Masters Thesis in Cognitive Sciences

REAL TIME ESTIMATION OF STRESS USING ELECTRO-ENCEPHALOGRAPHY

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ABSTRACT

Introduction. Stress is a major societal issue as it has a negative impact on health and economy. New methods, allowing a reliable real-time stress assessment are therefore explored, as they could be used in novel therapeutic techniques. One such method involves brain-computer interfaces (BCIs). To evaluate the feasibility of stress-detection via BCIs, we designed a protocol to induce stress, measured brain and physiological signals during the resulting stressful protocol conditions, and finally estimated stress levels from these measured signals using an EEG-based BCI.

Hypotheses. We hypothesized that: 1) our protocol induced stress; 2) stress had a negative impact on cognitive tasks performance; 3) EEG-based BCIs were efficient tools to assess stress levels.

Method. We designed a protocol in which the participants (N=14) have to do a cognitive task associated with two workload conditions (low / high), in two contexts: stressful and not stressful. During the task, we recorded physiological (heart rate and skin conductance) and EEG data. We also used neuropsychological questionnaires (STAI) to assess subjective level of stress.

Results-Discussion. We validated our protocol thanks to behavioural and physiological analyses: STAI scores, heart rate and skin conductance globally increased after stress induction. Moreover, we demonstrated that stress induces a decrease in performance and an increase in the perceived difficulty of the task in low workload conditions. Finally, using machine learning techniques, we have reached a classification accuracy rate of EEG data (stress vs. no-stress) of 76.9% (N=11). This rate proves that EEG-based BCIs are efficient tools to assess stress levels.

KEY WORDS
Stress, Brain-Computer Interfaces, Electro-encephalography, Real-time assessment, Machine learning.

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1. INTRODUCTION

1.1. Motivation

“The sharp rise in work stress in Britain is becoming a major social problem in the current economic crisis, a new British Academy report has found.” (K. Turnbull, E. Ray and M. Addelman, University of Manchester, 2010).

“Considéré comme ‘un des plus graves problèmes de notre temps’ selon le Bureau International du Travail, le stress est un fléau qui concerne 75 % des français.” (Jean Krakowiecki, Institut de recherche sur le stress).

“El estrés constante en nuestra sociedad ha aumentado los trastornos de ansiedad” (Dr Javier Cabanyes Truffino, Neurologist, Universitat de Madrid).

“Considéré comme ‘un des plus graves problèmes de notre temps’ selon le Bureau International du Travail, le stress est un fléau qui concerne 75 % des français.” (Jean Krakowiecki, Institut de recherche sur le stress).

“These quotes show us that stress really is a universal societal issue, affecting both economy and health. Thus, it is easy to understand why many people (in public research and industry) (Van den Broek et al. 2012; Bräuninger 2012) invest in finding ways to deal with stress: how to help people manage their stress is becoming a major preoccupation in many countries. For instance, the Lifestyle Research Association (LIRA project) is a 10-year partnership between Philips (Netherlands), Inria (France) and Fraunhofer (Germany) which goal is to conduct innovative research on health and well-being (LIRA Project Site).

Besides psychological questionnaires, many devices are now available to assess stress levels. They measure stress-related physiological markers such as heart rate, skin conductance or blood pressure. Indeed, it has been shown (Reinhardt et al. 2012) that, during a stressful episode, these constants are increased. Thus, physiological markers can help to recognize stress manifestations, but they are not reliable enough to measure emotions and mental states in general (Dickerson and Kemeny 2004). That is why efforts are made to develop technologies that allow organism stress-induced modifications to be recorded directly at their source: that is to say in the brain (Sinha et al. 2003 ; Lewis et al. 2007). These technologies are called Brain-Computer Interfaces (BCIs).

The field of BCIs is relatively young, but they already are used for many purposes, such as to increase the interactivity in video games (Plass-Oude Bos et al. 2010), to improve the student model, adding information about cognitive, emotional and motivational states in intelligent tutoring systems (Nkambou et al. 2010) or in medicine to help people suffering from locked-in syndrome (Gentiletti et al. 2009). Therefore, it should be interesting to use BCIs in order to assess stress levels and to help people manage stress. Indeed, in the instance of phobias or post-traumatic stress disorders, using a BCI during therapy would allow exposure to the stressor to be adapted according to stress levels and other BCI-recorded emotional and motivational indicators (Parsons and Rizzo 2008).
In this thesis, we studied real-time stress assessment using EEG-based BCIs. Indeed, although “real-time” assessments may seem essential in the fields described above, most studies use average assessments because this makes analyses much easier. Real-time assessment of stress could help, more particularly, in stress disorder therapy. Thus, we first had to explore neurobiological processes underlying stress in order to design an experimental protocol including a stress induction protocol. Then, we had to explore BCI operation, and more specifically the necessary algorithms used for classification. In the interests of clarity, we shall now give more details concerning stress and brain-computer interfaces (BCIs).

1.2. What is stress?

1.2.1. General definition

"When I look back on all these worries, I remember the story of the old man who said on his deathbed that he had had a lot of trouble in his life, most of which had never happened." (Winston Churchill). “Stress is like a spice. In the right proportion it enhances the flavour of a dish. Too little produces a bland, dull meal. Too much may choke you” (Donald Tubesing). These two quotes reveal important aspects of the concept of stress. Indeed, stress can be defined as an organism’s response to an environmental situation or stimulus perceived negatively - called a "stressor" - which can be real or imagined, that overtaxes the capacities of the subject, and thus has an impact on the body's homeostasis (that is to say that the constants of the internal environment are modified). Moreover, according to its level and its frequency, it will have a different impact on mental and physical well-being.

