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An Integral Solution for Assistive and Restorative Brain-Machine Interfaces: Current Approaches, Requirements and Design

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Abstract

Bio signal data acquisition and subsequent processing became not an option for neuroscience studies, but the requirement. A number of publications appeared during last decade, which brought some new core conceptions of brain-machine interfaces (BMI) as a valuable tool for science, medical and industry use and even entertainment. The BMI technology is far from maturity yet, but the number of real world applications grows rapidly. Because of the interest to close the gap between sensor device and driven equipment, various approaches were proposed. The purpose of this article is to propose the concept of a universal smart interface device based on current requirements for BMI system applications. This study consists of three main parts.

First, we briefly introduce the background and development of mind-controlled robot technologies and its applications. We focus on main requirements and features needed to be implemented in BMI devices.

Then, a structural scheme of a portable hybrid software-driven BMI device will be briefly explained.

And, after that, we'll review main methods and applications of BMIs in common, and proposed device, in particular, as a driver for a number of standard neurosignal-driven equipment and different data-processing systems.

Keywords: brain-machine interface; neuroscience; magnetoencephalogram; electroencephalogram.

INTRODUCTION

A Brain-Computer Interface (BCI) is a device that allows to control a computer by brain activity only, without the need for muscle control. However, electroencephalography (EEG) as a primary data source for such interfaces can also be reinforced with additional methods like electromyography (EMG), electrooculography (EOG), different acceleration and position sensors etc. That concept of merging data from different sources proved to increase efficiency of classification and data processing [1], as it lets to use different noise compensation algorithms, essential for real-world applications.

Recent studies clearly shows the diversity of concepts for such human-machine interaction devices, ranging from older tension/resistance tele-manipulation frameworks [2] to modern event-related potentials EEGs hybridized with other data channels [3]. The combination of these data channels utilized to generate drive commands for different devices like wheelchairs [4], exoskeletons [5], smart orthosis and prostheses [6], stimulation and feedback systems [7] and even computer game platforms [8]. Nevertheless, the other side of having such diverse set of data-acquisition equipment and driven machinery is the lack of compatibility and standards in terms of data and command formats, hardware interfaces, algorithms and such.

As different BMIs becomes more common in neuroscience labs and medical clinics, the concept of assistive and restorative designs appeared [9]. Different configurations of feedback and stimulation devices improves rehabilitation for patients with motor and cognitive disorders [10].

2. MATERIALS AND METHODS

2.1. EEG-based data acquisition systems. Main concepts.

There are several approaches to brain activity measurements, such as magnetoencephalogram (MEG), near infrared spectroscopy (NIRS), electrocorticogram (ECoG), functional magnetic resonance imaging (fMRI), electroencephalogram (EEG), etc. An invasive technology uses an array of electrodes implanted on the surface of motor cortex. Invasive BCI systems are mostly used to restore special sensations, such as visual sense, and motor functions for paralyzed patients. The quality of neural signals is remarkably higher because microelectrodes directly implants into the cerebral grey matter. However, invasive BCI systems have known disadvantage of causing immune reaction and callus, which, in most cases, leads to regression of neuronal signal quality.

An EEG device, because of noninvasive technology, found a wide application in both clinical and research fields due to its low cost and portability. EEG systems records brain signals from the scalp [11]. This method has a long history since Berger's works in 1935. Currently, EEG is one of the most widely used technique in noninvasive brain research to study correlates of perceptual, cognitive, and motor activity associated with processing of information. From the technical point of view EEG systems are quite simple and consists of several (up to 256 according to [12]) dry or gelled electrodes, fixed on the surface of scalp with a cap, semi-soft fixtures or other methods. Electrodes connects to the processing module with low-noise wires because of low amplitude of the signals. The processing module usually consists of different amplifiers, bandwidth filters and analog to digital converters (ADC). Digitized signal then usually used as a source for classification algorithms or just stores in some kind of memory device for further offline processing.

Despite of its long history and technological maturity, EEG systems rarely used outside of scientific labs or medical clinics. The problem is the vulnerability of EEG signal to artifacts and distortions. Besides, such systems often needs calibration before use and assistance during set up. Questions of the influence of the setup, system used and repetitiveness on the result discussed in [13].

