

Balancing an Inverted Pendulum by Thinking A Real-Time fMRI Approach

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Abstract

We present a method for controlling a dynamical system using real-time fMRI. The objective for the subject in the MR scanner is to balance an inverse pendulum by activating the left or right hand or resting. The brain activity is classified each second by a neural network and the classification is sent to a pendulum simulator to change the force applied to the pendulum. The state of the inverse pendulum is shown to the subject in a pair of VR goggles. The subject was able to balance the inverse pendulum both with real activity and imagined activity. The developments here have a potential to aid people with communication disabilities e.g., locked in people. It might also be a tool for stroke patients to be able to train the damaged brain area and get real-time feedback of when they do it right.

1. Introduction

Despite the enormous complexity of the human mind, fMRI techniques are able to partially observe the state of a brain in action. In offline fMRI the experiment is performed and the data is analyzed afterwards to calculate a level of brain activity for each voxel. In real-time fMRI the data is analyzed directly and used to change the stimulus presented to the subject, see figure 1. The brain state can be interpreted by a computer and the setup is then often called a Brain Computer Interface (BCI). We have tested our BCI with a dynamical pole balancing experiment. In the experiment, the subject was given the possibility to move an inverted pendulum. The pendulum could be pushed to the left or right by activating the parts of the motor cortex associated with activity of the left and right hand. Laconte et al. uses a similar setup in [1] but the arrow that they control can not be considered to be a dynamical system that changes by itself. The dynamical properties of the inverted pendulum make our setup a more challenging problem. We for example have to interpret the desire of the subject and set out a control signal

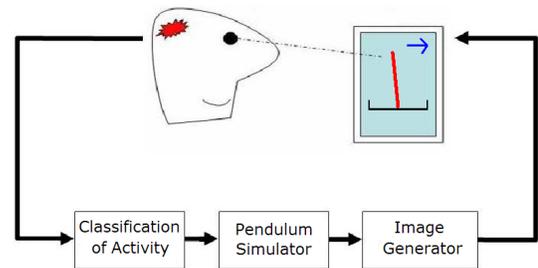


Figure 1. The experiment setup for real-time fMRI, resulting in a bio-feedback loop. The subject sees the red pendulum. The activity for each new volume of data is classified and sent to the pendulum simulator. The blue arrow shows the current classification of the brain activity.

moving the pendulum as often as once a second to have a chance to handle the fast dynamics of the pendulum.

2. Methods

2.1. Measuring brain activity by correlation

In fMRI, functional Magnetic Resonance Imaging, the objective is to find the intensity and spatial position of brain activity. Estimation of brain activity is based on the fact that the magnetic properties of the blood changes when the neurons demand more oxygen to compensate for their increased activity and the body overcompensates the amount of oxygen sent to the neurons. The signal that is detected in fMRI is called the BOLD signal, where BOLD stands for *blood oxygen level dependent*. In offline fMRI, brain activity is normally measured using correlation between the stimulus paradigm and the intensity time series of each voxel. Since the subject is told what to do we calculate the brain activity for each voxel as the correlation with the stimulus paradigm.

2.2. Classification of brain activity

In our real-time fMRI setup, the subject acts independently of any paradigms. Thereby we do not have anything to correlate with. The BOLD signal that we detect in fMRI does not occur directly when some brain activity is started but is delayed 3-5 seconds. This is a property of the human physiology that we can not change. This makes it hard to control a system in real-time. In offline fMRI it does not matter other than that the delay is unknown. Other difficulties in real-time fMRI are that it is harder, compared to offline fMRI, to detrend the time series of each voxel and that all calculations have to be made in real-time. Detrending is needed since there are drifts and trends in the fMRI data that will corrupt the estimates if not removed [2].

Instead of correlation, we classify each volume of data to estimate what the current brain activity is. In this project we classify between left hand activity, right hand activity and rest. A training phase is used to learn a neural network how to classify between the different types of brain activity.

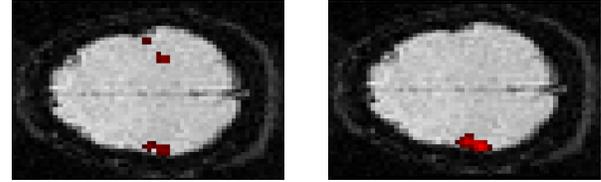
The area of real-time fMRI is relatively new compared to offline fMRI. Some examples of real-time fMRI setups are presented in [1], [3], [4], [5], and [6].

