Towards real-world brain-computer interface: The BASIL project

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Abstract

Affordable brain-computer interfaces (BCIs) working outside the laboratory environment are still rare. Their most limiting factors include low classification accuracy, information transfer bit rate, low variability of used approaches, and closeness of the hardware and software components of the system. The presented BASIL project has focused on designing, developing, and testing an affordable BCI system built on low-cost hardware and open-source software components. It provides people with motor impairments with an opportunity to control their basic home environment.

The concept of the BASIL prototype follows the best practices that are known within the construction of BCI systems, adds the concept of the cloud for remote BCI computations, relies on testing and customization of the whole system to the needs of individuals, and focuses on the solution affordable for ordinary users. The core components of the BASIL project solution include hardware components for signal acquisition and software components for local execution of online BCIs.

The BASIL system was tested on ten participants in laboratory conditions using various BCI paradigms. We failed to evoke a reliable P300 component with eight-trial averages. Eyes blinks, alpha activity, and steady-state visually

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evoked potentials were clearly observable. Dry electrodes with long pins were preferred by most users. Out of ten participants, six could control the system online, achieving more than 70 % accuracy.

The results show that a successful BCI system can be built on low-cost hardware for EEG signal acquisition and amplification. The benefits and weaknesses of known BCI paradigms for such a system have been identified. The current solution, the affordable BASIL BCI system prototype, is prepared for further community development and testing.

Keywords: BASIL, brain-computer interface, event-related potentials, P300 component, steady-state visual evoked potentials

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1. Introduction

Although research on brain-computer interfaces (BCIs) has been growing for decades, independent, open and affordable BCI systems working outside the laboratory are still rare. A few problems with state-of-the-art BCIs prevent them from becoming widespread. First, low classification accuracy and information transfer bit rate usually make the BCI system less convenient than other comparable communication solutions for people with motor impairments, such as eye-tracking or voice recognition. However, other means of communication may not be possible for locked-in patients. Another problem is that most electroencephalography (EEG) devices are costly using proprietary software solutions. Therefore, individual BCI systems for hospital settings and home care users have not been viable options.

The main goal of the Czech-Bavarian Brainwave-driven assistance system for people with motor impairments (BASIL) project has been to develop an affordable BCI system based on standard low-cost hardware components while applying state-of-the-art classification techniques and signal processing algorithms for successful BCI operation. An essential part of the project has been testing various BCI paradigms on possible end-users in both the laboratory and hospital settings in the Czech Republic.

The paper is organized in the following way. This section introduces BCI systems from the conceptual and technical points of view. Some well-known state-of-the-art BCI systems are referenced. Then BCI pipelines (workflows) and possible use of cloud environments are described. The Methods part deals with the central concept of the BASIL prototype, requirements specification, architecture, BASIL hardware components (electrodes, head-mounted device, base station), experimental design/protocols, testing and description of a workflow designer. The Results part evaluates preliminary experiments, subsequent design decisions, used BCI paradigms/approaches and more detailed experimental results. The Discussion section summarizes the current state of the BASIL prototype and important design and technical decisions.

1.1. Brain Computer Interface systems

In the first international meeting on BCI technology, which took place in 1999 at the Rensselaerville Institute of Albany (New York), Jonathan R. Wolpaw formalized the definition of the BCI system [1]:

> A brain-computer interface (BCI) is a communication or control system in which the user's messages or commands do not depend on the brain's normal output channels. The message is not carried by nerves and muscles, and neuromuscular activity is not needed to produce the activity that does carry the message.

Any BCI has an input (e.g., electrophysiological activity from the user), output (i.e., device commands), components that translate input into output, and a protocol that determines the operations. The EEG signal is acquired by electrodes located on the scalp and processed to extract specific signal features (e.g., amplitudes of event-related potentials) that reflect the user's decision. These features are translated into commands that operate a device (e.g., a simple word processing program). The user must develop and maintain a good correlation between his or her intent and the signal features employed by the BCI, and the BCI must select and extract features that the user can control and translate those features into device commands correctly and efficiently. [2]

All BCI systems currently face some challenges that prevent them from being accepted by most of the population. Typically, the most limiting factor is their classification accuracy and even more low transfer bit rate, especially when compared with other means of communication available to healthy people. However, different BCI paradigms exhibit different bit rates and training times needed before any particular BCI system can be used successfully. [3]

BCI systems are designed and developed at many workplaces around the world. However, there are still many more BCI models than real-world BCI systems that have been extensively tested and deployed outside the laboratory.

Existing BCI systems usually rely on detecting the P300 component or Visual Evoked Potentials (VEP). An improved P300 pattern was used to catch the user's attention within a BCI system with a promising result [4]. A contribution of a broad learning system to increase the classification accuracy of VEP-Based BCI systems has been advocated in [5].

BCI paradigms, EEG signal processing and classification methods are the core parts of any BCI system. A 10-year update of a review of classification algorithms for EEG-based brain-computer interfaces is given in [6]. One of the interesting outcomes is that deep learning methods have not yet shown convincing improvement over state-of-the-art BCI methods. Current BCI paradigms, signal processing and feature extraction methods, different combined modes of hybrids BCIs, and design of the synchronous/asynchronous BCIs are reviewed in [7].

Although BCI systems and their components are still considered a research topic, the BCI systems market dominated by the non-invasive BCI segment exists and is expected to grow in the following years. Currently, the popular ones are also wireless BCI systems; they rely on the wireless transmission of the brain signal and can provide more comfort to end-users. Some of the BCI systems offered at the market are shortly presented.