Stress can be of different natures, such as physical, psychological or psychosocial. Physical stress can be induced by extreme temperatures or a lack of sleep for example. Psychological stress is associated with difficult cognitive tasks, uncontrollability or negative emotions (Dickerson and Kemeny 2004). Finally, psychosocial stress is triggered by a social evaluation threat (that is to say a situation in which the person's own estimated social value is likely to be degraded). According to the frequency of the symptoms, one can speak of acute stress (“normal” stress, occurring times to times to help the organism to face a threat), episodic acute stress (Hewson 1997)(corresponds to acute stress with a high frequency: very little modifications of the homeostasis are enough to trigger the organism's response) or chronic stress (overexposure to acute stress -high frequency, intensity and duration- that has a negative impact on health; people suffering from chronic stress are over aroused, anxious and irritable).

1.2.2. The general adaptation syndrome model (Selye 1936)

Selye, who is considered as the “father of stress research”, defined the process of stress as being a "non specific response of the body to any demand upon it" (Selye 1974). According to Selye, whatever the kind of stressor and the agent, the organism’s response will be composed of the three following coping strategies
The first one is the *Alarm*. It is divided in *Shock* phase (the resistance to stress temporarily drops under the normal level) and the *Antishock* phase (the presence of a stressor is realised and thus the organism's response begins). Then, the next step is the *Resistance*, during which the body tries to face the threat, allowing much of its resources to deal with it. Finally, there are two possible ends. Either, during the *Resistance* phase, the compensation mechanisms managed to overcome the threat and there is no stress anymore (that is *Recovery*), or the stressor is "stronger" than these mechanisms. In the latter case, there is a third step: *Exhaustion*. Here, all the organism's resources have been used and thus it is impossible for the person to correctly face the threat. A prolonged period in this state will induce important damages in the organism.

1.2.3. **Neurobiology of this process: the stress response cascade**

During a situation of acute stress, the organism's response explicited by Selye, also called "*fight-or-flight response*", corresponds to a neurobiological process: the *stress-response cascade*. This process is associated to the activation of two brain circuitries (Sinha et al. 2003, Dickerson and Kemeny 2004, Taniguchi et al. 2009) (Figure 3): the sympatho-adrenomedullary axis (SAMa, also called the noradenergic circuitry) and the hypothalamus-pituitary gland-adrenal cortex axis (HPAa). Their goal is to restore homeostasis when it is disregulated, and thus to permit the organism to face the threat. The SAMa is a part of the sympathetic nervous system (SNS), which is constantly active at a basic level (to maintain homeostasis) and whose activation is increased in a stressful situation in the aim of triggering the stress-response cascade (*Alarm* phase). A stressful situation induces the frontal cortex, the limbic system or visceral organs to send an “alert input” to the hypothalamus. This latter then activates the locus coeruleus (LC) (part of the autonomic nervous system), whose goal is to mediate sympathetic effects of stress, and which increases the secretion of noradrenaline. The latter then activates the adrenal medulla, increases motivation (through the nucleus accumbens), alters some cognitive functions through the prefrontal cortex (PFC) and activates the HPAa. Finally, the adrenal medulla releases cathecolamines (mostly noradrenaline) into the blood. This process facilitates immediate physical
reactions (such as increased heart rate, blood vessels constriction, except for necessary muscles, or auditory and visual exclusion phenomena -inducing cognitive tunneling-) associated with a preparation for violent muscular action.

This circuitry is a fast-response circuitry, unlike the HPA circuitry, whose response is quite low (activated during Selye Resistance phase). Indeed, it is activated by the noradrenaline released from the LC (SAMa). This chemical message is combined with sensory input sent to the hypothalamus from the PFC. The hypothalamus releases Corticotropin Releasing Factor (CRF), which will attach to the anterior lobe of the pituitary gland. It induces the release of adrenocorticotropic hormone (ACTH). Once ACTH is fixed to the adrenal cortex, the latter will release cortisol into the blood. In the aim to restore homeostasis, cortisol redistributes energy (by acting on neoglucogenesis) to the organs that need it most and to critical organs (brain and heart), while it inhibits non-necessary organs for immediate survival (reproductive, immune and digestive systems). Once homeostasis restored and the threat no longer perceived, a negative feedback occurs by the activation of the parasympathetic nervous system, which releases acetylcholine in order to promote relaxation: the heightened levels of cortisol in the blood go back to the brain and attach to the pituitary gland and the hypothalamus, turning off the HPA axis while noradrenaline will inhibit its own production and thus turn off the SMA axis. This induces the end of the stress response cascade.

These two systems are not always activated. Indeed, physical stress (Dickerson and Kemeny 2004), like during the cold-pressor test (Hines and Brown 1936), induces an increase of blood pressure (Wood et al. 1984, Carroll et al. 1996), of skin conductance (Buchanan et al. 2006) and of subjective stress ratings (Cahill et al. 2003) but a low cortisol response (Cahill et al. 2003). These results let suppose that this kind of stress induces an activation of the SAMa but only a weak activation of the HPAa. Moreover, single use of psychological stress induces a low release of cortisol (Dickerson and Kemeny 2004) and so a low activation of the HPAa. Finally, psychosocial stress has been shown (Dickerson and Kemeny 2004) to induce an important activation of the HPAa, enhanced by uncontrollability, like in the Trier Social Stress Task (TSST) (Kirschbaum et al. 1993).

To resume, stress process is a loop composed of five phases: -1- an environmental demand that disrupts the homeostasis, -2- a personal perception of this demand by the person, -3- an activation of the stress-
response, -4- behavioural consequences of this activation, -5- a return to homeostasis once the threat is overcome, or exhaustion.