2.3. Neural networks

Neural networks [7] are used in many applications to classify data into a number of predetermined classes. Often some informative properties are first extracted from the data instead of using the raw data itself in the classification. We trained the neural network with all the brain voxels in each collected volume. A spatial mask was used to only include the brain voxels in each volume. Each volume consisted of 80x80x10 voxels and about 9000 of these were considered to be brain voxels. Each volume was also filtered by a 3x3x3 Gaussian low pass filter to make the classifications more robust to motions. In the training phase we used a 240 second long stimulus paradigm consisting of 20 seconds of left activity, followed by 20 seconds of rest and then 20 seconds of right activity, repeated 4 times. In the real-time phase, each volume was spatially smoothed (3x3x3 Gaussian low pass filter) and detrended (by removing the mean value calculated 45 seconds backwards for each voxel separately). A control signal (apply a force to the left, right or do nothing) was then computed by applying the, in the training phase computed, neural network. The control signal was used as an input to the simulation of the dynamical pendulum system. The simulation uses the control signal to change the state of the system by applying an according force to the pendulum.

2.4. Head movement

One potential cause of error in fMRI is that the subject may involuntarily move the head in pace with the stimulus



(a) The most important voxels for classification of left hand activity at one timepoint. (b) The most important voxels for classification of right hand activity at one timepoint.

Figure 2. *The figures show which voxels that are the most important for the classification of the brain activity at two timepoints. It is clear that the voxels in the motor cortex, as expected, are the most important. If head movement was the reason that the experiment setup worked, the voxels at the edge of the brain would have been important for each classification.*

paradigm and thereby induce high correlation in voxels on the edge of the brain or outside the brain. For a neural network it is straight forward to calculate the importance of each voxel for each classification. From this we can eliminate the possibility that the reason that our experiment setup works is due to head movement. If the distance to the decision boundary, for a classification at one timepoint t , is denoted with d_t^2 , then the importance i of voxel v_{nt} (voxel v_n at timepoint t) can be calculated as

$$i_{v_{nt}} = \frac{w_n v_{nt}}{d_t^2} = \frac{w_n v_{nt}}{\sum_n w_n v_{nt}}$$

where w_n is the weight in the neural network for voxel v_n . Before the calculation is made, one has to make sure that the voxel contributes to the right direction from the decision boundary, i.e. that $w_n v_{nt} > 0$. If these calculations are made for all the brain voxels, there will be a lot of voxels that are important for some timepoint but not for a set of continuous timepoints. In order to remove the flickering voxels, a median filtering of the time series of the activity value for each voxel can be made. The resulting importance maps are shown in figure 2. A 3 x 3 gaussian lowpass filter has been used to improve the appearance of the importance maps.

3. Experiment setup

The data was acquired using a 1.5 T Philips Achieva MR scanner. The acquisition resolution was 80 x 80 x 10 voxels. Field of view and slice thickness were chosen to obtain a voxel size of 3 x 3 x 3 mm. Echo time (TE) was set to 40 ms and repetition time (TR) was set to 1000 ms. The classification of the brain activity and the simulation of the inverse pendulum was carried out in Matlab on a standard laptop. The current state of the inverse pendulum was shown to the subject in a pair of VR goggles.

4. Results

The subject was able to balance the inverse pendulum both with real activity and imagined activity. When the subject used imagined activity, the pendulum was balanced by only thinking of activating the left or right hand. To justify the success of the controller figure 3 shows the angle of the pendulum and the classified activity during the real-time phase. The classified activity, marked with blue stars, is used to determine the force applied to the pendulum, i.e. if left activity is classified, a force to the left is applied to the pendulum and the angle of the pendulum decreases. The figure is not straight forward to interpret since the system is rather slow. The effective force applied to the pendulum also depends on the current angle of the pendulum as $\cos(\alpha)$. If the angle is 0, the full force is applied, if the angle is close to $\frac{\pi}{2}$ or $-\frac{\pi}{2}$ the effective force is very small. This means that the subject easily can affect the pendulum if the angle is close to zero while it takes a long time to straighten up the pendulum if the angle is close to $\frac{\pi}{2}$ or $-\frac{\pi}{2}$. The pendulum has a weight and continues to rotate in its current angular direction if no force is applied.

In the beginning of the real-time phase the subject in the scanner needed a couple of attempts to learn the dynamics of the system. Between approximately timepoint 350 and 600 in figure 3 the pendulum was successfully balanced by the subject.

5. Discussion

We have presented an fMRI based BCI realization. The human brain and a computer were here linked by fMRI and worked together as a controller of a dynamical system. The dynamical system was made up of an inverted pendulum. The subject had the ability to induce a force by evoking brain activity in the motor cortex. A force was applied to the left if the subject activated the left hand and to the right if the subject activated the right hand. If the subject was resting no external force was applied. A neural network was trained to separate between rest, activity induced by activating the left and right hand. The subject was able to balance the inverted pendulum both with real and imagined activity. In the future we would like to improve the detection speed of the system. One way to do this is to train the classifier on the transitions between the different states instead of the states them self, as mentioned in [1]. This can be done by looking back at the signal a number of seconds to learn what the different transitions look like, to earlier detect a change of activity. Another way is to look for the small initial dip of the BOLD signal [8]. We would also like to increase the bandwidth of the bio-feedback loop by including a larger number of different simultaneous activities to make the subject able to control a more advanced dynamical system. The developments here have a potential to aid people

with communication disabilities e.g., locked in people [9]. Other possible applications are to study real-time effects of medication, steer the brain into pre-determined states or to learn how control your own pain [5]. It might also be a tool for stroke patients [10] to be able to train the damaged brain area and get real-time feedback of when they do it right.

