Brain Mapping and Interpretation of Reading Processing in Children Using EEG and Multivariate Statistical Analysis

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Abstract

Difficulties in learning to read may have a number of causes and children tend to experience on the phonological route the most common disturbance in this cognitive task. Using two sample groups of children with and without reading difficulties and their corresponding EEG signals captured during the reading processing, we describe in this work a set of techniques that investigates such disturbance by generating whole brain mappings based on the entropy of each EEG electrode and non-supervised and supervised multivariate statistical analyses. Our experimental results have clearly showed specific neural organizations well suited to interpreting the word/phrase reading processing in these children. We believe that these techniques might become an effective computational tool in helping the diagnostic process of children with learning disabilities.

1. Introduction

Difficulties in learning to read may have a biological cause, the neural connections may not organize themselves accordingly during the neurological development since the fetal stage till the first childhood due to both genetic [52, 1, 35, 42, 17, 51, 38, 43, 15, 19] and environmental factors, such as malnutrition [39, 21, 41], preterm birth [31], mother depression [21], stress suffered by the mother during pregnancy [24, 41], use of drugs [41, 51, 8], among others.

These factors may disrupt one or both of the principal neural circuits appointed nowadays as underlying human reading ability according to the *dual-route model* [5, 7, 23, 37, 6, 53]. Figure 1 illustrates the brain areas involved on the *dual-route model* of reading. One circuit involves occipto-temporal connections and is described as the lexical route, the other involves parieto-frontal connections and is described as the phonological route [5, 7, 6], being the disturbance of each of these routes named as surface and phonological dyslexia respectively [23, 37, 53]. In other words, the first route translates the visual information transmitted by the string of letters of each word, processed by temporal neurons grouped in the previous identified *word-form area* directly in its meaning through the area of Wernicke, named from a neurologist. Neurons from this area establish the connection from the string of letters of each word to multiple brain regions depending on the word meaning and semantic field. The second route converts each grapheme or group of grapheme (syllable), identified by parietal neurons, to the sound it represents, what is operated by frontal neurons, to construct the sound of the word and finally access its meaning, again through Wernicke's area. Children may experiment one or both of these routes disturbance, but what is more frequent to observe is the difficulty children experience in the grapheme-phoneme conversation involved on the phonological route.

In this context, this work uses the Distributed Intelligent Processing System (DIPS) model [48, 11, 9] to process the EEG signal aiming to summarize the information provided by each electrode from the conventional 10/20 system [32] and analyse the reading processing in children. DIPS was first developed on the field of Artificial Intelligence in order to formalize systems composed of multiple agents, where each one of these agents could specialize itself in the processing of some specific kind of information and could participate on various different associations with other agents to solve complex tasks [4, 12, 36, 45, 46, 55].

More specifically, assuming that the brain can be understood as a DIPS model and based on the *neural efficiency theory* [22], we describe and implement here a technique of brain mapping that has been used to investigate the associ-

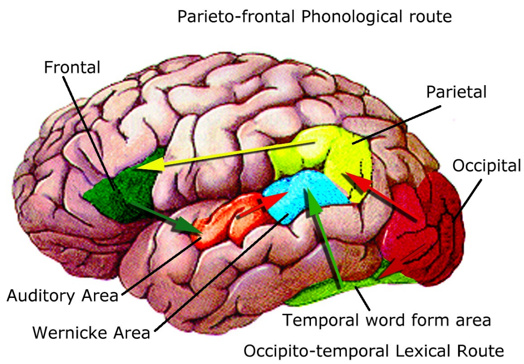


Figure 1. Brain areas involved on the *dual-route model* of reading.

ations among the agents of the neural system during cognitive tasks, illustrating these associations by means of a non-supervised multivariate statistical technique [16, 48]. Additionally, as a new contribution, we extend in this article the use of this methodology to investigate the efficiency of a supervised multivariate statistical technique in discriminating between the neural organization of a normal reading group and a group having learning difficulties possibly caused by neuronal disorder such as dyslexia. Our experimental results have showed specific neural organizations well suited to interpreting the reading processing in children.

