1. Data recording

Some voluntaries have been subjected to the following experiment: the subject was in front of a monitor by which some visual commands are imparted. Looking for these they think to move the right or the left hand. Our purpose is to investigate if it’s possible, from EEG data, to know at what time the mental task occurs. We have to be sure that the EEG changes are not related to the evoked potential due to the visual stimulus; so we made some records to compare imagined movements to an other mental task: a mathematical operation.

After this we try to find a way to discriminate baseline activity from imagined movements: neural networks are the best tool we have to solve classification problems. Data were recorded using 23 electrodes referred to a common electrode G placed in the center of the head (fig.1).

2. Signal pre-processing

Laplace filter

EEG signals are processed with a Laplace filter that transforms the channels making the difference between electrodes 4-5-6 and 13-14-15 and the mean with its cardinal neighbors (Fig 2a). This localizes the information of neighbors electrodes on the central electro-
de. In this way we reduce the number of electrodes from 22 to 6 and we localize the information on the area of the motor cortex of the hand (L2 and L4) and on the pre-motor cortex (L1, L3, L5 and L6) (Fig 2b).

**Downsampling**
The signal is downsampled of a factor L; this means that we pass from N to N/L samples getting a signal with sampling frequency \( f_s / L \) (\( f_s \) is the starting sampling frequency) and maximum frequency \( f_{max} = 1/L \times (f_s / 2) \) Hz.

To avoid aliasing we used an input low pass filter so the high frequency components didn’t fall down making interferences. We choose a FIR filter with a numbers of taps depending on the \( L \) value. The advantages of this approach, instead of a low pass filter, are that we reduce the number of data of a factor \( L \) (using the filter we always have the same data number and a too high maximum frequency). Since that we are interested of the Mu band (8 -12 Hz) we put \( L=3 \); so we obtain a maximum frequency of 20.8 Hz which includes very well the band of interest.

**3. Signal features analysis**

**Significant channels**
Being interested to understand what happens in EEG signal when we move or we imagine to move a hand we draw the averaged spectra of signal in two different temporal windows, one before and one after the command. To calculate the spectra we use a multivariate autoregressive model (MAR) with order 4. This model allows to draw spectra of all channels noting the correlation between them. For each spectrum we also calculate the statistic significance of desynchronization. We made this with the “Wicoxon rank test sum” that compares two data sequences and returns the probability they arise from the same population. To be significant the desynchronizations have to be smaller or equal to \( p=0.05 \). In this way we discover the significant desynchronizations occur on L3 channel for imagined movement of the right hand and on L6 channel for the left hand.

**Reduction of electrodes**
As the aim is to build a man-computer interface, it would be fit to reduce the number of electrodes to be applied on the subject’s head. To do this we verified that the desynchronization is also picked-up by the difference between channels 6 and 15. These two channels are 3 cm behind the C3 and C4 of the 10/20 system and we will call them C3’ and C4’. In addition they are particularly resistant to the EOG artefacts. In this case the MAR model is reduced to a simple autoregressive model (AR). Since we consider only one channel.

![Figure 2: a) Weights distribution of Laplace filter. b) Channels after Laplace filter](image)
Imagined movement vs mathematical task
To understand if the mu rhythm desynchronization is really due to the subject’s wish to move a hand and not to an potential evoked by the visual stimulus on the screen (or any other external stimuli), we compare the spectrum generated from a mathematical task between the spectrum of imagined movements. We can note they are very similar; on the contrary the spectrum of a mathematical task is very different from the spectrum of baseline activity. These results confirm the mu rhythm desynchronization is really due to the subject’s wish.

4. Classification
To distinguish between baseline activity and imagined movement, we built a "Multilayer Perceptron" neural network, with logistic activation (sigmoid),

\[ g(a) = \frac{1}{1 + \exp(-a)} \]  

where \( a_t \) is called activation of the network at time \( t \).
We took as the input of the network the coefficients of the autoregressive model, which number corresponds to the model order. In fact these coefficients contain all the information about the spectrum of the signal. As a consequence the number of the inputs of the network corresponds to the order of the AR model. The output is binary and it is calculated from:

\[ y_t = P(\hat{z}_t = 1 | w_t) = g(w_t^T x_t) \]  

where \( w_t \) is the column vector of the weights and \( x_t \) is the input vector at the time \( t \).
We did not make use a MAR model (more precise) because we choose to use only one input channel, which is anyway sufficient to reveal the mu rithm desynchronization. The network was trained with the “Bayesian Evidence Framework” method. This consists in the estimation of the weights of the network and their probabilistic distribution. This distribution is approximated by a gaussian with mean and covariance.

We can consider the distribution of the activations as a gaussian with mean

\[ \bar{a}_t = w_t^T x_t \]  

and variance

Figure 3: Comparison between spectra of baseline activity (continual line) and imagined movement of the right hand (dashed line) on channel C3’-C4’. These charts are averaged over 72 commands.
If we consider the uncertainty on the activations, the output is given by

$$s_i^2 = x_i^T S x_i$$  \hspace{1cm} (4.4)

This integral can be approached by

$$\widetilde{y}_i = P(\hat{z}_i = 1) = P(\hat{z}_i = 1 | a_i) p(a_i) da_i$$  \hspace{1cm} (4.5)

This operation is called moderation and transforms the normal output of the network in a moderated output that is closer to 0.5 (the prior probability of a 2 class problem) of a quantity which depends from the uncertainty on the weights. Normally the moderated output is better than a non moderated output, in terms of likelihood of the prediction. Moreover the moderated output was averaged on a number of consecutive outputs to improve the classification precision. The mean was not performed on the outputs, but in the space of the activations, as suggested by Husmeier (“Modelling conditional probability densities with neural networks”, 1998 Department of mathematics, King’s College London).

A group of outputs was build to perform this mean, combining the prediction of the model with the predictions at T previous steps. The distribution of the activations is considered a “Gaussian mixture”, with mean

$$a_{\text{com}}[t] = \frac{1}{T} \sum_{t=1}^{T} a_t$$  \hspace{1cm} (4.8)

and variance

$$s^2_{\text{com}}[t] = \frac{1}{T} s_i^2 + \frac{1}{T} \left[ k_t - a_{\text{com}} \right]^2$$  \hspace{1cm} (4.9)

The final output is

$$\tilde{y}_{\text{com}}(t) = g(K(s_i)a_{\text{com}})$$  \hspace{1cm} (4.10)

also called moderated committee output. Equations 4.8 and 4.9 are called committee equations.

Figure 4: Example of MLP network with 4 inputs, 3 hidden units and 1 output. W1 and W2 are matrix of weights (W1 is 4x3 and W2 is 3x1). Each neuron has a sigmoid activation function. y is the output.
5. Possible applications

To locate certainly a signal due to the wish of the subject can be useful to some elementary applications. One of the most interesting is to control the ‘Ez Keys’ software used by many disables with any motory activity they still have. To use this program just one external input stimulus is needed by which it is possible to write on a personal computer, often connected to a vocal synthetizer. For example Steven Hawking uses this software clicking a button with the only one finger he can move; other disables control it by blowing, by some muscles of the face or by other.

For all the disables that don’t have any motory activity but that are still in posses of their mental functions a device based on the desynchronisation characterized in this thesis work could be useful. Another very interesting application is to build a device for the control of cursor movement on a PC screen. In fact, thanks to the this signal, is possible to control a 1-D movement device joining at one direction the signal due to baseline activity and, at the other direction, the imagined hand movement.

References