A complete BCI research system that uses EEG and ECoG (Electrocorticography) signals and supports all common BCI paradigms/approaches (P300, SSVEP/SSSEP, Motor Imagery, cVEP slow waves) is promoted by g.tec [8].

g.tec's BCI environment provides complete MATLAB-based research and development systems, including all hardware and software components needed for data acquisition, real-time and offline data analysis, data classification, and neurofeedback [8]. BCI systems utilizing the P300 component and Steady-State Visual Evoked Potentials (SSVEPs) paradigms are developed by the BrainTech company [9]. They are supported by hardware devices such as wireless EEG headsets or SSVEP blinkers. A framework of various hardware and software components for BCI is developed and promoted by the BrainProducts company [10]. They offer, e.g., BCI+ electrodes and caps, various amplifiers, and software tools, e.g., BCILAB — a MATLAB toolbox and EEGLAB plugin for the design, prototyping, and testing of BCIs. The EMOTIV company offers brain-computer interface devices that can be paired with its brain-computer interface software EmotivBCI [11]. It can further cooperate with the open-source platform Node-RED (described later), which interfaces BCI outputs to many compatible external hardware devices. The Advanced Brain Monitoring company offers Wireless EEG Headsets (and related software) equipped with an accelerometer to quantify head movement and positions and automated wireless impedance checks [12] that seem to be suitable for BCI applications.

Since this paper focuses on an affordable BCI system, we also introduce some low-cost BCI platforms and systems. Performance assessment of a custom, portable, and low-cost BCI platform is described in [13]. The authors claim that the performance of their platform is comparable to that of conventional BCIs and is suitable for BCI applications outside of a laboratory. A low-cost real-time BCI system for automated door opening system is introduced in [14] using low-cost hardware/software components, modular and flexible configuration features and Bluetooth-enabled real-time data processing units. A low-cost, BCI virtual reality prototype of game control development environment for game-based neurorehabilitation is presented in [15]. A feasibility study of a complete low-cost consumer-grade brain-computer interface system is provided in [16]. The authors argue that an entirely low-cost motor imagery BCIs can be built if communication stability and artifact rejection are improved.

1.2. BCI pipelines and cloud computing

Once input EEG data are collected, they must be processed to deliver an applicable BCI output. Apart from setting up the environment for BCI deployment, quick prototyping of algorithms that can be expressed as a chain of signal processing and machine learning methods needs to be designed. Therefore, at least for the experimental phase, any workflow designer is helpful to evaluate various classification algorithms. Some approaches that aim at designing such workflows are presented with their advantages and disadvantages.

NeuroPype [17] is a Python-based programming application for neural data processing that can be accessed locally or on the cloud. It is released under proprietary licenses. Pipeline Designer [17] is an open-source (the GPL license is applied) visual application for designing workflows using a drag-and-drop interface. Both tools require installing a windows client, so they are not entirely online solutions. However, to the authors' best knowledge, this is the only widely available cloud workflow designer containing methods explicitly intended for BCI development.

Orange [18] is an open-source machine learning and data visualization tool. Since Pipeline Designer [17] is based on Orange, both projects share the same graphical user interface for drag-and-drop adding and editing processing blocks. The main difference is that Orange does not contain any library for neural data processing. Instead, many general methods useful in data science are supported, such as database access, clustering, classification, statistical evaluation, and advanced plotting. The system is also extensible using Python classes.

The Snakemake workflow management system [19] is a tool to provide reproducible and scalable data processing. Workflows are described using a Python-based language that resembles makefiles. They can be easily scaled to server, cluster, grid, and cloud environments without modifying the workflow definition. Moreover, Snakemake workflows can entail a description of the required software, which is automatically deployed to any execution environment. However, designing workflows in Snakemake is not straightforward as it requires basic programming knowledge.

Node-RED [20] is a programming tool and web-based editor for creating workflows that allow connecting hardware devices, APIs and online services. It is widely used for Internet of Things (IoT) applications.

One of the challenges BCI systems face is their ability to train and classify the EEG signal in real-time. Then a popular concept and successful technical solutions based on a cloud environment can be helpful. It is even more relevant for the training phase (especially when utilizing neural networks) because it is a time-consuming task requiring high-performance computers. Currently, remote servers with adequate performance with available resources are available on demand.

2. Methods

2.1. Concept of BASIL prototype

The concept of the BASIL prototype follows the best practices that are known within the construction of BCI systems, adds the concept of the cloud for remote BCI computations, uses various BCI approaches/paradigms, relies on testing and customization of the whole system to the needs of individuals, and focuses on the solution affordable for ordinary users.

The core components of the BASIL project solution include hardware components for signal acquisition and software components for local execution of online BCIs.

2.2. Requirements specification

The main BCI system requirements are the following ones. The system is developed to capture the brain waves on the scalp and convert them into a usable form. The system can detect the user's intention from the brain waves when various selection options represent the user's intention. The solutions developed for the BASIL project are designed according to the following key aspects that at least partly distinguish the BASIL system from other commercial BCI systems. The essential requirements on the BASIL prototype are as follows:

- **Easy to use**: To support caregivers of impaired people, the effort involved in installing and using the system is low.
- **Comfortable to wear**: Since the system is intended for daily use, it is comfortable for the user.
- **Affordable for ordinary users**: The system prototype is developed utilizing standard hardware components and open-source software tools.

2.3. Architecture

Based on these requirements and key aspects, the BASIL system architecture was designed (Figure 1). Its main components are a head-mounted device (HMD) connected to electrodes, a base station (BS), a BCI application, and a remote repository (cloud).