The paper is organized as follows. Next, in section 2, we provide information about the sample groups selected to study the reading processing in children based on a public school in São Paulo, Brazil. Then, section 3 describes the technique of EEG summarization and the non-supervised and supervised multivariate methods used to generate the whole brain mappings for interpreting the reading experiments. All the results of the experiments carried out in this work have been explained in section 4. Finally, in section 5, we conclude the paper, arguing about some findings highlighted in this work.

2. Material

Two sample groups of children were selected from a public school of the city of Mogi das Cruzes (São Paulo, Brazil), having (DL) and having not (CO) reading difficulty complains by their teachers.

A specific anamnese, which involved the relatives of the children, was used to investigate the possible neurological disturbance of the DL sample group. This anamnese considers environmental factors that could impair brain development from the fetal age until early childhood. The DL group particularly exhibited statistical significant occurrences such as motherly high stress index during pregnancy, use of tobacco and alcohol, low birth weight, among others, suggesting the aforementioned difficulties in reading by this group due to possibly neurological disturbances.

Both DL and CO sample groups have been composed of 10 children (5 boys, 5 girls). The age of the DL children has varied from 10 to 14 and of the CO children from 8 to 12. This age difference occurred owing to the school gap of DL children. Both groups had to solve a 6-word or -phrase reading task where they have to select an image (clicking on it) out of five that best describes the corresponding meaning of the word or phrase presented as written language above the image options. Figure 2 shows an example of a word reading task carried out in the experiments.

To demand from children an equivalent cognitive effort, the word or phrase reading task has been selected according to each child development - those who could read words without any error did the phrase task, whereas those who could not read phrases did the word one.

3. Methods

Children solved tasks while their EEG signals were registered using 20 electrodes placed according to the 10/20 system [32], as illustrated in Figure 3. Statistical analysis of their performance and the recorded EEG signals provided the data to investigate the aforementioned cognitive function, generating whole brain mappings based on the entropy of each EEG electrode [16, 48, 47] and on non-supervised and supervised multivariate techniques. The technique of EEG summarization is not new and has been successfully applied to study neural plasticity [16], arithmetic brain processing [48], dermatological treatment satisfaction [2], election decision making [11], DIPS model [9] and, more recently, moral dilemma [10] and medical diagnosis [44].

3.1. EEG signals summarization

EEG records the electrical field potentials generated by the activation of sets of neurons or source signals s_l located in several distinct cortical areas. The EEG data $d_i(t)$ recorded at a single electrode i represents a weighted linear sum of underlying source signals, that is:

$$d_i(t) = \sum_{i=1}^{k} w_i s_l(t). \tag{1}$$

The weights w_i are determined by the distance of the cortical source domains s_i from the electrode pair, the orientation of the cortical patch relative to the electrode pair locations, and the electrical properties of intervening tissues. The number k of active sources is determined by the task being currently processed by the brain.

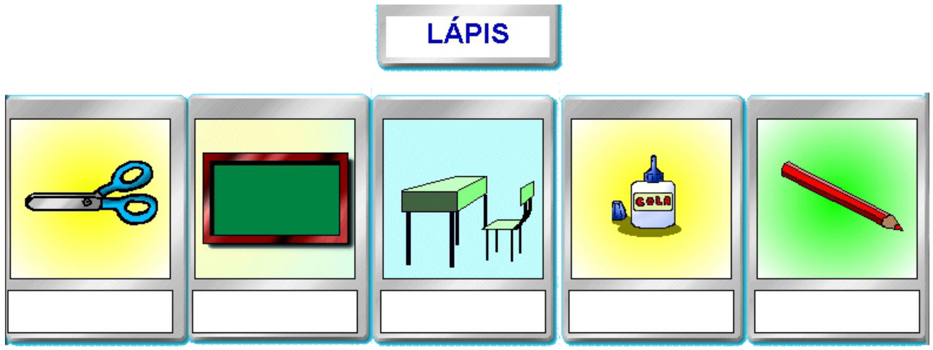


Figure 2. An example of a word reading task carried out in the experiments. Each child has to select an image (clicking on it) out of the five shown that best describes the corresponding meaning of the word presented as written language above the image options.