**1.2.4. Consequences of an overexposure to stress**

As we saw in the previous paragraph, the SAMa and HPAA activations induce organism modifications. A chronic stress exposure will overtaxe these systems, and the organism will not manage anymore to stop the stress-response cascade. As a consequence, noradrenaline and cortisol will stay longer in the blood stream. Too much noradrenaline can induce an hyper-arousal state in which heart rate is increased and vessels constricted, and this state enhances the likely of being subject to cardiovascular diseases and strokes, among others. Furthermore, too much cortisol will prolong the inhibition of the immune, digestive and reproductive systems. Thus, the organism will be more vulnerable to infections, stomach aches and the likely of being infertile will increase.

**1.3. WHAT IS A BCI?**

**1.3.1. General definition**

A Brain-Computer Interface (BCI) is a «communication system in which messages or commands that an individual sends to the external world do not pass through the brain’s normal output pathways of peripheral nerves and muscles. [...] A BCI provides its user an alternative method for acting on the world.» (Wolpaw et al. 2002).

**1.3.2. How does it work? What are the different kinds of BCIs?**

BCIs functioning can be described as a loop (Lotte, 2012), as we can see in Figure 4. The first step (1) is to measure the brain activity. Different kinds of sensors are available, they are characterized by their resolution (number of neurons recorded) and their invasiveness (the most invasive sensors are sub-cortical; the less invasive ones are on the scalp) - both parameters are linked: the more invasive they are, the more precise they are, and the less neurons they record-. In the case of stress assessment in this work, electroencephalography (EEG) is used. It is a non-invasive technique that measures the difference of potential between large populations of neurons. It is really efficient for real-time recordings as its temporal resolution is...
excellent (although the spatial resolution is not that good). The second step (2) is the **signal pre-processing**. This step aims at reducing artefacts and noise (using frequency and spatial filters), in order to have a cleaner signal where the relevant information is available. The third step (3) is the **features extraction**. It aims at describing the signal by few values (features), grouped into feature vectors (Bashashati 2007). The fourth step (4) is the **classification**: each vector is associated to a class by using classification algorithms such as neural networks or (more often in BCIs) linear discriminant analysis (LDA). Once processing is finished, the two last steps will permit the interaction between the human and the computer. Indeed, once the mental state identified, it is **translated into a command** (5)(either to the user to permit him to control a device or to the system to induce an adaptation). Finally, a **feedback** (6) is given to the user, in order to help him to learn from experience.

There are different kinds of BCIs: four main criteria allow classing them. The first one is the nature of the sensors, which can be, as seen previously, **invasive** or **not invasive**. Second, as we can see in the definition, BCIs do not use the brain’s normal output pathways. Nonetheless, they can be more or less dependent of the activity of these pathways. Indeed, on the one hand, **dependent** BCIs need the normal output activity to work. This kind of BCI will, for instance, record visual evoked potentials (VEP) in the primary visual cortex (Wolpaw et al. 2002), which depends on the gaze direction (and thus on the peripheral nerves and muscles). On the other hand, **independent** BCIs do not need the normal output activity. For instance, they will focus on motor imagery (that is to say the signals characteristic of a person who is imagining himself doing a movement). Furthermore, there are **spontaneous** BCIs (recording continuous brain activity, such as slow cortical potentials) and **evoked-potentials** BCIs (recording brain responses resulting from a specific event, like the P300). Finally, there are **active** BCIs (based on a voluntary control of the user) and **passive** ones (in which the interaction between the human and the machine is implicit: neither voluntary control nor mental command is required).

In this experiment, we use a non-invasive, independent, spontaneous and passive EEG-based BCI.

### 1.4. Previous Work: Stress-Related EEG Features

Many offline studies on average stress measure by EEG have already been led. In this section, we try to present the principal results. People having a high trait anxiety seem to have more attentional control over reaction and an increased use of processing resources as compared to people with low anxiety (Savostyanov et al. 2009). This assessment seems to be related to the fact that people with a high anxiety show greater tendency towards alpha augmentation than the others (Nowak et al. 1981). Moreover, several differences between people suffering from anxiety disorders and other people have been depicted. Indeed, socially anxious people would seem to have a greater relative right frontal alpha EEG activity than other people at rest (Blackhart et al. 2006; Moscovitch et al. 2011; Schmidt et al. 2012) and when they face a social threat (Crost et al. 2007). Some
authors go further, assessing that EEG activity asymmetry, with greater activity on the right frontal cortex, may predict future development of anxiety symptoms (Davidson et al. 1995; Blackhart et al. 2006). Greater right frontal cortical activation is related with high cortisol levels (Hewig et al. 2008). During a stressful situation, people with a greater right centro-parietal cortical trait activation release more cortisol in anticipation of the stressor whereas all the others release more cortisol in response to the stressor (Hewig et al. 2008).

There are more conflicting results when we deal with brain asymmetry. Indeed, while Tops et al. (Tops et al. 2006) propose that cortisol administration (which simulates a stress situation) leads to a global decrease of cortical activity (except for the left frontal cortex in which activity is increased), other studies (Lewis et al. 2007; Hewig et al. 2008) showed that stress was associated with a higher activity in the right hemisphere, and that the right hemisphere activation was correlated with negative affect. For Crost et al. (Crost et al. 2007), the explanation of these conflicting results would be that an association between EEG-asymmetry and personality characteristics may only be observed in relevant situations to the personality dimensions of interest. Furthermore, anxious people show a stronger right-sided parieto-temporal theta and beta activity in a low arousal situation (closed eyes) (Aftanas and Pavlov 2005). Moreover, in highly anxious people, while non-emotional arousal is associated with a greater beta activity in the right hemisphere, an aversive movie watch leads to a significant decrease of the right parieto-temporal beta power (Aftanas and Pavlov 2005). Finally, during a stressful situation, the correlation between beta and delta powers might reflect a functional synchronization between limbic and cortical brain systems (Putman 2011).