First, dry electrodes are connected with cables to the head-mounted device that digitizes the analogue signals. These two components are placed on the user's head and connected to the base station via a Bluetooth Low Energy (BLE) protocol to provide more comfort to the user. The base station runs on a common low-cost hardware component – Raspberry Pi (Raspberry Pi 1 in Figure 1).

An extra circuit board is connected to the base station as a counterpart of the BLE connection. A plugin module with the same BLE-capable microcontroller (as it is in the head-mounted device) was developed. This solution provides an opportunity for more flexible radio communication than Raspberry's internal BLE interface.

The base station receives the EEG signal for further processing and makes it available for the BCI application evaluating EEG data. The data are transmitted via the Lab Streaming Layer (LSL) protocol; data processing takes place on the Raspberry Pi 1 or any other computer in the network. Complex computing and persistent data storage are provided in the cloud. The stimulation protocol runs on another common hardware component (Raspberry Pi 2 in Figure 1) connected to Raspberry 1 using LSL to ensure time synchronization if it

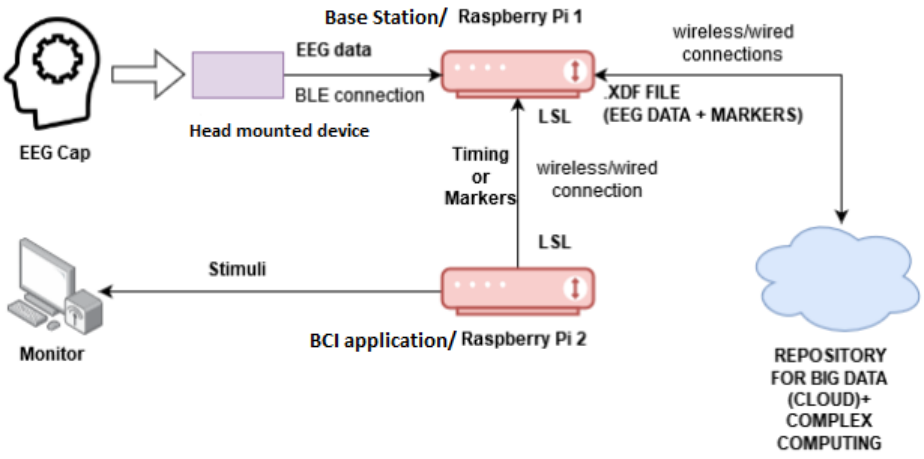

Figure 1: BASIL system architecture. Its main components are a head-mounted device connected with electrodes for EEG data capturing, base station for EEG data receiving, synchronizing with event (stimuli) markers, and processing (all running on Raspberry Pi 1), BCI application implementing the stimulation protocol (running on Raspberry Pi 2), and remote repository (cloud) for long-term data preserving and complex computing.

is necessary (e.g., for the P300-based experiments).

2.4. Hardware components for data acquisition

EEG-related hardware is a crucial system component to realize a reliable, comfortable, affordable, and easy to use BCI system. Besides these goals, for any BCI application, it is essential to obtain high-quality recordings of the brain signal. The resulting hardware components (electrodes, head-mounted device, and the base station) represent some compromise among these requirements; dry electrodes together with a device digitizing analogue signals and sending them over Bluetooth Low Energy (BLE) protocol from the head-mounted device to the base station were designed and developed.

The detailed overview of the BASIL hardware components is shown in Figure 2. The head-mounted device and the internal signal flow from the electrodes to the BLE connection can be seen on the blue background. In the green middle part, there is the base station with the BLE counterpart processing all the data and sending them over LSL to the BCI application (the orange background).

The following parts describe the main BASIL hardware components: electrodes, head-mounted device, and base station.

2.4.1. EEG electrodes

Setting up traditional gel-based electrodes is a time-consuming task; their removal is not comfortable, and depending on individuals, they cause skin irritation. As a result, they were not considered to be an appropriate solution for our BCI system. Theoretically, capacitive electrodes are the best types of electrodes for a BCI system. The attempts to use them for BCIs are described, e.g. in [21]. However, their development proved to be too demanding and risky within the BASIL project.

Another electrode solution is based on using metal pins. Dry electrodes overcome most of the troubles caused by gel-based electrodes, but they have poorer impedance when compared to gel-based electrodes. Another concern is their typical design. Rigid metal pins cause discomfort or even pain in some individuals. Besides, only a few pins likely touch the scalp with rigid contacts. Besides dry electrodes with rigid metal pins, there are investigations for electrodes made from conductive polymer [22] or flexible metal-coated polymer bristles [23]. Water-based electrodes were introduced in [24] and porous ceramic-based semi-dry electrodes in [25]. Although promising results with testing such electrodes are reported in these papers, we do not have any prior experience with them.

We coped with the presented problems and challenges in the design phase to keep the signal-to-noise ratio high and ensure high comfort for both users and healthcare providers. We decided to design and develop dry electrodes as a possible compromise considering a suitable material structure and electrode shape. As a result, we designed individually spring-loaded pins as contacts with an active amplifier to improve the signal quality. The electrodes consist of a printed circuit board (PCB) with an amplifier and spring-loaded gold-coated pins (Figure 3). The contacts are arranged in a circle, assuming that the head is spherically formed. Each pin has about the same distance from the PCB

to the scalp and touches the scalp directly and equally. Since the pressure is distributed over the pins, the user's comfort is higher. Besides the pins, an amplifier is placed as close as possible to minimize the noise coupled in. The electrodes have four connections: the 5V power supply, the output signal, and the shielding.

