A Brain Computer Interface classification method based on SIFT descriptors

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Abstract— **In the context of Brain Computer Interfaces, research community is endlessly searching for new automatic methods to understand the mental state of a person wearing a non-invasive Electroencephalography (EEG) device. Since the inception of EEG technology physicians have successfully developed an eye to undercover the intrinsic patterns of EEG, scouring for hints of diseases and pathologies. This works approaches the BCI problem following this direction, by translating each signal into a 2D plotted image, and mimicking the physician approach though using an image processing technique, the Scale Invariant Feature Transform (SIFT) classification. Is it possible to discriminate EEG signals based on their plots? In this paper we aim to take the first steps to answer this question, and we show the results of applying this method to two different datasets.**

Keywords— **BCI, SIFT, Feature Extraction, Feature Matching, Classification**

I. INTRODUCTION

In recent years, the appealing idea of a direct interface between the human brain and an artificial system, called Brain Computer Interface (BCI) or Brain Machine Interfaces (BMI), has proved the feasibility of a distinct non-biological communication channel to transmit information from the Central Nervous System (CNS) to a computer device. Its most important and straightforward application is for people affected by neuro-degenerative diseases [1].

Outstanding success has been achieved with invasive BCI, i.e. with surgically implanted electrodes, from the total reproduction of arm movement [2] to the remote control of a manipulator by a macaque using brainwave information [3]. However, Biocompatibilities issues and the pervasive complexity and risks of surgical procedures are the main drive to enhance current non-invasive technologies. Above all, Electroencephalography (EEG), is the most widespread method to gather information from the CNS in a non-invasive way. It measures the summed activity of post-synaptic potentials from electrodes positioned over the scalp. EEG has been used in various working prototypes, as assisting devices, mainly wheelchairs [4, 5]. In order to derive information out of the subject's volition, different mental paradigms have been discovered and applied [6]. There have been many algorithms developed so far for processing EEG signals, based on time, frequency, spatial domains or combinations [6, 7]. However, the exploration of alternative paths is ongoing, because non-invasive BCI still lacks the required performance to be used in real-time environments and to be ready for mainstream production [8, 9].

We propose a novel method to study EEG signals for BCI, based on the automatically processing of binary signal plots. Image processing techniques are currently a mature discipline widely used in Computer Vision and Visual Object Recognition [10]. The utilization of EEG information to derive images has been applied so far, mainly in the context of the Inverse Problem Resolution [11]. We hypothesize that the usage of a transformation of a signal into an image given by a plot of EEG signal, allow us to apply efficient feature extraction techniques and to extract valuable information from the EEG. Due to the high degree of information integration that can be achieved in image-space, this procedure can be helpful by reducing sampling window size, i.e. the required amount of data points per time-window, thus improving the Information Transfer Rate (ITR) of the whole system. Additionally, subtle distortions and even wiggles of the signal, which are generally attributed to noise, can be studied systematically by those algorithms, and their inner relation with any underlying cognitive process could be inferred.

This work is organized as follows: first, we describe the two datasets that we used in this work. We continue giving some insights about the image processing feature extraction method that we used, and its implementation details. Moreover, we show how this method can be effectively utilized as a feature extraction mechanisms for BCI and how it can be adapted to implement a Feature Translation scheme. Finally, results of the application of the described method on the datasets are presented.

II. MATERIALS AND METHODS

A. Datasets

A1   Dataset I - Drowsiness Detection

We gather the first dataset using the EEG EPOC Emotiv Headset using the C++ SDK library provided by the manufacturer and an in-house developed program. The device has

14 channels, and a sampling rate of 128 Hz [12]. Ten random healthy subjects between ages 20-50 were recruited and they accepted to wear the device and to participate in the experiments. A 30 minutes procedure was required to adjust the headset to each user, in order to decrease the impedance on each electrode. Once the set up was finished, each subject was instructed to sit in a relaxed position. Subsequently, she/he was instructed to watch the screen for 15 seconds, trying to avoid, as much as possible, to abruptly move its body or head. During that time, a single-trial of 10 seconds-length window of EEG signals data was transferred to a PC and logged into standard binary files. After a 5 minutes pause, the subject was asked to close the eyes avoiding any movement while keeping the same pose for another batch of 15 seconds. Again, 10 seconds of EEG information were transferred and logged into the PC. This finally gave us a sample of 10 subjects, 2 trial per subject, one for each class, composed of 14 channels, 10-seconds length or 1280 samples per window. Alpha Waves are 8-12 Hz signals, physiologically well consistent across subjects, and they are associated with synchronous inhibitory processes and attention shifting, more prominent while the eyes are closed [13]. The results of applying a 8-12 Hz band-pass filter and calculating the Power Spectral Density (PSD) across subjects for each channel can be seen in Fig. 1, where the values obtained for class 2 (eyes closed) are higher than the values for class 1 (eyes open), showing that the differentiation information is contained in the frequency-domain.