All these results have been collected using average measures of the stress rate. Indeed, only a few studies got interested by a real-time measure of stress, as we do in our experiment. The main reason must be that real time assessment of stress is much more complex, as the techniques used must permit to process and classify the signal in real time. Riera (Riera et al. 2012) showed (thanks to real-time signal processing and classification) that, in the frontal cortex, while beta-alpha power ratio is related with arousal (calm vs. excited), alpha asymmetry is related with valence (positive vs. negative affect) and that these beta-alpha ratio and alpha asymmetry evolve accordingly to the level of stress during cognitive tasks (Riera et al. 2012).

1.5. Previous work: Stress impact on cognitive tasks

People with high cortisol levels (as a result of stress exposure) show lower performance during cognitive tasks (Bohnen et al. 1990). The dynamic adaptability theory of stress, which aims at predicting an adaptive stability across stress intensities, and the progressive changes in this adaptive response when stress level overtaxes the person’s resources (due to an increase of task difficulty or an external source) (Szalma et al. 2012) can explain this phenomenon. Indeed, these changes will first be an increase of perceived stress and workload.
and then a drop of the performance (Szalma et al. 2012). The adaptive stability depicted above would be the consequence of a compensatory control mechanism that dynamically allocates resources to the different elements necessary to perform the task (Robert and Hockey 1997). Thus, performance rate would be “protected” from stress by the recruitment of further resources. However, this mechanism will have behavioural and physiological costs that could lead to exhaustion, and so to a decrease of the performance.

1.6. HYPOTHESES

In order to study on the one hand real-time stress assessment by BCIs and on the other hand stress impact on cognitive tasks (according to the workload level), we designed a protocol. Thus, our first hypothesis is that our protocol induces stress. In order to validate the efficiency of the protocol, we analyzed questionnaires (filled up by the participants) to see if subjective experience of stress was increasing in the stress condition of our protocol relative to the control condition. For a more objective evaluation, we also analysed the physiological and neurophysiological data differences according to the condition (stress vs. no-stress) and tried to extract specific stress-related features. For the physiological part, we were expecting an increase of the heart rate and skin conductance.

Second, we wanted to assess stress influence on cognitive tasks performance and perception, according to their difficulty (low vs. high workload). We actually hypothesized that stress would induce a decreased performance, especially in cognitive tasks associated with high workload. In the aim of validating this hypothesis, we set up a double-dissociation experimental protocol. Indeed, we had two parameters, with two conditions each: low workload vs. high workload; stressful condition vs. non-stressful condition. We then recorded and compared the performance rates.

Third, we hypothesized that EEG-based BCIs were valid and useful devices to assess the stress level of a person. In order to validate this last hypothesis, we trained a classifier to discriminate EEG signals corresponding to stress from those corresponding to non-stress trials, and then used it to classify independent EEG recordings accordingly. We then assessed how accurately the classifier could estimate the condition of the task (stress vs. non-stress).
2. **Material and Method**

2.1. **Population**

The subjects were recruited thanks to e-mails sent to students and members of INRIA and LaBRI. A cinema ticket was offered to each of the participants.

<table>
<thead>
<tr>
<th>Number of subjects</th>
<th>Age</th>
<th>Sex</th>
<th>Lateralisation (x - handed)</th>
<th>Education (Bac + x years)</th>
</tr>
</thead>
<tbody>
<tr>
<td>14</td>
<td>Mean 26.46</td>
<td>Women 4</td>
<td>Right 10</td>
<td>Mean 3.16</td>
</tr>
<tr>
<td>Std 9.75</td>
<td>Men 10</td>
<td>Left 4</td>
<td>Std 2.90</td>
<td></td>
</tr>
</tbody>
</table>

Table 1: Subjects’ characteristics

To be included, people had to be 18 year old or more, to speak French and to sign an informed consent. We also had some criteria of non inclusion: bad vision, neurological and psychiatric diseases, and affective troubles. Moreover, people were ask to schedule on a day and time they feel good, not too tired. Finally, we asked them not to drink coffee and tea less than two hours before the experiment.

2.2. **Material**

For our recordings, we used the following sensors: electroencephalogram (EEG, 28+8 -see below- active electrodes -g.LADYbird-) (Figure 5), electrocardiogram (ECG, 2 active electrodes), electromyogram (EMG, 2 active electrodes), electrooculogram (EOG, 4 active electrodes), breath belt (SleepSense), pulse (g.PULSEsensor), and a galvanic skin response sensor (g.GSRsensor²). All these sensors are connected to three active electrode driver boxes (g.GAMMAbox), plugged to three synchronized amplifiers (g.USBamp 2.0 and 3.0). Finally, these amplifiers are plugged to the acquisition computer (AlienWare, Windows 7) in which we installed OpenViBE (INRIA, www.openvibe.inria.fr), an open source software platform permitting to inspect and record the signals. We used a conductive gel (g.GAMMAgel) for the EEG, EMG, EOG and ECG electrodes. For the workload task, we used an IBM computer (Windows XP), with a 24 inches screen, two active 10W Kinyo speakers and a classic mouse. The workload

![Figure 5: EEG electrodes locations (in blue) for our experiment](image-url)
The computer running the task environment was connected via the parallel port to the g.USBamps, transferring precise stimulus timing information.

