where λ is the length in seconds covered by the patch, F_s is the sampling frequency of the EEG signal (downsampled to 16 Hz) and $\Delta\mu V$ corresponds to the amplitude in microvolts that can be covered by the height of the patch. The geometric structure of the patch forces a squared configuration, then we discerned that by using $s = s_x = s_y = 3$ and $\gamma = 4$, the local patch and the descriptor can identify events of 9 μV of amplitude, with a span of $\lambda = 0.56$ seconds. This also determines that 1 pixel represents $\frac{1}{\gamma} = \frac{1}{4}\mu V$ on the vertical direction and $\frac{1}{F_s\,\gamma} = \frac{1}{64}$ seconds on the horizontal direction. The keypoints $\mathbf{p_k}$ are located at $(x_{p_k}, y_{p_k}) = (0.55 F_s\,\gamma, z^l(c)) = (35, z^l(c))$ for the corresponding channel c and location l (see Equation 4). In this way the whole transient event is captured. Figure 4 shows a patch of a signal plot covering the complete amplitude (vertical direction) and the complete span of the signal event (horizontal direction).

Lastly, the number of channels C is equal to 8 for both datasets, and the number of intensification sequences k_a is fixed to 10. The parameter k used to construct the set $N_T(\mathbf{d}^{(l,c)})$ is assigned to $k = 7$, which was found empirically to achieve better results. In addition, the norm used on Equations 8 and 9 is the cosine norm, and descriptors are normalized to $[-1, 1]$.

3 RESULTS

Table 1 shows the results of applying the Histogram of Gradient Orientations (HIST) algorithm to the subjects of the public dataset of ALS patients. The percentage of correctly spelled letters is calculated while performing an offline BCI Simulation. From the seven words for each subject, the first three are used for calibration, and the remaining four are used for testing. The best performing channel bpc is informed as well. The target ratio is $1 : 36$; hence theoretical chance level is 2.8%. It can be observed that the best performance of the letter identification method is reached in a dissimilar channel depending on the subject being studied. This table shows for comparison the obtained performance rates using single-channel signals with the Support Vector Machine (SVM) (Scholkopf and Smola, 2001) classifier. This method is configured to use a linear kernel. The best performing channel, where the best letter identification rate was achieved, is also depicted.

The Information Transfer Rate (ITR), or Bit Transfer Rate (BTR), in the case of reactive BCIs (Wolpaw and E., 2012) depends on the amount of signal averaging required to transmit a valid and robust selection. Figure 5 shows the performance curves for varying intensification sequences for the subjects included in the dataset of ALS patients. It can be noticed that the percentage of correctly identified letters depends on the number of intensification sequences that are used to obtain the averaged signal. Moreover, when the number of intensification sequences tend to 1, which corresponds to single-intensification character recognition, the performance is reduced. As mentioned before, the SNR of the P300 obtained from only one segment of the intensification sequence is very low and the shape of its P300 component is not very well defined.

In Table 2 the results obtained for 8 healthy subjects are shown. It can be observed that the performance is above chance level. It was verified that HIST method has an improved performance at letter identification than SVM that process the signals on a channel by channel strategy (Wilcoxon signed-rank test, $p = 0.004$ for both datasets).

Tables 3 and 4 are presented in order to compare the performance of the HIST method versus a multichannel version of the Stepwise Linear Discriminant Analysis (SWLDA) and SVM classification algorithms for both datasets. The feature was formed by concatenating all the channels (Krusienski et al., 2006). SWLDA is the methodology proposed by the ALS dataset's publisher. Since authors Riccio et al. (2013) did not report the Character Recognition Rate obtained for this dataset, we replicate their procedure and include the performance obtained with the SWLDA algorithm at letter identification. It was verified for the dataset of ALS patients that it has similar performance against other methods like SWLDA or SVM, which use a multichannel feature (Quade test with $p = 0.55$) whereas for the dataset of healthy subjects significant differences where found (Quade test with $p = 0.02$) where only the HIST method achieved a different performance than SVM (with multiple comparisons, significant difference of level 0.05).

The P300 ERP consists of two overlapping components: the P3a and P3b, the former with frontocentral distribution while the later stronger on centroparietal region (Polich, 2007). Hence, the standard practice is to find the stronger response on the central channel Cz (Riccio et al., 2013). However, Krusienski et al. (2006) show that the response may also arise in occipital regions. We found that by analyzing only the waveforms, occipital channels PO8 and PO7 show higher performances for some subjects.

As subjects have varying *latencies* and *amplitudes* of their P300 components, they also have a varying stability of the *shape* of the generated ERP (Nam et al., 2010). Figure 6 shows 10 sample P300 templates patches for patients 8 and 3 from the dataset of ALS patients. It can be discerned that in coincidence with the performance results, the P300 signature is more clear and consistent for subject 8 (A) while for subject 3 (B) the characteristic pattern is more difficult to perceive.

Additionally, the stability of the P300 component waveform has been extensively studied in patients with ALS (Sellers et al., 2006; Madarame et al., 2008; Nijboer and Broermann, 2009; Mak et al., 2012; McCane et al., 2015) where it was found that these patients have a stable P300 component, which were also sustained across different sessions. In line with these results we do not find evidence of a difference in terms of the performance obtained by analyzing the waveforms (HIST) for the group of patients with ALS and the healthy group of volunteers (Mann-Whitney U Test, $p = 0.46$). Particularly, the best performance is obtained for a subject from the ALS dataset for which, based on visual observation, the shape of they P300 component is consistently identified.

It is important to remark that when applied to binary images obtained from signal plots, the feature extraction method described in Section 2.1.3 generates sparse descriptors. Under this subspace we found that using the cosine metric yielded a significant performance improvement. On the other hand, the unary classification scheme based on the NBNN algorithm proved very beneficial for the P300 Speller Matrix. This is due to the fact that this approach solves the unbalance dataset problem which is inherent to the oddball paradigm (Tibon and Levy, 2015).

4 DISCUSSION

Among other applications of Brain Computer Interfaces, the goal of the discipline is to provide communication assistance to people affected by neuro-degenerative diseases, who are the most likely population to benefit from BCI systems and EEG processing and analysis.

In this work, a method to extract an objective metric from the waveform of the plots of EEG signals is presented. Its usage to implement a valid P300-Based BCI Speller application is expounded. Additionally, its validity is evaluated using a public dataset of ALS patients and an own dataset of healthy subjects.

It was verified that this method has an improved performance at letter identification than other methods that process the signals on a channel by channel strategy, and it even has a comparable performance against other methods like SWLDA or SVM, which uses a multichannel feature. Furthermore, this method has the advantage that shapes of waveforms can be analyzed in an objective way. We observed that the shape of the P300 component is more stable in occipital channels, where the performance for identifying letters