2.4.2. Head-mounted device

The head-mounted device (HMD) (Figure 4) has been designed and implemented to record the analogue voltages of up to 8 electrodes with up to 250 samples per second. Since HMD is a mobile battery-powered device, low power consumption is essential; signals are forwarded over the BLE protocol. HMD digitizes the amplified signals from up to 8 electrodes using an ADS1299 analogue front-end from Texas Instruments and sends them over BLE using a microcontroller.

The ADS1299 front-end has appeared to be the most suitable analogue to digital converter for our BCI project since developing the EEG front-end from discrete components would be more complex and expensive. A CC2640 microcontroller handling the BLE connection was used since it requires little energy and offers all the necessary interfaces.

2.4.3. Base station

The signals are sent from the head-mounted device to the base station for further evaluation. The base station is the Raspberry Pi computer equipped with an extra PCB containing the same microcontroller as the HMD to ensure the best possible BLE communication. It was equipped with the Google Coral USB Accelerator for testing machine learning algorithms. A web-based user interface was deployed on the base station (Figure 5). Using it, all necessary settings for the base station (e.g., network settings), HMD (e.g., sample rate or signal amplification), and communication between these two devices can be easily changed.

2.5. BCI system design and evaluation

Several BCI paradigms are potentially suitable for the online BCI system based on the recording device presented. Both the P300 component and steady-state visually evoked potential (SSVEP) paradigms have certain advantages because they require little to no training [26], and can easily fit the purpose of controlling the home environment utilizing corresponding stimulation.

To evaluate our design decisions, we conducted a series of preliminary experiments. Based on their results, we decided on the future development of the BASIL prototype.

2.5.1. Experimental design - stimulation protocols

As indicated above, two basic experimental protocols were designed and implemented within the BASIL project. The first one was based on detecting the P300 component, while the second one used SSVEPs. In both cases, visual representation of the user's basic needs/activities (for example, opening a door, expressing that they are hungry, or that they need some help) was used. These visual representations (pictures) can be easily changed (by defining other images representing various people's needs/activities). PsychoPy was selected as a suitable open-source tool for designing experimental protocols and running the visual stimulation itself. This Python code-driven tool works well on the Raspberry Pi computer used for the stimulation. A standard 24-inch LCD monitor with a typical response time of 8 ms (grey to grey) was used in all cases.

In the case of the P300 based experiment, the pictures corresponding to the user's needs/activities were presented sequentially or in a matrix (Figure 6). In both cases, the user focused on one stimulus selected from the presented set of stimuli. In the case of sequential presentation of stimuli, the user focused/not focused just on one picture appearing on the screen. When using the matrix, the row or column containing the selected symbol was highlighted. In all cases, stimuli or highlighted rows and columns appeared randomly. The inter-stimulus interval was 1.5 s (1.2 s of stimulation, 0.3 s of rest). The channels Fz, Cz and Pz were used to record and evaluate the EEG signal.

In the case of the SSVEP experiment, three pictures corresponding to the user's needs/activities were selected (turn on the radio, turn on the light, and make a phone call, see Figure 7) and flashed with the frequencies of 10, 12 and 15 Hz in line with common recommendations [27]. The goal was to allow each participant to freely choose one of the activities for each trial. Each run consisted of six 20s long trials of stimulation followed by 10s long period rest. Between runs, there were two other minutes to rest. The O1, O2, P3, and P4 channels were used to record and evaluate the EEG signal.

2.6. Classification of SSVEP data

SSVEP data were received from the base station over LSL and evaluated online for spectral peaks that would indicate the object the user focused on. Figure 8 shows the application. The algorithm applied required no training; instead, classification was based on two weighted components:

- Canonical correlation analysis (CCA) has been frequently used for SSVEP BCIs [28]. The CCA applied followed the code publicly available [29]. The algorithm was based on the following procedure:
  1. Generate a vector of sinusoidal reference templates for all SSVEP flicker frequencies. The template was generated for the first and second harmonics.
  2. These templates were concatenated into one matrix.
  3. Canonical correlation analysis was performed with one component to keep. EEG signal was compared with predefined frequency templates.
  4. Maximum correlation coefficients for each flicker frequency were stored into the feature vector.
  5. The feature vector was normalized.
- Spectral difference. Because the SSVEPs are observable in the frequency spectrum, spectral analysis can be applied [27]. In the neighbourhood of each frequency (10 Hz, 12 Hz, 15 Hz), the spectral difference was calculated

by dividing signal energy in close proximity of the frequency (+− δ_1 Hz) by signal energy in a broader neighbourhood (+− $(\delta_1 + \delta_2)$ Hz excluding the close proximity). Figure 9 explains the method. The feature factor was normalized.

Finally, feature vectors from both methods were averaged. The maximum average feature vector component indicated the output classification class.

2.6.1. Testing of BASIL system

Various experiments were performed to assess EEG signal quality when evaluating the presented BASIL BCI system. The process of finding optimal conditions included experiments both in and outside the laboratory (in two Czech hospitals), with various types of electrodes (gel-based electrodes, dry electrodes with short pins, dry electrodes with long pins) and multiple tasks (eye blinks, eyes open/closed, stimulation with flashing pictures/SSVEP frequencies, stimulation with images to detect the P300 component). A standard router was used to simulate the home infrastructure. The sampling frequency of the EEG signal was 250 Hz.

Since only the experiments performed in the laboratory conditions used all the components designed and developed within the BASIL project, their outcomes are provided in the Results section.