2.3. EXPERIMENTAL DESIGN

2.3.1. General procedure of the experiment

When the subject arrives, he is asked to sign the informed consent and to fill up three questionnaires. The first one is about personal characteristics (such as gender, age and education). The second and the third ones are State-Trait Anxiety Inventory (STAI) form Y-A and Y-B (Spielberger 1970) (see next section for more details). Once done, we install all the sensors on the subject: EEG, ECG, EMG, EOG, breath belt, heart rate and skin conductance sensors. Moreover, we record a three minutes baseline. From this point, as we wanted to counterbalance the conditions (not to have any order effect), we set up four scenarios (Figure 6) composed of two blocks each, separated by a STAI form Y-A questionnaire. Therefore, we randomly begin with either relaxation or stress induction, and we randomly start with either low workload (0) or high workload (2). During both the first and the second block, the subject does six times each workload condition (low/high) (6x2x2=24min per block), with a short break after six tasks. Once the two blocks are completed, the subject fills in the STAI form Y-A a last time before the sensors are taken off. Finally, the subject is debriefed about the aim of the experiment.

The recording is separated in three phases in order to facilitate the analysis: baseline, stress (from the beginning of the stress induction to the end of the STAI form Y-A that follows the block) and relaxation (from the beginning of the relaxation induction to the end of the STAI form Y-A that follows the block).
2.3.2. **Neuropsychological evaluation: STAI**

In order to measure the level of anxiety of the subjects, we used the "State Trait Anxiety Inventory" (Spielberger 1970). This test is composed of two scales of 20 propositions each: STAI form Y-A and STAI form Y-B. STAI form Y-A is an evaluation scale for state anxiety. It measures stress, nervosity and worrying felt by the person at this moment. The score is increased when the person currently experiences a psychological stress and is decreased in response to relaxation. It is a good indicator for transitory modifications of the level of anxiety.

STAI form Y-B evaluates the clinical anxiety (trait), and thus permits to recognize generally anxious people (who have higher scores). A score between 46/80 and 55/80 corresponds to a "medium anxiety" (Spielberger 1970). As STAI form Y-B can influence the answers of STAI form Y-A (but not vice versa), at the beginning of the experiment, we first ask the subject to fill up the STAI form Y-A and then the form Y-B. Then, at the end of each of the two blocks (stress and relax), we ask again the person to fill up the STAI form Y-A in order to check that he feels like being in the state we would like him to be in (stressed or relaxed).

2.3.3. **Stress Induction**

In order to induce stress, we set up a stress-induction protocol based on the Trier Social Stress Task (or TSST, Kirschbaum et al. 1993) which is a validated protocol. The stress induction is composed of three parts and requires the participation of three people, “the committee”, who are presented as being body language experts. In the first part, a member of the committee asks the subject to prepare, during five minutes, a fake job interview for a teacher position. During the second part, the committee asks the person to do this job interview and to speak about himself for 5 minutes. They tell the subject that he is filmed (for a future behavioural analysis) and they take notes. It is very important that the committee really is serious and neutral/unresponsive towards the subject. The third part is an arithmetic task (the subject has to count from 2083 to 0 by steps of 13) and to begin again at the slightest mistake or hesitation. At the end of this protocol, in order to keep the stress level high, the committee tells the subject he will be filmed during the workload tasks and that he will have to do another interview, which will be longer, and a self-evaluation after it.

2.3.4. **Relaxation Induction**

For the relaxation induction, we asked the people what could make them feel good and relax. We proposed them a list of music and videos known to be relaxing. They were also allowed to bring some and watch them or to rest (in silence). This induction lasted around ten minutes.

2.3.5. **Workload Task**

We used the n-back task as workload task, as it was easy to modify the workload without changing any other parameter (such as visual stimulation or motor behaviour). Indeed, 0-back (low workload) and 2-back
(high workload) are very similar. In both, sixty white letters (font-size 48) appear (during 500ms) the ones after the others (1500ms of break between them) on a black background. Thus, each part lasts two minutes. Among these letters, 25% are targets. In both tasks, when the letter that appears is a target, the subject has to do a left click, and a right click otherwise (like this, there will not be a big difference at the motor level between targets and non target letters: this motor difference could have induced unexpected differences in the EEG). Thus, for the 0-back task, that is to say the low workload condition, the target is the letter “X”: each time a "X" appears, the subject has to do a left click, and in all the other cases he has to do a right click. For the 2-back task, the high workload condition, the subject has to do a left click when the letter that appears is the same than two letters before (for example, if the sequence “C A C” appeared, the second “C” would be a target). At the end of each task, the subject has to report his level of arousal (on a scale from 0 to 10) and the difficulty he felt (Rate Scale of Mental Effort -RSME- test) (Brouwer et al. 2012). Finally, a screen with his performance at the last task (number of targets correctly identified) appears. While in the no-stress condition the real feedback is given, in the stress condition, 5 to 10% of the real performance are taken off in order to increase uncontrollability and thus psychological stress (Dickerson and Kimeny 2004).

2.4. PILOT STUDY

Before beginning our real experiment, we did a pilot study on 10 people (without physiological and EEG sensors) in order to check that: 1) the software was running well, 2) the 2-back task was much more difficult for people than the 0-back (lower performance and subjective questionnaire), 3) the “fake performance” we gave in half of the trials was not too obvious. The results of the pilot study confirmed these three points.