To enhance the quality of the EEG signal acquired several methods can be used. First, it is often possible to use less number of channels. This approach can be advantageous because of the mostly linear correlation between overall signal quality and number of channels. For many real-world tasks like driving some external equipment, there is no need to use too many channels. According to [12]: "Results indicate that on average an EEG montage with as few as 35 channels may be sufficient to record the two most dominate electrocortical sources (temporal and spatial $R2 > 0.9$). Correlations for additional electrocortical sources decreased linearly such that the least dominant sources extracted from the 35 channel dataset had temporal and spatial correlations of approximately 0.7. This suggests that for certain applications the number of EEG sensors used for mobile brain imaging could be vastly reduced, but researchers and clinicians must consider the expected distribution of relevant electrocortical sources when determining the number of EEG sensors necessary for a particular application". Besides, the influence of the experimental setup, calibration, subject and device configuration can also affect the digitized data according to [13]. Considering the fact that in many studies the results, obtained with limited number of EEG channels, were sufficient for the target task, it is often depends more on the researcher, then on equipment. Even for large 256-channel systems, only 125 were usable, because of the poor recordings due to large movement artifacts and/or degrading electrodescalp connections [12]. Besides, the preparation and electrode placement stage of the experiment can be time-consuming as, on average, two skilled research assistants took 35 min to affix an electrode cap, 64 electrodes, apply gel, and get electrode impedances within an acceptable range, according to [14]. No doubts, such configuration is not acceptable for mobile or e-Health BMI.

A novel approach to wearable EEG system was offered in [15]. The conception of transparent EEG and concealed EEG sensor array placed around the ear with wireless data-transfer to smartphone showed its feasibility and needs for further development as it seems to be the future of BMI for mobile devices.

Next approach for enhancing the total quality of the signal for classification is the reinforcement method, when EEG , considering as the base signal source, merges with the data from other types of sensors like EMG, EOG, functional near-infrared spectroscopy (fNIRS), magnetoencephalography (MEG) etc. It leads to the idea of hybrid BMI in different configurations, tunable for any requirements or set up. According to [16], that approach is feasible for restorative feedback systems too.

Hybrid BCI can be used in vast number of configurations for various tasks. Novel approach of improving the accuracy of classification by hybridization becomes more and more popular. For example, study [17] proposes a method of forging Steady state visual evoked potentials (SSVEPs) method with the eye-tracking system to enhance the quality of classification for 30-target spelling application. The similar hybrid electroencephalography–functional near-infrared spectroscopy (EEG–fNIRS) scheme was used to resolve eight basic commands to control the quadcopter. The novelty of the proposed method is that brain state self-regulation learning based on mental arithmetic and resolving the directions of eye movements and blinks through EEG data processing. As given EEG command had to match with an opposing fNIRS command for the driving command generation, the classification accuracy improved noticeably. Besides, registering eye movement with EEG device let to simplify the design, because separate hardware eye-tracker became unnecessary. The study confirms the statement of resolving the same events with different sensors, as the common technique to process the data of eye movement is EOG [18].

Similar NIRS-EEG hybrid device can be improved to become portable as it was proposed in study [19]. In that configuration, 16 EEG electrodes and eight NIRS probes (5 sources and 3 detectors) were sufficient for cognitive task research with mental arithmetic and rest state baseline experimental protocol. However, the subjects were sitting still in an armchair during the experiment, so, actually, mobility features of the device and accuracy during movements were not tested.

Another growing trend in neuroscience is feedback-featured approach, also known as "closed-loop technique". This is more advanced scenario, when some kind of interaction between brain state and actions exists during the experiment or treatment. Feedback devices becomes popular for support and rehabilitation of motor impaired patients, as it allows fine tuning of the feedback and command modes. The application includes FES feedback for gait [20], hand movement [21], and even swallow assistance [22], different brain stimulations - transcranial magnetic stimulation (TMS) or transcranial electric stimulation (TES) for and mental decays [23], visual feedback for cognitive training for older adults [24], electrical deep brain stimulation (DBS) for patients with advanced Parkinson's disease [25].