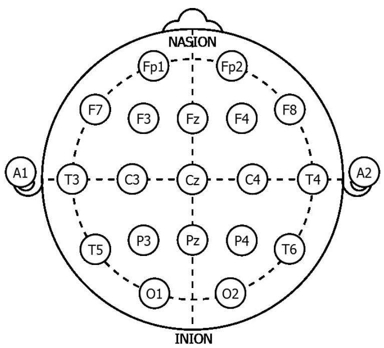


Figure 3. The position of each one of the 20 electrodes according to the 10/20 conventional system [32]. The letters F, T, C, P and O stand for frontal, temporal, central, parietal, and occipital lobes, respectively. The markers A1 and A2 are used as references to the midline of the brain.

The statistical complexity of the investigation increases as the number of EEG and behavioral variables increase as well. Therefore, it is necessary to summarize the information provided by each electrode e_i about all sources s_l into a single variable to make statistical analysis amenable. Since EEG data are assumed to be a weighted sum of the electrical activity of the different sources, correlation analysis of the EEG activity $d_i(t)$ recorded by the different electrodes e_i may be used to calculate the entropy information $h(e_i)$ provided by each electrode e_i about all k involved sources s_i into a single variable [16, 48].

The rationality of this process can be briefly explained as follows. Given that data $d_i(t)$ and $d_j(t)$, furnished by two electrodes e_i and e_j, provide equivalent information about sources s_i then the absolute value of correlation coefficient $c_{i,j}$ calculated for $d_i(t)$ and $d_j(t)$ will approach 1, otherwise it will approach 0. The highest uncertainty about the information equivalence provided by e_i and e_j occurs when the correlation strength $c_{i,j}$ approaches 0.5.

Therefore, in the same line of reasoning used by Shannon [50] to define the amount of information provided by a random variable, it is proposed that the *informational equivalence* $h(c_i, c_j)$ of $d_i(t)$ and $d_j(t)$ furnished by e_i and e_j is the expected value $E(I(c_{i,j}))$ of the information $I(c_{i,j})$ provided by $c_{i,j}$ [16, 48, 47]. However, because $c_{i,j}$ may theoretically assume values equal to zero, instead of using Shannon's logarithm function, the $h(c_{i,j})$ estimate has been calculated by:

$$\begin{aligned} h(c_{i,j}) &= E(I(c_{i,j})) \\ &= -[c_{i,j} log_2(c_{i,j}) + (1 - c_{i,j}) log_2(1 - c_{i,j})]. \end{aligned} \quad (2)$$

Now, given q electrodes and the average correlation coefficient

$$\bar{c}_i = \frac{\sum_{j=1}^{q-1} c_{i,j}}{q-1}, \quad (3)$$

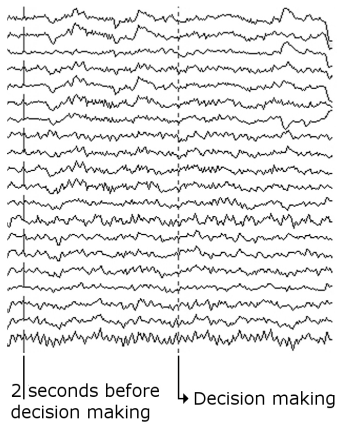
the *informational equivalence* measured by $\bar{c}_i$ can be written by the following formula

$$h(\bar{c}_i) = -[\bar{c}_i log_2(\bar{c}_i) + (1 - \bar{c}_i) log_2(1 - \bar{c}_i)], \quad (4)$$

which calculates the information provided by $d_i(t)$ concerning that provided by all other $d_j(t)$. Thus,

$$h(e_i) = \sum_{j=1}^{q-1} [h(\bar{c}_i) - h(c_{i,j})] \quad (5)$$

computes the information provided by $d_i(t)$ recorded by e_i about the sources s_i. In short, in a cognitive task solving, we shall expect:



Electrodes	$c_{i,j}$	$h(c_{i,j})$
C3		
C4	0,985	0,11
CZ	0,812	0,70
F3	0,818	0,68
F4	0,945	0,31
F7	0,813	0,70
F8	0,714	0,86
FP1	0,763	0,79
FP2	0,836	0,64
FZ	0,761	0,79
O1	0,629	0,95
O2	0,680	0,90
OZ	0,697	0,88
P3	0,665	0,92
P4	0,597	0,97
PZ	0,613	0,96
T3	0,014	0,11
T4	0,370	0,95
T5	0,220	0,76
T6	0,269	0,84
$\bar{c}_i$	0,642	

Figure 4. An illustrative example of an EEG summarization calculated in the experiments for the C3 electrode. All the calculations have been made using the previous 2 seconds immediately before the decision making.

a) if $c_{i,j} = 1$ for all e_j then $\bar{c}_i = 1$, $h(c_{i,j}) = h(\bar{c}_i)$ for all e_j, and consequently $h(e_i) = 0$. This indicates that $d_i(t)$ and the corresponding e_i do not provide any additional information about the sources s_i;

b) if $c_{i,j} = 0$ for half of e_j and $c_{i,j} = 1$ for the other half, then $\bar{c}_i = 0.5$, $h(\bar{c}_i) = 1$, $h(c_{i,j}) = 0$ for all e_j, and consequently $h(e_i)$ is maximum and equal to 1. This indicates that $d_i(t)$ and the corresponding e_i discriminate two different groups of electrodes providing information about distinct groups of sources s_i, and

c) for all other conditions, i.e. $0 < h(e_i) < 1$, $h(e_i)$ quantifies the information provided by $d_i(t)$ about the sources s_i .

Figure 4 shows an illustrative example of an EEG summarization calculated in the experiments for the C3 electrode.

3.2. Factor Analysis

We have used Factor Analysis (FA), a well-known multivariate statistical technique, to describe the association between the entropy values of the electrodes in a non-supervised way. The main idea behind FA is to disclose the correlation relationships among the original variables using a few unobservable random ones, called common factors, to adequately represent the data [33].

In particular, let an $N \times n$ data matrix X be composed of N input signals (or trials) with n variables (or electrodes). This means that each column of matrix X represents the EEG summarization of a particular electrode observed all over the N trials. Let this data matrix X have sample correlation matrix R with respectively P and Λ eigenvector and eigenvalue matrices, that is,

$$P^T R P = \Lambda. \tag{6}$$

It is a proven result that the set of m ($m \leq n$) eigenvectors of R, which corresponds to the m largest eigenvalues, minimizes the mean square reconstruction error over all choices of m orthonormal basis vectors [18]. Such a set of eigenvectors scaled by the square root of the corresponding eigenvalues [33] and calculated as

$$\hat{L} = [\sqrt{\lambda_1} p_1, \sqrt{\lambda_2} p_2, ..., \sqrt{\lambda_m} p_m] \tag{7}$$

is known as the factor loadings of the data matrix X estimated by the principal component method.

The estimated factor loadings $\hat{L}$ of X can be rotated in order to improve the understanding of the factors, specially if R deviates significantly from a diagonal matrix. If $\hat{L}$ is the $n \times m$ matrix of estimated factor loadings then

$$\hat{F} = \hat{L} T \tag{8}$$

is a $n \times m$ matrix of rotated estimated factor loadings, where T is assumed to be an orthonormal $m \times m$ rotation matrix, that is, $TT^T = T^T T = I$.