A2   Dataset II - BCI Competition 2003 IV self-paced 1s

We validated our method against the "BCI Competition 2003, dataset IV *self-paced 1s*" [14]. This dataset is composed of 28 channels, in 416 epochs of 50 samples per epoch (500 ms length at 100 Hz) each one with the corresponding label, where subjects were asked to type at will a letter on a keyboard with the right or left index finger. It is based on the Bereitschaftspotential [15], which is a Slow Cortical Potential, particularly a slow change in voltages towards a negative potential drift, around 1000-500 ms before the onset of the self-initiated movement. In this case, the information lies strongly on the time-domain.

B. Image Generation

Data points are divided in non-overlapping rectangular window samples. For each sampling window, we generate a binary image of a fixed height and width, which can be scaled by a factor δ. The width is the size of the time interval of each window sample, and according to the sample rate of each dataset, it is 1280 data points for the Drowsiness

dataset, and 50 for BCI Competition. The height comes from the peak-to-peak amplitude according to the following equation:

$$h(c) = |\max x(t,c) - \min x(t,c)| \qquad (1)$$

where x is the signal, t is time and c is the channel. Therefore, the height is calculated for each sample window and no clipping of the signal was performed. Additionally, the mean over time of the signal $\bar{x}(c)$ was subtracted from each window sample obtaining $\tilde{x}(t,c) = x(t,c) - \bar{x}(c)$. The image coordinate system assigns the point $(1,1)$ to the upper left corner (increasing from top-to-bottom, from left-to-right). Hence, image $I(z_1, z_2)$ can take two values, which are:

$$I(z_1, z_2) = \begin{cases} 255 & z_1 = \delta \cdot t, z_2 = \delta \cdot \tilde{x}(t,c) + \frac{1}{2}h(c) \\ 0 & \text{otherwise} \end{cases} \qquad (2)$$

Finally, assigned pixels in the image were interpolated using the **Bresenham** [16] algorithm (see Fig. 1 for an example).
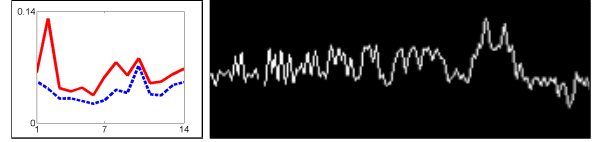

Fig. 1: PSD values for every channel (x-axis) are being shown for class 1, dashed line, and class 2, solid line, for Dataset I (left). Sample EEG plot image corresponding to the subject 1 (center) for class 1 (eyes open), for the channel 7 (O_1)

C. Feature Extraction: SIFT Descriptors

The Scale-Invariant Transform Features (SIFT)[17] is a feature detection and classification method for images based on the extraction of salient intrinsic characteristics image keypoints, i.e. affine invariant image regions, and its characterization into a 128-dimensional *Descriptor* vector. Using SIFT, different regions of different images can be compared and if the distance between the vectors is bellow a certain threshold, it represents some level of similarity (Fig. 2).

D. Matching Strategy

The procedure is detailed in Alg. 1 and it works in a channel by channel basis. In the first part, the set of descriptors $\mathscr{DI}(c,s)$ per channel c is obtained from the image $\mathscr{I}(c,s)$, where s indicates subject for the first Dataset and epoch for the second Dataset. In order to properly give more weight to edges in the binary image, the SIFT parameter edge-threshold
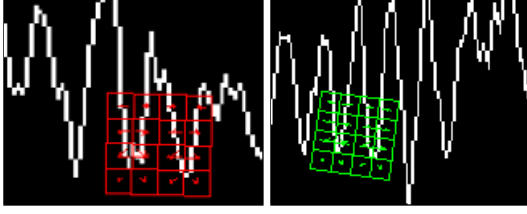
Fig. 2: A region around a keypoint in the left image was matched against a corresponding and visually similar region on the right image. These images correspond to the Dataset I, channel 7 (O_1) for the class 1 (eyes open) for two different subjects.