2.7. Workflow designer

Existing workflow solutions do not provide sufficient user interactivity or are too complicated to be easily used with existing methods in BCI systems. As a solution, a part of the BASIL infrastructure is a dynamic workflow designer [30] that allows users to visually create specific workflows using a drag-and-drop approach in a web-based toolkit. This web toolkit allows creating workflows driven by existing signal processing methods and providing particular annotations that serve as metadata defining inputs, outputs, and parameters. A part of the Workflow designer is a language defined in the JSON format that allows

the user to store the workflow once it is designed and run it out of the workflow designer tool later on any computer or even on microcomputers such as Raspberry Pi. [30]

Although the Workflow designer provides general support for data processing methods, we mainly focused on BCI data and BCI processing methods. Typical workflows used for BCI data evaluation and pre-processing rely on extracting ERPs (event-related potentials) from ongoing EEG while minimizing noise. The standard procedure is based on extracting parts of EEG related to stimuli (epoch extraction) and filtering ERP epochs. Another optional but typical step is averaging to amplify non-random ERPs and suppress ongoing EEG activity. Finally, either EEG plotting or machine learning follows [31].

In the context of the Workflow designer, it is required to have a good variety of methods from several categories, including data reading, pre-processing, feature extraction, classification and visualization. Approximately twenty methods have been annotated and imported into the Workflow designer to verify the concept. Most methods transform an EEG input into an EEG output based on required or optional parameters. In most cases, the EEG data flowing through the workflow can be represented as 2D arrays of doubles.

An example workflow for training BCI classifiers is shown in Figure 10. In this workflow, the channels suitable for further processing were first extracted. Subsequently, band-pass-filtering was applied. Then, wavelet features were selected from (extracted and baseline corrected) EEG epochs. Finally, a simple two-layer neural network was used for classification.

3. Results

This section provides the results we achieved during testing the BASIL system in laboratory conditions (gel-based and dry electrodes with shorter/longer pins were used alternatively to make comparisons). Although some parts of the system were also tested in hospitals, only the testing results of the entire BASIL system are provided.

3.1. Evaluation of preliminary experiments

During initial testing, the BASIL system was performed on ten participants (all males between 21 and 55 years), and we observed the following results:

- In any settings, we failed to evoke an observable P300 waveform with eight-trial averages using the presented EEG device. It can be explained by the generally low P300 amplitude and relatively low signal-to-noise ratio of the device.
- Both eyes blinks and alpha activity were clearly observable, especially with gel-based and dry electrodes with longer pins.
- SSVEPs were clearly observable, independent of frequency (frequencies between 8.5 Hz and 20 Hz were evaluated).

3.2. Design decision

The following observations were considered for optimal BCI design:

- Because data quality is highly dependent on electrode attachment, environmental noise and other factors, it was challenging to collect representative and practical training datasets.
- The P300 was less reliably observed, especially given its low amplitudes and high inter-subject variability.

As an alternative to P300 BCIs, steady-state visually evoked potentials (SSVEP) were chosen as preferable ones because they were easier to detect and stable across participants. Moreover, time-consuming training could be avoided. The experimenting with SSVEPs is described further.

3.3. Participants in SSVEP experiment

Ten subjects participated in the SSVEP experiment, all males aged 21 to 55 years. All of them were right-handed and had normal or corrected-to-normal vision. They were asked about epilepsy which would exclude them from the study. All of them were informed about the course of the experiment and signed informed consent.

3.4. SSVEP online results

For each tested participant, predictions of the classifier (phone, lamp, radio) were collected. Moreover, during the online session, the participant selected the object he/she focused on to receive ground truths for the evaluation. Classification accuracy for both methods and overall results were computed. The results are shown in Table 1. Six participants achieved more than 75 % accuracy in controlling this online BCI. For those high-performing subjects, a combination of spectral difference (SD) and the CCA method brought better results than using any of them alone.

Table 1: The results achieved for SSVEP online detection for each participant are depicted. More than half of the participants were able to control the BCI with a relatively low error rate. SD — spectral difference method, CCA — CCA-based method.

		Accuracy (%)		
Subject ID	Number of trials	SD	CCA	Combination
1	53	35.9	49.1	45.3
2	35	68.6	74.3	80
3	60	61.7	73.3	78.3
4	60	58.3	35	45
5	60	78.3	78.3	88.3
6	60	80	95	96.7
7	60	36.7	46.7	50
8	60	78.3	73.3	85
9	60	38.3	40	38.3
10	60	86.7	78.3	88.3
Summary	568	62.3	64.1	69.4

4. Discussion

The BASIL system has been developed to come with an easy to use and comfortable to wear BCI solution composed of reasonable price components

and affordable for ordinary users (of course, when research, development and testing costs are not calculated). While the third goal was successfully fulfilled by using low price hardware components and open-source software libraries and tools, ease of use and participants' comfort have to be discussed more.

The users of the BASIL system needs assistance that includes mainly the initial system setup (decisions related to a suitable stimulation protocol, the layout of system components in space, the definition of user needs/activities and selection of a suitable representation of these needs/activities with images), placement of electrodes, and system control and assistance when some troubles with the system happen. The system's initial setup is done once and then repeated when the user needs/requires changes in the stimulation protocol or the set of his/her needs/activities. However, we have not worked with any user for enough long time to estimate a frequency of changes possibly required.

The placement of electrodes is an everyday routine that has to be done by an assistant. Based on our experimental work, an entirely inexperienced assistant can place the electrodes and start the system routinely in a working week when he/she places the electrodes and starts the system twice a day. Generally, proper electrode placement is the most challenging task. However, after a week of experience, it takes several minutes. The troubles related to the non-functionality of the system during the testing phase (such as a destroyed electrode, failing LSL connections or high electrode impedance) have happened relatively regularly. However, their number has decreased over time.