Ideally, we would like to see a pattern of loadings where each subset of electrodes is highly represented by a single factor and has negligible coefficients on the remaining ones, allowing an interpretation of the EEG brain mappings with no overlappings. Thus, our natural choice of the orthonormal matrix T has been based on the varimax criterion proposed by Kaiser [34], which has been followed by others in analogous works [16, 47, 48, 11] .

Therefore, those $\hat{F} = [\hat{f}_1, \hat{f}_2, ..., \hat{f}_m]$ can then replace the initial n variables on m rotated common factor loadings where not only the association between the EEG electrodes would be most expressive in terms of variance information, but also the brain mappings would be the most independent ones given by the perpendicular rotation T of the initial factor loadings estimated by the principal components method.

3.3. Linear Discriminant Analysis

The association between the entropy values of the electrodes in a supervised way has been performed here using Linear Discriminant Analysis (LDA) and the technique of hyperplane navigation [54, 20, 49]. The primary purpose of LDA is to separate samples of distinct groups by maximizing their between-class separability while minimizing their within-class variability.

Let the between-class scatter matrix S_b be defined as

$$S_b = \sum_{i=1}^{g} N_i(\overline{x}_i - \overline{x})(\overline{x}_i - \overline{x})^T \quad (9)$$

and the within-class scatter matrix S_w be defined as

$$S_w = \sum_{i=1}^{g}(N_i - 1)S_i = \sum_{i=1}^{g}\sum_{j=1}^{N_i}(x_{i,j} - \overline{x}_i)(x_{i,j} - \overline{x}_i)^T, \quad (10)$$

where $x_{i,j}$ is the n-dimensional signal (or trial) j from class π_i, N_i is the number of trials from class π_i, and g is the total number of classes or groups. The vector $\overline{x}_i$ and matrix S_i are respectively the unbiased sample mean and sample covariance matrix of class π_i [18]. The grand mean vector $\overline{x}$ is given by

$$\overline{x} = \frac{1}{N}\sum_{i=1}^{g} N_i\overline{x}_i = \frac{1}{N}\sum_{i=1}^{g}\sum_{j=1}^{N_i} x_{i,j}, \quad (11)$$

where N is, as described earlier, the total number of input signals, that is, $N = N_1 + N_2 + \ldots + N_g$.

The main objective of LDA is to find a projection matrix W_{lda} that maximizes the ratio of the determinant of the between-class scatter matrix to the determinant of the within-class scatter matrix (Fisher's criterion), that is,

$$W_{lda} = \arg\max_{W} \frac{|W^T S_b W|}{|W^T S_w W|}. \quad (12)$$

The Fisher's criterion described in equation (12) is maximized when the projection matrix W_{lda} is composed of the eigenvectors of $S_w^{-1}S_b$ with at most $(g-1)$ nonzero corresponding eigenvalues [18, 13]. In the case here of a two-class problem, the LDA projection matrix is in fact the leading eigenvector w_{lda} of $S_w^{-1}S_b$.

Once the leading eigenvector w_{lda} has been computed, we can move along its corresponding projection vector and extract simultaneously the discriminant differences captured by the entropy of each EEG electrode. In mathematical terms, assuming that the spreads of the sample groups follow a Gaussian distribution, this procedure of navigating on the most discriminant projection [54, 20, 49] can be generated through the following simple expression:

$$y_{i,j} = \overline{x} + j\sigma_i \cdot w_{lda}, \quad (13)$$

where $j \in \{-3, -2, -1, 0, 1, 2, 3\}$ and σ_i is the standard deviation of each sample group $i \in \{1, 2\}$.

4. Results

Figures 5 and 6 describe the rotated estimated factor loadings of the neural organization of the CO and DL sample groups, respectively, with corresponding eigenvalues greater than 1.