ε was modified to reduce the sensitivity of the threshold filter which is applied in the proposed algorithm [17]. The set of descriptors $D(c) = \bigcup_i \mathscr{D}I(c,i)$ per channel are clustered using **k-medoids** [18] into F clusters. This algorithm assigns as cluster center an original descriptor from $D(c)$, not an interpolated one. The set of F descriptors is then stored into $kmD(c)$ and each one will be considered as a *visual feature* f. The next step is to identify which ones are actually present on each image. In order to perform this operation, the original descriptors are classified around the k-medoids centers using the nearest neighbour algorithm, i.e. **k-nn** [10]. Finally, for every channel c and feature f, binary feature vectors $O_i(c,f)$ for the whole set of images from both classes ($i = 1, 2$), are created based on the clustering of the descriptors around features. If a particular descriptor from any image of the same class is assigned to cluster f for the channel c then $O_i(c,f)$ is set to 1, and 0 otherwise. The entire code was implemented in MATLAB (Mathworks, Natick, MA), and we used the VLFEAT library [19] for SIFT processing.

E. Feature Translation

The elements from $O_1(c,f)$ and $O_2(c,f)$ that are equal to zero, determine that none of the images from that class contains the feature f for some specific channel c. The set of tuples (c,f) can be used to classify to which set each image belongs, hence, to which class each sample window is classified. This can be finally used as discrimination information, as long as $O_1(c,f) \neq O_2(c,f)$

III. RESULTS

Results can be summarized in the Table 1. Confusion Matrices for both datasets show that every training sampled window was matched to its proper class, and no mismatch was found.

Parameters for both the Feature Extraction and the Matching Strategy can be found on Table 2: the scale δ that was

Data: Image per Sample Window $\mathscr{I}(c,s)$
Result: Discrimination Matrices O_1 and O_2
for *each epoch or subject s* **do**
   for *each channel c* **do**
      $\mathscr{DI}(c,s) \leftarrow$ SIFT($\mathscr{I}(c,s)$);
      Add $\mathscr{DI}(c,s) \rightarrow$ D(c);
   end
end
while *per each channel* **do**
   kmD(c) $\leftarrow$ kMedoids(D(c));
end
for *each epoch or subject s* **do**
   for *each channel c* **do**
      for *each descriptor d in $\mathscr{DI}(c,s)$* **do**
         $f \leftarrow$ **knn**(d, kmD(c)) ;
         $O_1(c,f) \leftarrow 1$ when class is 1;
         $O_2(c,f) \leftarrow 1$ when class is 2;
      end
   end
end
Algorithm 1: Construction of Discrimination Matrices

Table 1: Confusion Matrices for Dataset I (left) and Dataset II (right). Columns are predicted values for both training sets.

	Positive	Negative			Positive	Negative
True	10	0		*True*	159	0
False	0	10		*False*	0	157

used to generate the image plot, the edge-threshold ε which controls the sensitivity of the SIFT algorithm to filter borders and the Feature Vector Dimension F which controls the number of k-medoids cluster centers. We used $k = 1$ for the number of neighbours to consider on the **knn** algorithm.

Table 2: Parameters values

Dataset	δ	ε	F
I	1	10	200
II	2	40	700
II	4	15	700
II	8	10	700

The selection of these parameters was performed empirically based on the following guidelines: in order to obtain an adequate number of descriptors from SIFT, the edge-threshold ε was adjusted accordingly (i.e. greater than the default value of 10). This was due to the fact that a binary image

is basically a contour image, and the sift edge response filtering should be loosen [17]. At the same time, having too many descriptors is in detriment of the algorithm in terms of processing time and memory, thus its number must be bounded. Lastly, the number of features F was increased accordingly until perfect classification was achieved. A value slightly less than the one specified for F is unable to classify images with low information content.

IV. Discussion

Currently, our objective is to extend these results in order to devise a set of SIFT descriptors which can characterize EEG signals with their corresponding and underlying mental activity. Once a set of relevant descriptors can be found off-line for a given cognitive pattern, they could be used on single trial on-line procedures implementing protocols to transmit volition or any other control signal.

We used a direct image generation algorithm but other approaches can be selected to verify if better results regarding generalization performance can be obtained. Additionally, empirical work on SIFT parameters and its usage on EEG images should be encouraged. We found that the sensitivity of the parameter selection is very high. Extension to other BCI mental paradigms like P300, SSVEP, Visual Spatial Covert Attention, ErrP [1] and other similar phenomena, as well as, passive mental states, like alertness, will be desirable.

V. Conclusion

We presented a method for EEG signal feature extraction and classification. We verified here that the procedure can be successfully applied to two physiologically meaningful datasets and that it is possible to discriminate known EEG signals based solely on their plots according to the proposed algorithm. If the correct values for parameters are used, the proposed method could successfully classify the signals of both datasets without any a priori knowledge of the signals. This is an advantage since the classical way to address the classification problem for the first Dataset is analysing the frequency space, while for the second Dataset, the analysis is done in the temporary space.

Conflict of Interest

The authors declare that they have no conflict of interest.

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