The important goal was to eliminate gel electrodes during EEG data collection since their use requires additional costs for a gel substance and a more skilful assistant who has to master the placement of gel electrodes, possible skin irritations, or uncomfortable removal of these kinds of electrodes. It led us to decide on dry electrodes and invest in designing and developing several dry electrode solutions with different types and lengths of pins. Moreover, a capacity electrode was designed and developed, but we had not succeeded to get a usable signal in the natural environment when we applied it.

However, there were also troubles with dry electrodes. The noise to signal

ratio was too high when they were not firmly placed on the scalp. Finally, dry electrodes with longer pins ensured lower impedance and the exact comfort reported by the participant. No participant complained about pain or tension from wearing the dry electrodes.

It is difficult to compare the developed dry electrodes and the analogue front-end with similar systems, as no direct comparison can be made. The comparison is to be seen more like a rough assessment and only serves to provide an overview of the strengths and weaknesses of the BASIL hardware. In [32] a similar setup is presented, also with specially developed dry electrodes. The BCI system presented presumably delivers better accuracy. However, a separate data acquisition hardware had to be developed within the BASIL project to make the system usable for home-care use. Thus, commercially available EEG amplifiers and data acquisition modules were out of the question. Another example is the system presented in [33]. A mobile EEG system with dry electrodes was developed here, following similar requirements set for the BASIL project. However, this system has not been studied for use as a BCI system for home care.

The P300 protocol was considered to be practically used within the BASIL project. However, during experiments, the P300 component was less reliably observed. The data quality was variable and highly dependent on electrode attachment and environmental noise.

In contrast to the P300 protocol, the SSVEP protocol proved to be feasible with the presented hardware. However, as seen in Table 1, there has been high variability in classification accuracy among different subjects. While six out of ten participants achieved a classification accuracy of more than 75 %, four others failed to use this BCI while achieving an accuracy of 50 % or lower. For the high-performing subjects, a combination of two state-of-the-art methods (spectral difference and CCA) reached higher accuracy than any of them alone. The participants achieving poor results typically complained about an unpleasant feeling from stimulation, the experiment's duration, or the subjective feeling of interference from the non-target stimuli. The interference problem might be

addressed using a wider LCD monitor to allow the stimuli to be farther apart.

The literature review highlights the relative stability of SSVEP under different perturbations, such as speaking, listening, or thinking [34]. In [35], the classification accuracy of 93.2 % and information transfer rate of 92.35 bits/min was achieved with dry electrodes. Twelve flickering stimuli with frequencies from 9.25 to 14.75 Hz were displayed. In our system, 60Hz monitor limited the number of classification classes, and we used low-cost hardware, including the amplifier, while still having a successful BCI for most participants. Moreover, our system did not require any training, further limiting user preparation time.

The Workflow designer was proposed and developed as an essential part of the BASIL project infrastructure, allowing quick prototyping and testing algorithms for BCI signal processing and machine learning. Although similar tools are available for scientific workflow design, to the authors' best knowledge, only the Pipeline designer contains blocks for BCI computation, and it has a restrictive license policy [17]. The Workflow designer and the corresponding cloud architecture were not used directly within the presented experiments; they have served as an offline tool for EEG data storage and processing.

5. Conclusion

We have demonstrated that a successful BCI system can be built on low-cost hardware for EEG signal acquisition and amplification. Moreover, we collected users' experience on various EEG electrodes (gel-based and two types of dry electrodes) and assessed related signal quality. Following these considerations, the dry electrodes with long pins were preferred by most users, as they are fast to set up, and the quality of the obtained EEG signal is sufficient. In parallel, we also tested various BCI paradigms. Visual assessment of EEG waveforms revealed that SSVEP signals were much more apparent than the P300 components. Consequently, the subsequent experiments were based on the SSVEP protocol.

The SSVEP protocol contained three stimuli corresponding to the requests

that can be useful for motor-impaired people who need assistance. A trainingless algorithm combining two state-of-the-art methods (CCA and spectral analysis) was applied to detect the desired activity. Out of ten participants, six could control the system online (achieving more than 70 % accuracy). Low performing users typically complained of discomfort (primarily because of the SSVEP stimulation). Future work could address these complaints (e.g., using different stimuli or frequencies).

The current prototype of the BASIL BCI system is prepared for further community development and testing.

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Abbreviations

BCI: Brain-Computer Interface
CCA: Canonical correlation analysis
ECG: Electrocardiography
EEG: Electroencephalography
EMG: Electromyography
JSON: JavaScript Object Notation
LSL: Lab streaming layer
SSVEP: Steady-state visually evoked potentials

Availability of data and materials

The datasets used and/or analysed during the current study are available from the corresponding author on reasonable request.

Ethics approval and consent to participate

All participants provided informed consent to participate in the testing of the BASIL system prototype. It was approved by the Ethical Committee of the New Technologies for the Information Society research centre.

Competing interests

The authors declare that they have no competing interests.

Author's contributions

LV designed and implemented BCI experimental protocols and classification algorithms. LV and PB prepared, performed and evaluated BCI experiments. IH revised the BCI experimental protocols. PJ developed the cloud environment. PJ and LV proposed and implemented the workflow designer. RM led the Czech part of the project. JS and PL designed and developed the hardware part of the BASIL system while JS focused on the development of electrodes, head-mounted device and base station and PL developed the web interface for the base station and worked on machine learning for quick interpretation of the EEG signal. PM worked on alternative protocols. Each author wrote the parts of the manuscript that related to their work. RM prepared the final version of the manuscript. All authors read the manuscript and agreed to its final version.