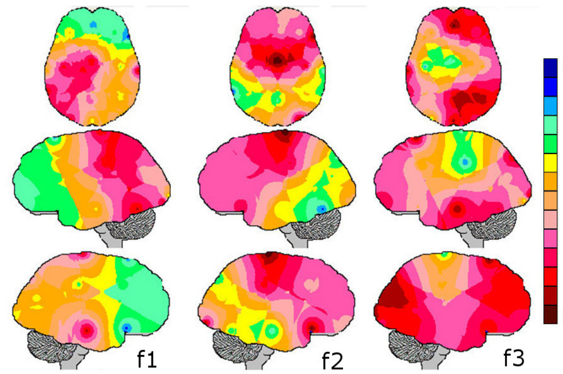


Figure 5. Brain mapping of the most expressive factor loadings of the CO sample group with corresponding eigenvalues greater than 1.

As can be seen from Figure 5, FA using the entropy information from the CO sample group has disclosed three patterns of cortical neural organization. The common factor 1 (f1, on the left) discloses a higher loading value to electrodes FP1, FP2, FZ, F7 and F8; the common factor 2 (f2, in the middle) has clustered T4, T5, T6 and PZ; and the common factor 3 (f3, on the right) shows the connection between CZ and C3. In words, f1 shows a bilateral high correlated activity at the anterior brain that may be associated with the reading executive functions [3, 14], target word loading in the working memory and the temporal and spatial eye scanning control of the possible matching words or figures. The second factor, f2, shows a bilateral correlated activity at the temporal brain that may be associated with both the visual recognition of words and figures and the associated meaning processing [56, 40, 57]. The last factor considered, f3, discloses a relation between medial and left central electrodes possibly associated to decision making. It is important to note that the bilateral association disclosed by the first two common factors (f1 and f2) is in accordance with the fact that our word/phrase reading tasks involved both visual (a preferential right hemisphere function) [29, 30, 25] and verbal (the left hemisphere specialization) [26, 27, 28] processing and association of these results.

However, from Figure 6, it is possible to see that using the entropy information from the DL sample group FA has disclosed only two patterns of brain activity for word/phrase reading solution in children with learning difficulties. The common factor 1 (f1, on the left) of Figure 6 discloses a high correlated bilateral anterior activity encompassing a greater amount of sources than factor 1 of CO group. Here it consumes resources from basically all central and frontal brain but the prefrontal. This could be in accordance with

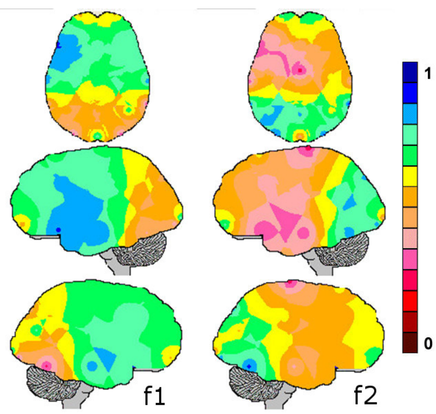


Figure 6. Brain mapping of the most expressive factor loadings of the DL sample group with corresponding eigenvalues greater than 1.

the fact that these individuals, being unable to disclose the meaning of the words, had to compute much more executive functions in controlling the possible associations between the images processed by right neurons and the sounds they could produce from their poor grapheme-phoneme conversion operated at left neurons. In factor 2 (f2, on the right) we see a strong covariation at the posterior and prefrontal brain, enrolling the temporal T5 and T6 and occiptal O1 and O2 regions. This association may be related with the attempt to associate meaning to the target written word directly from the visual analysis of the possible matching figures by the lexical route but demanding executive efforts from prefrontal neurons showing a not well established temporo-occiptal integration. From these two maps we may argue that this group tried to use both reading routes, but disrupted one from another, failing in use executive functions to coordinate the interaction between them.