Such diversity also lets to take into account another classification of feedback-BMIs as assistive and restorative. Assistive BMIs supports the motion intentions of the patient without direct behavioral gains. It does not depend of feedback or external stimulation, because even combination of BMI with physiotherapy does not result in effect of relevant functional improvement. Moreover, the underlying neurophysiology of BMI therapy has not yet fully explored to the moment [9]. Therefore, the concept of restorative BMI is abstract to the moment.

According to [9], "BMIs may be referred to as restorative tools when demonstrating subsequently (i) operant learning and progressive evolution of specific brain states/dynamics, (ii) correlated modulations of functional networks related to the therapeutic goal, (iii) subsequent improvement in a specific task, and (iv) an explicit correlation between the modulated brain dynamics and the achieved behavioral gains".

To summarize the stated designs and requirements, we can clearly say about the demand for portable, modular, multi-channel autonomous device, capable to process and store raw data from variety of sensors, provide feedback and/or generate drive command for external robotic devices.

2.2. Conceptual design of portable modular hybrid device

A conceptual device with modular portable design, rich data acquisition and processing features, numerous interfaces was developed and tested in laboratory on Neurobiology and Medical Physics of Immanuel Kant Baltic Federal University.

Fig. 1 shows block schematic of the proposed design (left side) and the photo of actual device during the experiment (right side). Main input interface acquires data from 16-channel EEG cap with gelled Ag/AgCl electrodes. Raw EEG data digitized by two ADS1299 analog-to-digital converters (ADC) in daisy-chain mode. Other interface is RS-485 wired interface that lets connection of various wired sensors, actuators and feedback equipment via UART protocol. The core consists of Cortex M4 microprocessor with powerful processing capacity that manages both ADC microchips, RS-485 interface, power management module with 4500 mA/h battery and output interface to Intel Edison module. USB interface, SD card and interfaces of Intel Edison board are not shown. The presence of powerful computer module on board gives an opportunity to directly process biosignals and control external devices without additional wireless or wired transmission. Additionally, Intel Edison board is equipped with wireless modules, so it is possible to use Wi-Fi sensors or feedback devices too. Operation system of Intel Edison board permits execution of Python code, written for desktop systems, so it simplify software development and upgrade.