2.5. VARIABLES AND FACTORS

In this study, we analysed the effects of two factors (with two possible values each) on different dependent variables (VD). The first factor is the stress level: condition “stress” (after the stress induction) vs. condition “no-stress” (after relaxation induction); the second factor is the workload level: low (low-WL, 0-back task) vs. high (high-WL, 2-back task). Thus, we had four experimental conditions: stress/low-WL, stress/high-WL, no-stress/low-WL and no-stress/high-WL. The VDs are: the performance at the tasks, the score at the STAI form Y-A, the subjective arousal evaluation, the subjective evaluation of the difficulty of the task, the EEG signal, the heart rate and the skin conductance.
2.6. Data analyses

2.6.1. Behavioural Data

We decided to analyse the effect of the stress condition (stress vs. no stress), of the workload condition (low vs. high) and of both of them (stress+low vs. stress+high vs. no_stress+low vs. no-stress+high) on performance, subjective evaluation of arousal, subjective evaluation of the effort (RSME). Moreover, we analysed STAI form Y-A scores evolution according to the stress condition, as well as its correlation with STAI form Y-B score. Behavioural data have been statistically analysed using Matlab and SPSS. Our sample is small (N_subjects<30), so we had had to use non parametric tests. Moreover, all of our assessments are paired ones as all the subjects passed all the conditions. Analysis results have been considered as significant for p<0.05.

2.6.2. Physiological Data

I did not do these analyses myself, but I used the results for the EEG data analysis.

As a consequence, I will here briefly explain the method used to explain the choices made in the following parts. Analyses have been led on heart rate (HR) and galvanic skin response (GSR) differences between stress and no-stress conditions. Thus, Wilcoxon (paired and non parametric) tests have been used. Before doing statistics, data had to be pre-processed by extracting the GSR value (µS) for each block and then averaging these values for stress and no-stress blocks; and by filtering ECG signal between 5 and 200 Hz, applying a notch-filter 48-52 Hz to reduce power line noise, extracting HR for each block and averaging these values for stress and no-stress blocks.

2.6.3. EEG Data

So far, we explored binary classification of the EEG signal according to two classes: stress and no-stress. In order to do this processing, we used the machine learning techniques described below.

First, pre-processing is necessary to filter different frequency bands (delta(1-4Hz), theta(4-8Hz), alpha(8-12Hz), beta(12-30Hz) and gamma (30-40Hz)). In this experiment, we had 28 EEG channels, we sampled each trial of 2s at 256Hz and we had 60 trials in each of the 24 blocks for each of the 14 subjects. Thus, our matrix dimensions were [28*513*20160].

After this pre-processing, the first step of processing is optimisation (or training). Here, we decided to do a "leave-one-subject-out-cross-validation".

![Figure 7: EEG Signal Processing Illustration for two classes (stress and no-stress)](image)
that is to say that to test the classifier on one subject, we first train it on a data set composed of all the other subjects. Thus, testing and training data sets are independent and we are sure there will not be a “by heart” classification (ie. “overtraining”). Moreover, we will have a very large number of trials in the training data set: 45*24*13= 14040 trials. The first step of optimisation is the features extraction. We chose to use the Common Spatial Patterns (CSP) algorithm (Blankertz et al. 2008). The CSP finds spatial filters that lead to optimally discriminant band power features, since their values would be maximally different between the two classes. This algorithm is rather quite simple and efficient but not very resistant to noise and artefacts (which is why we pre-processed the signal). Once the filters have been learnt by the CSP, the most relevant features, corresponding to the pairs of CSP filters obtained, are extracted from the initial training data set, as features vectors (Figure 7). We chose to take 3 pairs of filters, which is recommended (Blankertz et al. 2008). Thus, the dimension is reduced, only the important information is kept. The second step of the optimisation is the training of the classifier. We used a Linear Discriminant Analysis (LDA) classifier (Lotte et al. 2007). The LDA will learn how to identify the class of a feature, thanks to the labelled feature vectors extracted from the training data set by the CSP. Then, it will generate the hyper-plane that separates the training features of each class the most. Finally, the last step of processing is the test. Its goal is to use the classifier and spatial filters optimised on the training data set to classify the data of the subject we want to test. Thus, the CSP will, in the same way, extract the feature vectors of the testing data set. Then, these feature vectors will be given to the previously trained LDA classifier (that has never seen them, as the testing set is independent from the training set). The estimated class (Figure 7) of each feature vector will thus depend on which side of the hyper-plane it is located. As we balanced the conditions, we used the classification accuracy rate for performance assessment.
3. **Results**

3.1. **Stress Protocol Validation**

3.1.1. **Subjective Questionnaires: STAI**

Each subject (N=14), filled in three “STAI form Y-A” (state) questionnaires: one at the beginning (STAI_Beg) of the experiment and one after each of the conditions (stress-STAI_Stress- and no-stress-STAI_NoStress-). We then analysed the scores (Figure 8), and the results show that STAI_Stress scores are significantly higher than STAI_Beg scores (Wilcoxon test, p=0.048). However, there are neither any differences between STAI_Beg and STAI_NoStress scores (Wilcoxon test, p=0.247), nor between STAI_Stress and STAI_NoStress (Wilcoxon test, p=0.293). Then we did analyses to know if the increase in STAI form Y-A scores after stress induction was correlated with the STAI form Y-B (trait) score. Let DIFF_SB be the difference between STAI_Stress and STAI_Beg scores; and DIFF_SnoS the difference between STAI_Stress and STAI_NoStress scores. In both cases, there is a positive correlation: the higher the STAI trait scores are, the more the STAI state scores will increase after stress induction (Pearson test: correlation between DIFF_SB and STAI trait CR=0.698 and p=0.005; correlation between DIFF_SnoS and STAI trait CR=0.713 and p=0.006).

3.1.2. **Physiological Sensors**

Wilcoxon’s test on the mean of physiological data showed a significant difference between stress and no-stress conditions for the HR (p=0.05) and a close to significant result (p=0.09) for the GSR.