Lastly, the LDA brain mapping is shown in Figure 7. LDA hyperplane navigation has disclosed a left to right differentiation between CO and DL, grouping mainly the left central and prefrontal regions of the electrodes C3 and FP1 on CO group and the right central and frontal regions of the electrodes C4 and F8 on the DL group. In other words, LDA showed that what most discriminated controls from those with reading difficulties might have been the activity on language/reading circuits located on left hemisphere, whereas right activity, possibly associated to visual processing of the image options, discriminated the children with reading difficulties. According to the fact that DL children did not retrieve the meaning of the words, it might be suggested that this group relied less on language circuits to solve the task and more on visual processing trying to find out what image could be selected by examining and comparing each one with the verbal sounds they achieved to translate through the grapheme-phoneme conversion.

5. Discussion

In this work, we have used EEG and multivariate statistical analysis to disclose cortical neural organization of different groups of children having distinct performances on word/phrase reading tasks.

Given the design of the reading task we should expect the recruitment of at least the following three main cognitive functions: verbal to read (words), visual to recognize (images) and executive to control attention between the various information stimuli carried out (1 target word and 5 image options). Since the work from Baddeley [3], it has been suggested that our working memory, that is, our ability to deal with various information for a short period of time, involves three components which comprise the temporal verbal-acoustic storage system, the visual sketchpad and the central executive, having each one of these components a respectively major correspondence to left, right and frontal-prefrontal brain areas.

Therefore, based on our DL sample group results and linking the briefly mentioned Baddeley model with the *dual-route* reading language model, we may argue that: (factor 1) the temporal verbal-acoustic storage system and the visual sketchpad were associated trying to correlate the sounds produced by the left frontal neurons during grapheme-phoneme conversion to the image options and positions processed by the right central frontal areas; (factor 2) the occipital-temporal lexical route needed the enrollment of pre-frontal neurons in order to use the central executive to coordinate the interaction between the *word-reading area* (temporal neurons) and the visual occipital neurons.

As a final consideration, the differences found between both sample groups, i.e. the number of factors with eigenvalues greater than 1 and the left to right regions discriminating CO and DL children, show that the set of techniques used here to generate the brain mappings may become an effective tool in helping the diagnostic process of children with learning disabilities. We believe that these mappings used jointly with an anamnesis and a set of cognitive tasks may at least help us better understand the neural organization underlying the ability to solve different kinds of problems by different sample groups.

Acknowledgements

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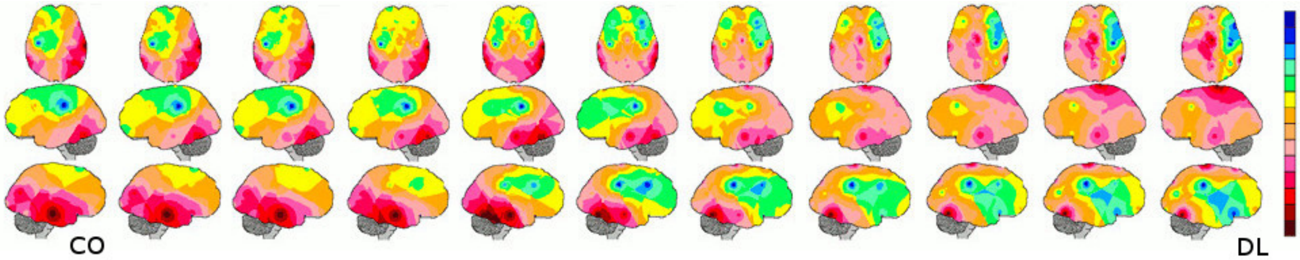

Figure 7. Brain mapping of the most discriminant entropy values captured by the LDA hyperplane navigation. From left (group of CO samples) to right (group of DL samples): $[-3\sigma_1, -2\sigma_1, -1\sigma_1, \overline{x}_1, +1\sigma_1, boundary, -1\sigma_2, \overline{x}_2, +1\sigma_2, +2\sigma_2, +3\sigma_2]$.

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