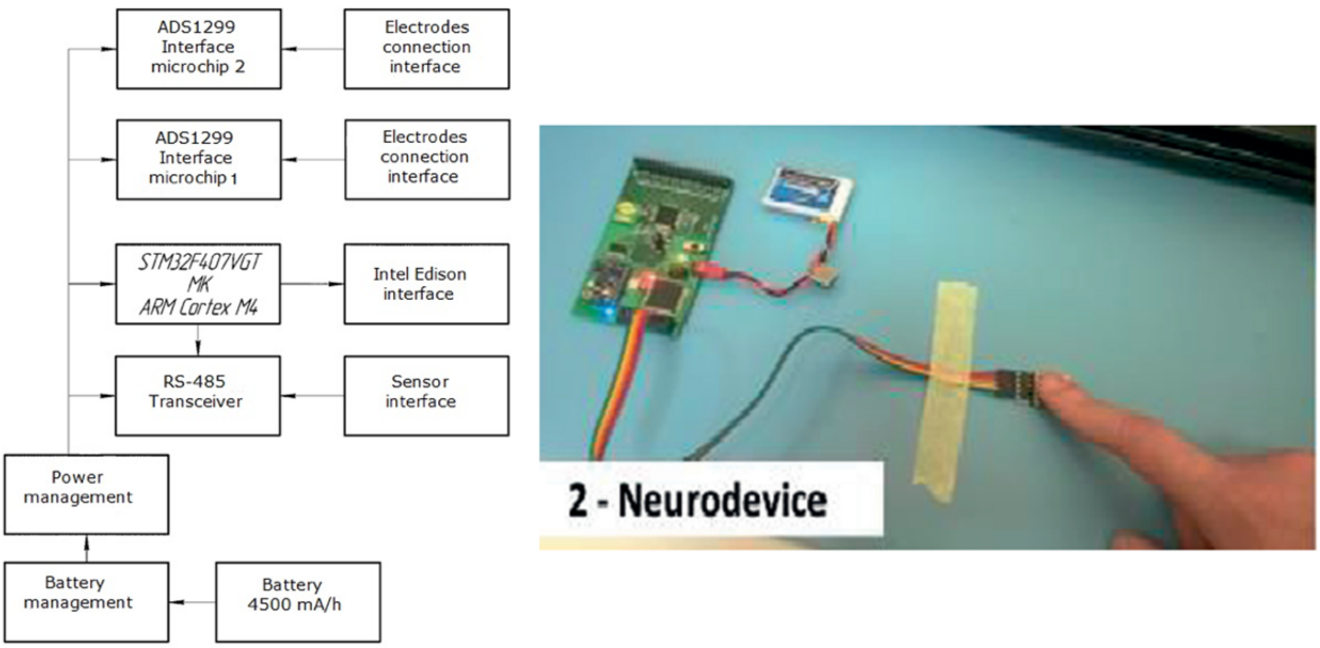

Figure 1: Proposed design of a modular portable neurodevice for biosignal registration, processing and drive command generation. Block schematic diagram (left) and photo from actual experiment with photoplethysmography (PPG) sensor.

For the test purposes, the device was connected to EEG, EMG, EOG, PPG, position-accelerometer and thermometer sensors, respectively. Results obtained proved its feasibility as laboratory or medical device in terms of accuracy, portability, data storage capability, low response time [26; 27].

Proposed design is suitable for different experimental protocols and real life applications. External robotic exoskeletons, prosthesis/orthosis devices can connect through wireless or wired interfaces, because processing power of Intel Edison module allows onboard generation of drive commands. Feedback and restorative models, in many cases, consists of the feedback hardware and control algorithms. Such architecture can be easily implemented with EEG, RS-485 and Wi-Fi interfaces of the device with all software installed on Intel Edison board. This setup excludes the need of any PC or laptop and consists only of sensors, neurodevice and feedback system. Portability, wireless interface and embedded SD card slot makes the neurodevice preferable for telemetry transmission task. Hybrid design allows using different sensor configuration, necessary for e-Health programs with constant and long-term monitoring. Wi-Fi protocol can be used to transmit data to smartphone with special application installed. It allows keeping constant connection with remote medical database server via Internet connection of the cellphone. Besides, this neurodevice in similar configuration can be used for fatigue and drowsiness detection systems for truck, train drivers and airplane pilots [28; 29; 30].

The novelty of the design is the integral structure of the “sensor-digitizer- processor software-drive command” chain, when every operation can be performed on single board. Many real-time BCI models are highly affected by delays between data acquisition and command generation. As many algorithms based on sliding window, even 0..2 sec time frame can be not sufficient to control fast mobile device, for example, quadcopter [18], and additional stages of coding/decoding, transmitting, etc., makes the situation even worse.

This way, proposed “all-in-one board” concept can become the best solution, as it minimize the number of steps and execution time for the driver algorithm. Fig. 2 shows block schematic diagram for open-loop hybrid device data flow, capable to store (and transmit) the obtained data on all stages, which makes it adaptive to variety of protocols.

An ability to not just process, but also store and transmit data is valuable for telemetry, e-Health and post-processing research systems. Stored pre-processed data can later be used to train classifiers and as the reference for neural networks. In combination with class and feature sets these data blocks forms a complete model for neural network. Open-loop systems covers mostly any configuration of driven robotic equipment or stimulation system, but cannot provide therapeutic or learning effect. From the other side, restorative interfaces attracts interest in both the scientific and medical communities.

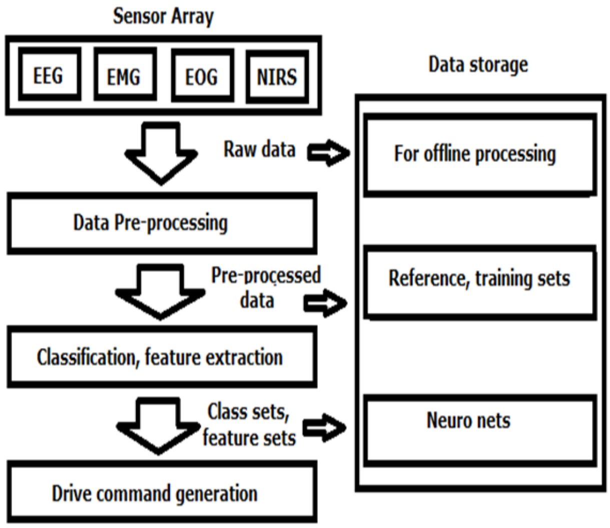

Figure 2: Open-loop algorithm data flow and processing stages.