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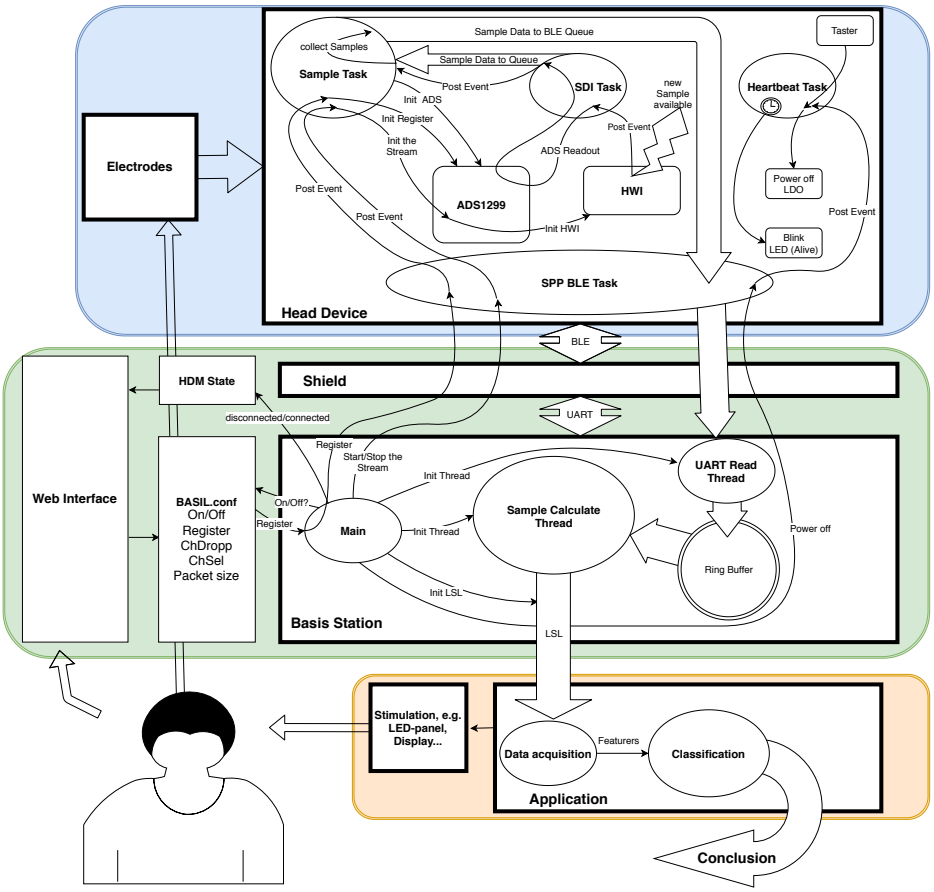

Figure 2: Detailed overview of the BASIL hardware. On the blue background, you can see the head-mounted device and the internal signal flow from the electrodes to the BLE connection. The base station with the BLE counterpart is shown on the green background. It processes all the data and sends them over LSL to the BCI application (the orange background).

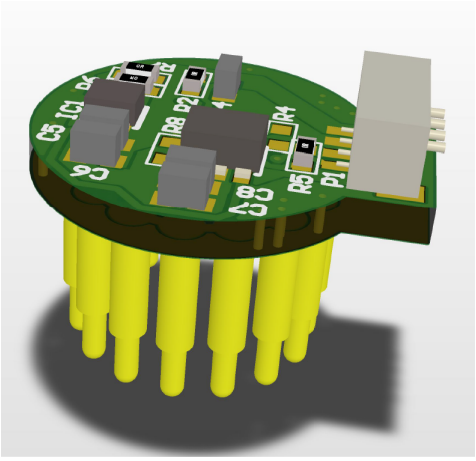

Figure 3: Dry electrodes designed for the BASIL project. They consist of a printed circuit board (PCB) with an amplifier and spring-loaded gold-coated pins. The contacts are arranged in a circle.The electrodes have four connections: the 5V power supply, the output signal, and the shielding.

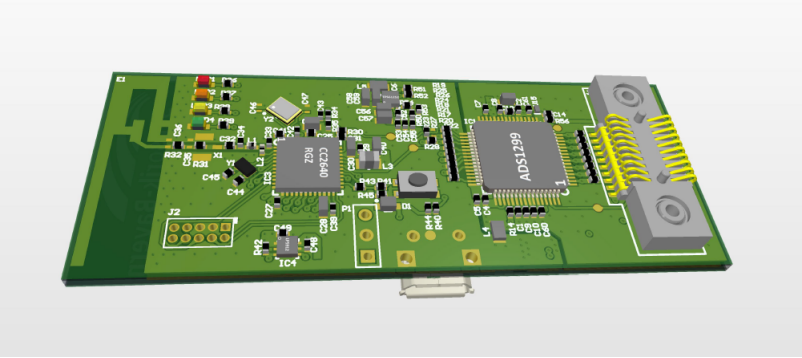

Figure 4: Head-Mounted Device. It is a mobile battery-powered device; signals are forwarded over the BLE protocol. It records analogue voltages of up to 8 electrodes with up to 250 samples per second.

Figure 5: Web-Interface deployed on the base station. All necessary settings for the base station and head-mounted device, as well as communication between these two devices, can be easily changed.