<table>
<thead>
<tr>
<th></th>
<th>GSR</th>
<th>HR</th>
</tr>
</thead>
<tbody>
<tr>
<td>Stress</td>
<td>Mean</td>
<td>78.8</td>
</tr>
<tr>
<td></td>
<td>Std</td>
<td>8.18</td>
</tr>
<tr>
<td>No Stress</td>
<td>Mean</td>
<td>75.2</td>
</tr>
<tr>
<td></td>
<td>Std</td>
<td>8.36</td>
</tr>
</tbody>
</table>

*Table 2: GSR (µS) and HR (beat/min) values according to the stress condition*

Wilcoxon tests were then done for each of the participants. Only the ones with a significant difference between stress and no-stress for at least one of the two measures (GSR or HR) have been kept for the EEG study, considering that stress induction did not work for the others. Thus, only three subjects have been...
rejected, and eleven have been kept. These results allow us to confirm that our stress induction protocol has been efficient.

### 3.2. Stress Influence on a Cognitive Task

In order to analyse stress influence on people performing cognitive tasks with different workload (WL) conditions, we did several tests comparing performance, arousal and RSME according to the different parameters (WL, stress and the interaction of both of them) and according to the order of the conditions. The analyses showed that performance at 0-back task is always significantly higher than at 2-back task (stress: Wilcoxon test, \( p < 0.001 \); no stress: Wilcoxon test, \( p < 0.001 \); both: Wilcoxon test, \( p < 0.001 \)). Moreover, RSME scores are always higher for 2-back than for 0-back (stress: Wilcoxon test, \( p < 0.001 \); no stress: Wilcoxon test, \( p < 0.001 \); both: Wilcoxon test, \( p < 0.001 \)). These results show that 2-back is much more difficult for people than 0-back, at the beginning (6 first 0-back vs. 6 first 2-back; perf: Wilcoxon test, \( p < 0.001 \); RSME: Wilcoxon test; \( p < 0.001 \)) as well as at the end (6 last 0-back vs. 6 last 2-back; perf: Wilcoxon testy, \( p < 0.001 \); RSME: Wilcoxon test, \( p < 0.001 \)). However, there seems to be a learning process, as performance increases between the first 12 and the last 12 blocks (Wilcoxon test, \( p = 0.02 \)), and this learning process concerns mostly the 2-back task (performance is increased between the first 6 and the last 6 2-back tasks: Wilcoxon test, \( p = 0.01 \); but it is not the case for the 0-back: Wilcoxon test, \( p = 0.4 \)). Furthermore, for the 0-back task, there is a significant decrease of the performance (Wilcoxon test, \( p = 0.01 \)) and increase of the RSME (Wilcoxon test, \( p = 0.03 \)) between the stress condition and the beginning. This is not the case for the 2-back task. Finally, arousal significantly decreases between the first 6 and the last 6 blocks in the stress condition (Wilcoxon test, \( p = 0.02 \)).

### 3.3. EEG Data Classification

We did the classification on 11 subjects (14 – (3 taken off because stress induction has had no effect on physiological sensors)). For each subject, we had a 5400 trials training data set and a 540 trials testing data set because we only do the classification on the 0-back task trials (indeed, behavioural study showed that the stress induction protocol had a bigger effect on this condition) and we did not take the

![Classification Accuracy Rate](chart.png)

**Table 3**: Classification accuracy rate (%) per subject. The chance level (classification accuracy of 50%) is represented by a line.
target trials (because the P300 was much bigger than for non-target, and it could have distort the classification). Furthermore, 5 subjects did the stress condition first, and 6 did the no-stress condition first (so that there should not be an order effect); three women and 8 men; three left handed (using their right hand to manipulate the mouse) and 8 right handed people participated to the classification. When we do the classification with all the frequency bands, the average accuracy is 76.9%. For 10 subjects out of 11, classification accuracy rate is between 58.3 and 96.7% (Table 3). For one subject (subject 08), classification rate is 40.4%. When we train the classifier on the different frequency bands separately, θ and α bands are the most relevant ones: 73.5% of accuracy on average for the θ band and 67.0% of accuracy on average for the α band (Annex 1). The accuracy rates of δ, β and γ are respectively 54.3%, 54.0% and 44.3% (Annex1), that is to say they are not significant (ie. Classification accuracy is at chance level). Indeed, we have 5400/2 = 2700 trials per class in the training data set. In figure 6, we can see that the signification threshold is quite stable from 100 trials per class and is around 55.6% for α=5% and 56.9% for α=1% (Figure 9) (Müller-Putz et al. 2008)(rates under 50%, will be significant under 44.4% for α=5% or 43.1% for α=1%). Furthermore, the electrode weights learnt by the training data set and generated by the CSP (Annex 2) show not only a predictable strong contribution of the left motor cortex (as people were using their right hand to respond) and of the visual areas, but also a strong contribution of a more frontal areas: fronto-parietal, central (a little bit on the right for some subjects) (Figure 10).
4. Discussion

In this section, we are going to attempt to interpret and discuss the results described in the previous part.

Let us begin with the validation of the protocol. On the one hand, behavioural results show that at the end of the no-stress condition, participants are not significantly more relaxed than after the stress condition. Indeed, their STAI form Y-A scores (state) are higher than at the beginning (but not significantly). This can be explained by the fact that the task is long and difficult (at least for the 2-back task) and thus it must induce a certain psychological stress itself. However, the fact that these scores are significantly higher after the stress than after the beginning (and higher after the stress than after the no-stress condition, but not significantly) proves that, in addition to the psychological stress induced by the task itself, participants are subject to psychosocial stress provoked by the stress induction protocol. Thus, it suggests that our protocol is efficient. Moreover, the correlation between the STAI form Y-B (trait) and the augmentation of the STAI form Y-A (state) (between the beginning or the no-stress condition and the stress condition) shows that the more anxious a person is, the more susceptible to the stress induction protocol he/she will be. On the other hand, physiological results, with a significant increase of galvanic skin response or heart rate for 11 subjects out of 14, confirm that our protocol induced stress. During the next weeks, the continuation of our study and the inclusion of more subjects will help to gain more conclusive evidence. Moreover, we will also analyse pulse and breathing to detect stress more accurately. Finally, instead of rejecting some of the participants, we may be able to define different profiles of response to stress and see if these profiles are associated with different EEG patterns.