3. RESULTS AND DISCUSSION.

Restorative BMIs, based on neurofeedback paradigm, requires closed-loop design of the device and strong supplemental theoretical foundation. Because of the relative novelty and immaturity of the restorative BMI paradigm there is no unified classification of experimental or clinical protocols and designs.

Many existing neurofeedback protocols targets different neuronal phenomena observed in EEG measurement. Such protocols differ regarding the frequency band addressed (e.g., alpha-, beta, theta-, gamma-training), the utilization of different electrode locations (Fz, Cz, Fz1, etc.), and the recording of the EEG under different activity states of the subjects, e.g., eyes-open or eyes closed. Based on findings about hippocampal theta-rhythm and its relation to memory, for example, a theta-upregulation neurofeedback at electrode Pz was performed which indeed led to improved memory consolidation (Reiner et al., 2014). Notably, different protocols can influence varying brain networks as long as they rely on biologically relevant frequencies (Hutcheon and Yarom, 2000). A protocol can be considered operational, if the EEG signal is modulated in accordance with instructions, even though such changes might not always be accompanied by cognitive or behavioral changes; the latter, however, usually is the aim of most neurofeedback studies, according to [31].

Fig. 3 shows an overview of main areas, given to neurofeedback applications. That figure is an excerpt from the article [31] and, in our opinion, clearly illustrates current view on neurofeedback applications. As it can be clearly seen, areas of applications can be divided into three threads, depending of the task of learning. Feedback systems as a therapeutic tool is two-stage algorithm. First, after the observation of patient’s brain activity and comparing it to the reference set of parameters of healthy subjects, the protocol of stimulation has to be defined. According to [25], certain combinations of oscillations, mostly in theta- and beta- band, can be utilized as biomarkers. Such biomarkers can be resolved and classified with adaptive feedback algorithms. The purpose of the stimulation is the correction of brain state parameters and bring it closer to normal, affecting target motor or cognitive functions of the patient or subject. The term “feedback” can mean certain combinations of oscillations, registered via EEG, muscle activity, recorded with EMG, actual physical movement or any other feature. In any case, the feedback from the subject has to be relative to some criterion, and feature of brain activity has to meet some threshold or state. As every application means certain degree of voluntary control of the brain state, the subject became an important part of the scheme. Not all subjects can benefit from such reinforcement learning and according to [31] about one third of all participants not able to show any long-term gains or cannot achieve the desired state of brain. However, feedback paradigm is still one of the most promising and perspective, because of the rapid development of hardware and software components for neurodevices. Feedback devices heavily depends on robust algorithms and complex mathematical models [25] because of the requirement to adapt to individual type and level of feedback of subject or patient.