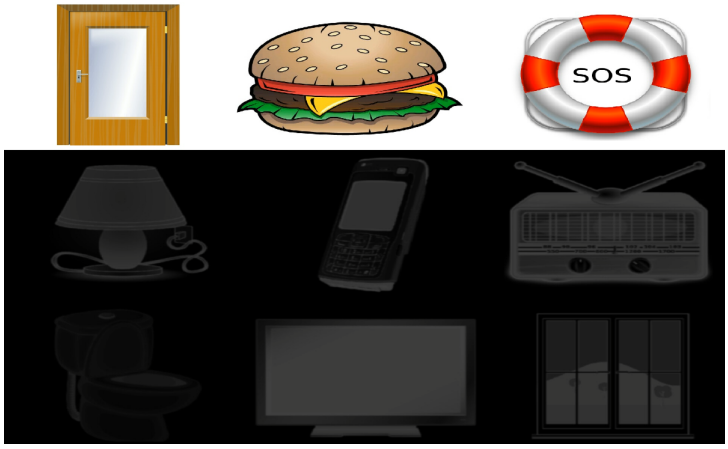

Figure 6: P300 stimulation protocol. The user focuses on one of nine stimuli within matrix representing his/her possible activities and needs; it means he/she focuses on the row or column containing the selected symbol when this row or column is highlighted.

Figure 7: SSVEP stimulation protocol. Each of the three objects flashed with a different frequency depicted in green.

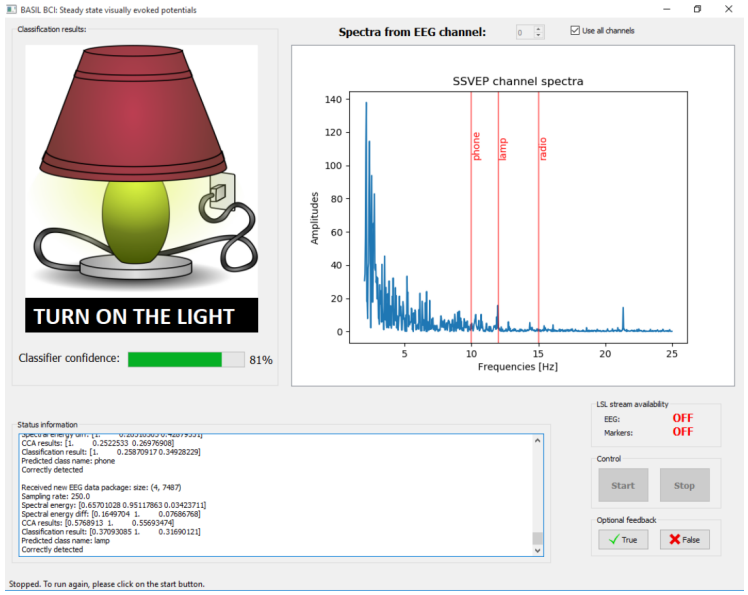

Figure 8: SSVEP on-line classification. The application for SSVEP on-line classification. The figure on the left depicts the predicted classification results. The plots on the right show power spectral density allowing the user to check spectral peaks corresponding to classification images manually.

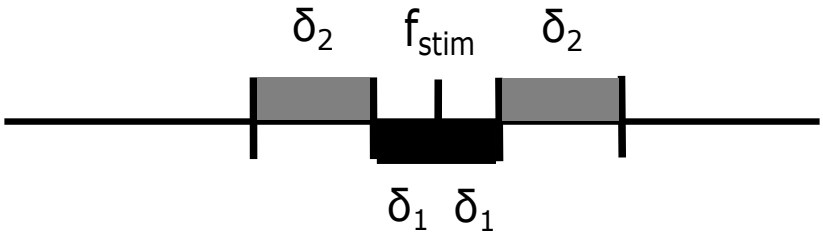

Figure 9: Spectral difference method. Energy of the close neighborhood (depicted in black): $E_1 = \sum_{n=f_{stim}-\delta_1}^{f_{stim}+\delta_1} x[n]^2$ is divided by the energy of the broader neighborhood (depicted in gray): $E_2 = \sum_{n=f_{stim}-(\delta_1+\delta_2)}^{f_{stim}+(\delta_1+\delta_2)} x[n]^2 - E_1$. The stimulation frequency with the highest proportion is the winner.

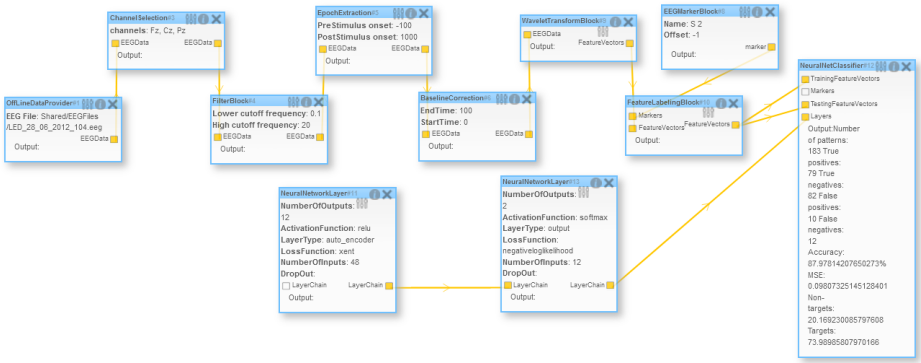

Figure 10: Workflow designer. An example of a simple single-trial classification workflow that forms the central part of a P300 BCI system. This workflow consists of several steps ensuring signal pre-processing (e.g. channel selection, band-pass filtering, and epoch extraction), feature extraction (discrete wavelet transform) and classification (neural network). In this workflow, for simplicity, the same data were used both for training and for testing. The results of the classification are depicted in the NeuralNetClassifier block.