Electroencephalogram (EEG) based brain-computer interface (BCI) is a rapidly expanding field of research due to importance of the application and the facilitation offered by the increased accessibility of EEG devices which even stepped into the wearable era.

The importance of the application is crucial for an important segment of patients: these with severe neurological and muscular impairments, such as neuromuscular disorders, muscular dystrophy or spinal cord injury. These patients encounter critical challenges in sensorimotor functions so for many, the only way of communication and interaction with the environment may be a brain-computer interface. The quality of life that a performance BCI can add for these patients is difficult to quantify.

Although the medical applications are the main drive for research in the BCI area, there are also new domains more and more interested in this field, like computer game industry, which is interested in new ways of interacting with the virtual environments, or automotive sector for driver assistance applications, where a BCI can be used to detect, for example, the level of attention. [1]

Acquiring a high fidelity EEG signal is the first difficult part for an EEG based BCI. Moreover, to have a practical application we need to employ a dry electrode design [2], as opposed to wet electrode which use an electrolytic gel as conductor between the skin and the electrode, or to the implanted electrodes which would increase the costs and the risks to such a level that the affordability of the BCI system will render such an application irrelevant.

Another major challenge of a BCI system is the training required for the system to adapt to each individual – a specific mental representation will trigger a different EEG reading for different subjects. Moreover, the same representation will be visible in different channels of the EEG signal, for different individuals [3]. Aside the channel diversity, the complexity of analyzing an EEG signal and correlations of similar events across different individuals is made possible only through machine learning techniques. In this way, the burden of training is relocated from a learning subject toward statistical learning machines which could allow a naïve user to achieve BCI communication already in the first session [1], [5], [6].

If we go further into decomposition of an EEG signal we can find in literature [7] [14] at least three major types of waves, defined by the signal frequency or by the trigger, relevant for BCI systems: slow cortical potentials (SCPs) – 0.1-2 Hz; sensorimotor rhythms (SMR) – with two major bands: alpha or mu (8-13 Hz) and beta (13-35 Hz); and P300 potential, an event-related potential (ERP) component elicited in decision making process. The current approach of EEG based BCI considers only one of these type of EEG waves – SCPs [8], SMR [9] [10] [11] or P300 [12] [13] – while considering at least two of these waves (SCPs and SMR) in the same analysis could reveal new approaches in perfecting a BCI communication system with near-zero training requirement.

Another limitation of current approaches for BCI systems we found to be related to the mathematical tools employed in signal analysis, specifically in categorizing, indexing and retrieval of EEG identified events.

However, the present computational and technical advancements making possible machine learning algorithms justifies the attempt to develop a Decision Hashing Algorithm (into colors/numbers/activities) based EEG Signal Processing for automated systems in healthcare.

Considering the recent technical advancements in dry Electroencephalogram (EEG) acquiring devices which became more and more accessible and the computational power available on wearable devices, the research in the field of brain-computer interface is accelerating. This acceleration is also facilitated by the machine learning algorithms which helps identifying patters without the need of a predefined algorithm.

In this context, the **main objective** of this project is to develop a Decision Hashing Algorithm (into colors/numbers/activities) based EEG Signal Processing and machine learning algorithms which can be used in various automated systems in healthcare, focusing on life quality improvement for patients with sensorimotor disorders.

This can be obtained through the analysis of EEG signals from which, using hashing algorithms and different machine learning algorithms. The **novelty** **element** we propose in this project is the addition of hashing algorithms to the machine learning techniques of EEG signals processing through which we aim a greatly improved computational performance by significantly reducing the digital size of EEG events descriptors and reaching the goal of a universal EEG interpreter by achieving a near-zero calibration requirement for a brain-computer interface. Specifically, the first hashing technique we want to explore is the locality-sensitive hashing [15] which differs from the conventional hashing techniques in that hashing collisions are maximized, not minimized. In literature this hashing technique is applied only for image retrieval [16] or speech recognition [17] but not used in a BCI system.

A hashing algorithm is a cryptographic hash function. It is a mathematical algorithm that maps data of arbitrary size to a hash of a fixed size, being designed to be a one-way function, infeasible to invert. A hash function is any function that can be used to map data of arbitrary size to fixed-size values. The values returned by a hash function are called hashes. The values are used to index a fixed-size table called a hash table. The hashing function is generally developed so that a hash can be identified in a unique way, the function needs to be deterministic and a small change to the input should change the hash value so extensively that the new hash value appears uncorrelated with the old hash value. For the purpose of our application the latter is of great interest. Generally, when we talk about a classification problem, we expect small variations around a known classification to fit the same category, but brainwaves are so volatile that small modifications in the signals can mean completely different things, hence the advantage of hashing must be exploited. These algorithms can be used when processing EEG signals as follows: the EEG signals will be filter and only the relevant features from the signals will be extracted, such as amplitude, variation or mean value. These features will be fed to a function that will transform the information into a hash which can represent a string, a number or any other way of codification. Only the resulting hashes will be classified into colors, actions or any other allocation method. In terms of natural language this process can be viewed as a dictionary for EEG signals where one can determine the action to be taken based on the hash classification. EEG signals may vary drastically from one person to another, that means the algorithm needs to be calibrated when used by another user. Machine learning algorithms use large amounts of data and extensive training in order to generate a correct classification [18-24]. The advantage of the proposed method stands in its simplicity, based on a reduced number of examples from the user the hash function will be generated so that the classification done beforehand will still be feasible.

**Specific objectives** of our project are:

1.The **first objective** refers to pattern identification in the EEG events for similar icons (colors cards, numbers, actions representations) presented to or evoked by the subject, across multiple subjects by using machine learning algorithms.

2. The **second objective** is focused on indexing the representation of EEG patterns in shorter sequences, for faster retrieval, using hashing algorithms.

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