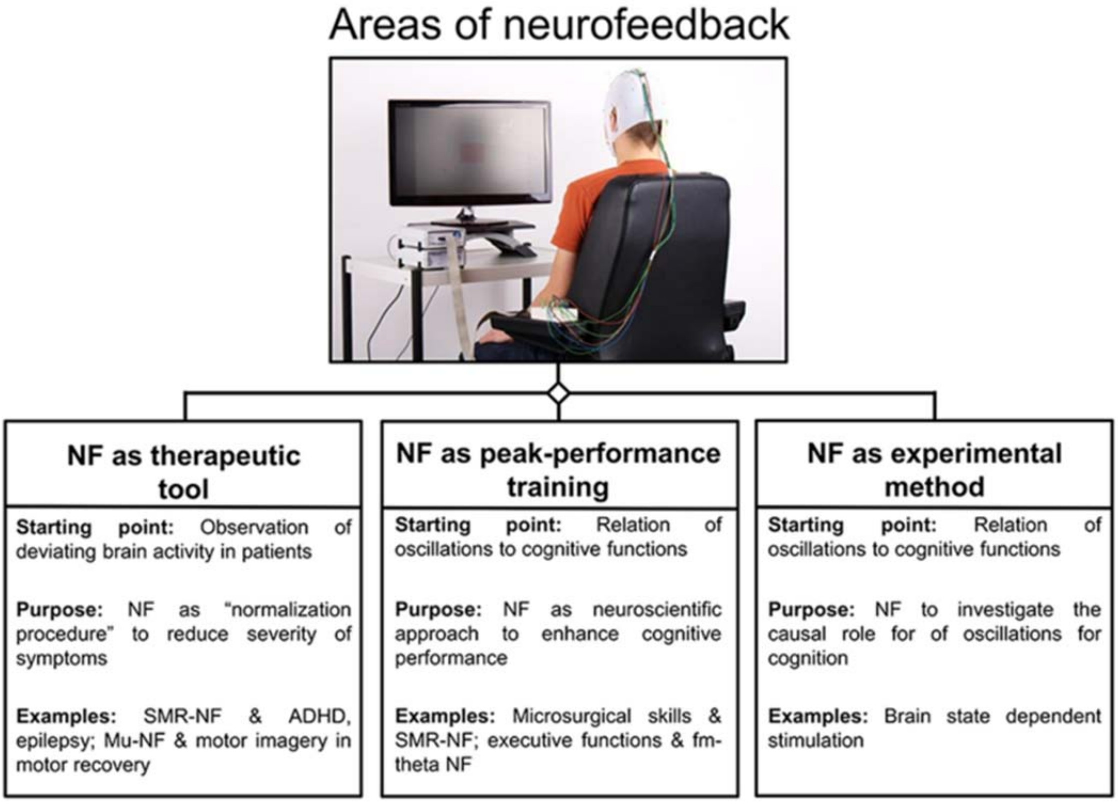

Figure 3: An overview of main neurofeedback application areas according to [20]

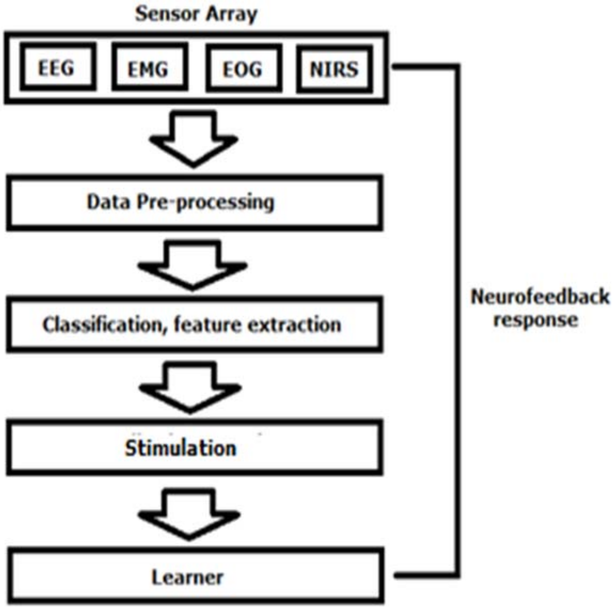

Figure 4: Main steps of closed-loop feedback algorithm

The similar approach leads to experimental and peak-performance protocol. Cognitive functions and its relation to brain activity still the subject of scientific interest, so feedback systems utilized in many ongoing researches.

All feedback systems designed to work in cyclic fashion, providing stimulation and reading feedback parameters from the Learner. Fig. 4 shows block diagram for closed-loop feedback system.

As it can be seen, the whole sequence is made as constant adaptation loop. The structure of the feedback signal can be quite complex, and, for EEG recordings, can include EMG signals. Muscles on the head (occipitofrontal, auricular and temporal muscles) or even more distant, can interfere with EEG on higher frequencies with most of the power between 20 Hz and 150Hz. So, in fact, signal recorded by EEG electrodes is a mixture of different oscillations and can consist of inherit brain oscillations, voluntary modulation of brain state and involuntary head muscle contractions, connected with mental efforts to achieve brain self-regulation. Recent study [32] discovered extensive muscle employment, which increased during the training sessions. Automatic online muscle control was suggested not only as the requirement for quality EEG signal, but for genuine BMI-feedback training.

