov, and Alarcos Cieza. "The world report on hearing, 2021". In: *Bulletin of the World Health Organization* 99 (Apr. 2021), 242–242A. DOI: 10.2471/BLT.21.285643.

[5] Loay George and Hend Hadi. "User identification and verification from a pair of simultaneous EEG channels using transform based features". In: *International Journal of Interactive Multimedia and Artificial Intelligence* 5.5 (2019), p. 54. DOI: 10.9781/ijimai.2018.12.008.

[6] Lei Jiang et al. "Emotion recognition using electroencephalography signals of older people for reminiscence therapy". In: *Frontiers in Physiology* 12 (2022). DOI: 10.3389/fphys.2021.823013.

[7] Gautam Krishna et al. *Speech Recognition using EEG signals recorded using dry electrodes*. 2020. DOI: 10.48550/ARXIV.2008.07621. URL: https://arxiv.org/abs/2008.07621.

[8] Gautam Krishna et al. *State-of-the-art Speech Recognition using EEG and Towards Decoding of Speech Spectrum From EEG*. 2019. DOI: 10.48550/ARXIV.1908.05743. URL: https://arxiv.org/abs/1908.05743.

[9] Anne Porbadnigk et al. "EEG-based Speech Recognition - Impact of Temporal Effects." In: Jan. 2009, pp. 376–381.

[10] Kamalakkannan Ravi et al. "Imagined Speech Classification using EEG". In: *Advances in Biomedical Science and Engineering* 1 (Dec. 2014), pp. 20–32.

[11] Saeid Sanei and JonathonChambers. *EEG signal processing*. John Wiley amp; Sons, 2011.

[12] Luis Carlos Sarmiento et al. "Recognition of EEG signals from imagined vowels using deep learning methods". In: *Sensors* 21.19 (2021), p. 6503. DOI: 10.3390/s21196503.

[13] Michal Teplan. "Fundamental of EEG Measurement". In: *MEASUREMENT SCIENCE REVIEW* 2 (Jan. 2002).

[14] Ayush Tripathi. *Analysis of EEG frequency bands for Envisioned Speech Recognition*. 2022. DOI: 10.48550/ARXIV.2203.15250. URL: https://arxiv.org/abs/2203.15250.

[15] Laurent Uldry and Jose del R. Millan. "Feature Selection Methods on Distributed Linear Inverse Solutions for a Non-Invasive Brain-Machine Interface". In: (Jan. 2007).

[16] YiYan Wang, P. Wang, and Yuguo Yu. "Decoding English Alphabet Letters Using EEG Phase Information". In: *Frontiers in Neuroscience* 12 (Feb. 2018). DOI: 10.3389/fnins.2018.00062.