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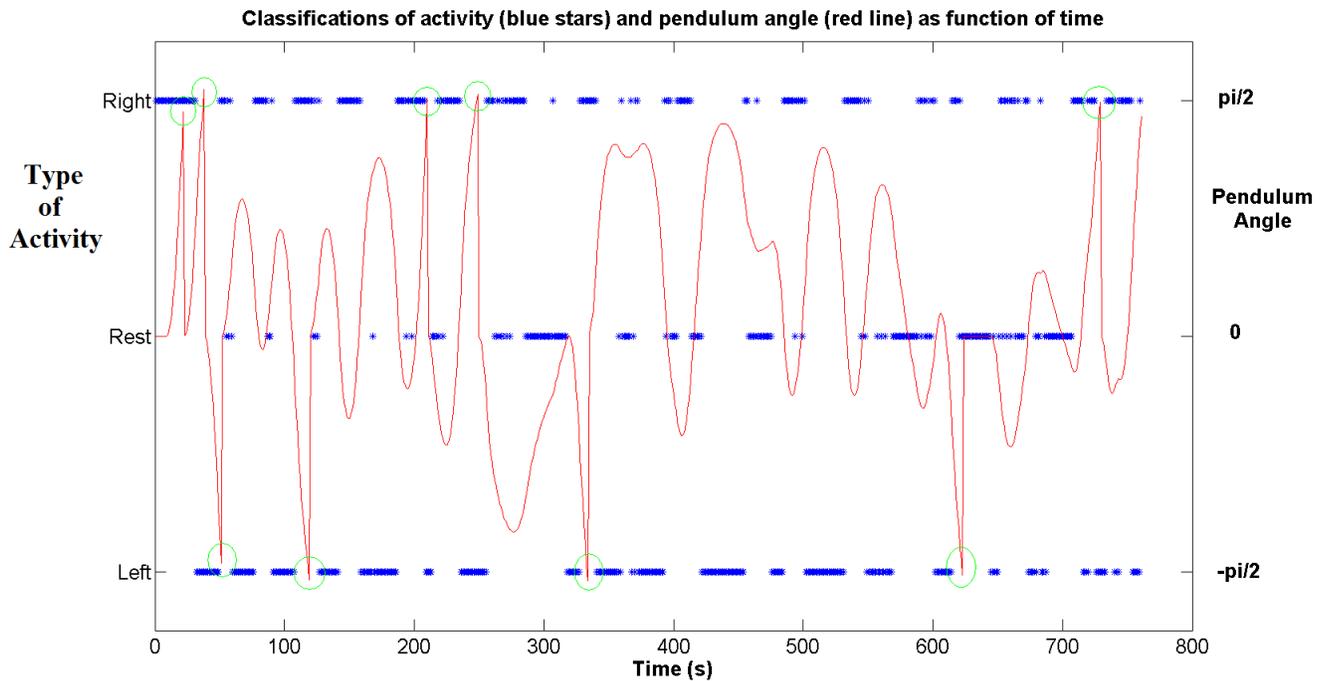


Figure 3. The figure shows the angle of the pendulum, the red line, and the classifications of activity, the blue stars, as a function of time in the real-time phase. If the angle exceeds $\frac{\pi}{2}$ or $-\frac{\pi}{2}$ the pendulum is restarted and the angle is set to zero. This happened 9 times and these timepoints are marked with green circles. The test subject has to compensate for the delayed BOLD-signal by changing activity a few seconds in advance. It is easy to see that the test subject needed a couple of attempts first to learn the dynamics of the system. The effective force applied to the pendulum depends on the angle of the pendulum as $\cos(\alpha)$. Angle 0 means that the pendulum is standing straight up, $-\frac{\pi}{2}$ means that the pendulum lies along the negative x-axis and $\frac{\pi}{2}$ means that the pendulum lies along the positive x-axis. If the activity is classified as left activity, a force to the left on the pendulum is applied and the angle of the pendulum decreases. If the activity is classified as right activity, a force to the right is applied and the angle of the pendulum increases. If the activity is classified as rest, no force is applied and the pendulum continues to rotate in its current angular direction. Between approximately timepoint 350 and 600 in the figure the pendulum was successfully balanced by the subject.