Based on aforementioned protocols and descriptions it is possible to list set of common requirements for BMI and propose unified hardware platform. Proposed neurodevice has a number of features to suit current and perspective experimental protocols:

- portability and compatibility with current and perspective sensors. Proposed neurodevice has independent power module, equipped with 4500 mA/h battery, different wired (USB, RS-485, analog) and wireless (Wi-Fi) interfaces, capable to temporary store data on memory SD card.
- hybrid feature. An option to use different sensors and sensor arrays and embedded pre-processing and processing modules permits different hybrid configuration. Ability to acquire data from different sensors (e.g. EEG, EMG, EOG, PPG and thermometer) was demonstrated during test phase.
- Telemetry. Proposed device can store, process and transmit data from all sensors.
- generating drive commands for external robotic equipment. Embedded powerful processing module Intel Edison can handle complex calculations and software and capable to execute Python code written for desktop computer, that simplify programming and software update. Wired and wireless interfaces can connect different types of actuators or electronic control boards.

Closed-loop feedback applications has slightly different requirement set, mostly because of the demand to adapt for individual parameters of each subject and flexible experiment protocols.

- Software and hardware update. The neurodevice has USB, Wi-Fi hardware interfaces and Linux operation system, that makes software update easy. Modularized architecture allows cascading of such devises (as wireless network nodes) for external or offline processing and scalability.
- Two-stage processing (Cortex M4 and Intel Edison) allowed to separate software applications into pre-processing and processing stages. As all calculations and command generation performed "onboard", neurodevice can execute real-time feedback applications with low latency.
- Different stimulation methods and feedback. Proposed neurodevice is capable to connect all modern sensors from analog to wired RS-485 UART and smart Wi-Fi models. The same is applicable for stimulation and feedback equipment. As most part of stimulation (FES, TES) devices controlled by computer, the neurodevice can connect as network node.
- Logging. Feedback training can last for numerous prolonged sessions, so logging of parameters is valuable. The neurodevice has SD-card slot onboard, so logging is a matter of software installed.

Proposed device is not a universal single choice for everything, of cause. A number of issues are a subject of future development and study. Among them: latency tests, position resolution for driven robotic arm, artificial neural net for control module, etc. Proposed device may become an illustration of classical hardware design merged with Internet of Things approach "all-in-one board". This promising combination can become very popular within "e-Health" and "remote medicine" concepts. Besides, as was shown, modern BMIs has many similar or identical modules, so unified approach seems logical. Moreover, recent studies, such as [33] proposes standard approach for neuroimaging data processing. Standard software libraries and utilities for pre and post processing of neuroimaging data receiving considerable attention by the community. A further contribution may be creating similar standards for EEG signal processing and drive command generation for BMI devices.

Another perspective task is adding multi-mode capability to the device. According to e-Health conception, patients goes though different activities in daily life, interacting with different smart devices, and, at the same time, keeps connection to health center. From technical side, it can be described as a mixture of sensors and systems connections/disconnections events, running different software modules, storage and transmitting telemetry data.

"In order for neurofeedback to be effective as a tool for cognitive enhancements or clinical applications, it needs to be shown that learned self-regulation transfers to situations where neurofeedback is not available anymore, and that learned self-regulation is maintained beyond the initial training period" [34]. Such approach dictates constant monitoring of physiological parameters of patient or subject and demand to tune the stimulation or feedback to achieve the best gain.

4. CONCLUSION

BMIs became a valuable standard tool for brain-machine interaction for researchers, doctors and engineers. With time, purpose and limitations of BMIs became clearer and sets of requirements has been defined. A number of studies was analyzed and common features briefly explained. A compact hybrid neurodevice that meets most experimental set ups and protocols was proposed. Its main features are portability and processing capacity, different wired and wireless interfaces and onboard storage, mobility. The feasibility of the device was proved in test phase, but further development needed to evaluate its practical applications and limitations. A brief discussion revealed the demand for further concept development in terms of standards and hardware/software design to comply the e-Health paradigm.

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