Let us now discuss the results concerning the influence of stress on the cognitive task. First, we can say that the higher RSME (subjective effort level necessary to perform the task) and the lower performance in both the conditions (stress and no-stress) proves that the 2-back is much more difficult than the 0-back task. However, we saw that there was a learning process for the 2-back task only (higher performance during the 12 last blocks). This can be due to the fact that the participant elaborates strategies for this difficult task in order to have better performances, while for the 0-back, there is no need of a strategy (as it is quite easy) and performance is high from the beginning (and thus cannot be improved much). Furthermore, we saw that for the 0-back task, performance is decreased and RSME increased during the stress condition. We can thus say that stress influences the performing of a cognitive task, especially when the latter is associated with low workload: it induces a decrease in performance and a feeling of increased difficulty. It may be supposed, as discussed previously, that the 2-back task itself induces some kind of psychological stress in both conditions (stress and no-stress), as it is difficult to perform. Thus, additional stress will not have a major impact on performance and RSME. Once more, these results suggest that our stress induction protocol was efficient, as these patterns
correspond to the changes in adaptive response depicted by the dynamic adaptability theory of stress (Szalma et al. 2012). Moreover, there is a drop in the subjective rate of arousal between the beginning and the end of the stress condition. This can be explained by the fact that the task is rather long and thus there can be a kind of "habituation" to stress in favour of a focus on the task, a redirection of resources on the cognitive task, in order to perform better. The fact that people try to concentrate on the task can also be a kind of avoidance strategy. It could also be explained differently: by the fact that the stress condition induces a faster fatigue ("exhaustion" phase of Selye), and thus there is a kind of resignation phenomenon. More inclusions and maybe other questionnaires would allow us to choose the right explanation. Finally, in future work, we also intend to study reaction times to see if there are differences according to the conditions (stress/no-stress and 0/2-back tasks).

We are now going to discuss the results obtained by the EEG classification. With the 11 out of 14 validated subjects we kept as a result of the physiological analysis, we had an average classification accuracy rate of 76.9% when we combined the different frequency bands (δ, α, θ, β and γ). This rate is rather a good one, especially since we had a subject-independent design, with the BCI optimised on data from a set of subjects, and tested on a different subject, who was not included in the training set (whereas in most of the BCI paradigms, the training is done on data coming from the person tested, and thus learning is easier). Among all the frequencies, α and θ are those that contribute the most to the high accuracy rate (taken separately, mean accuracy with α band is 67.0%, and 73.5% with θ band). These results are relevant when we consider that α waves are associated with relaxation (and thus with stress), whereas θ waves are associated with the release of catecholamines (Cherf 2009) (and thus noradrenalin, the production of which is increased in stressful situations). These results confirm not only that our stress induction protocol is efficient, but also that the high classification accuracy rate is not due to EMG activity recorded by EEG sensors, since γ waves, generally associated with EMG activity, allow a classification accuracy rate of 44.3% (which is below chance level with α=1% and at the limit of significance for α=5% (Figure 9)). However, α being a motor rhythm, and given the filters learnt by the CSP (located on the left motor cortex), α increase in the stress condition could be due to the fact that participants click harder when they are stressed. Nevertheless, even though the electrode weights (filters 1 and 6, that is to say the most relevant ones) (Annex 2) show an important contribution of left motor cortex and visual areas, it also shows an important contribution of more frontal areas, central (and slightly to the right), ahead of the pre-motor cortex. This is coherent with literature, as greater activation of the right frontal cortex is related to high levels of cortisol (which is released in stressful situations) (Hewig et al. 2008). Moreover, it has been shown (Riera et al. 2012) that frontal alpha activity was also associated with negative valence and stress.

The results are very promising, as very few studies have used real-time stress assessment (Riera et al. 2012), especially with a subject independent classifier. We are now going to continue the study in order to
reinforce the value of our findings. Moreover, since we did the classification with the 0-back trials only, we would now like to do it with the 2-back task and then both of them together. Furthermore, we would also like to classify the signal not according to stress condition, but according to the workload condition to see if we also find stress patterns, difficulty-related one this time. Finally, we tried to train the classifier with the three subjects we first rejected because they did not respond to stress (according to physiological sensors analysis). Surprisingly, their classification accuracy rates were very low (between 3.10% and 35.9%). This means that the stress induction protocol produced a significant effect, opposite to that experienced by other subjects. Including more subjects would also allow us to see if different subgroups have different (yet stable) patterns of response. Moreover, it would be a good argument in favour of BCIs instead of, or at least in addition to physiological sensors, as it would mean that BCIs are able to detect different stress-related patterns than physiological sensors.

This project is part of the LIRA project, a European partnership between Philips, Fraunhofer and INRIA, whose goal is to work on life style. Now we have shown that EEG-based BCIs are an effective way of assessing stress, we would like to have a continuous classification (instead of having only two classes: stress and no-stress), maybe using new and more efficient algorithms (Vézard et al. 2013) in order to make it more ecological. Indeed, the final goal of this project is to provide BCIs that people can use at home to deal with their day to day stress, and thus improve their living standards.
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Annex 1: Classification accuracy rates per subject, and mean over all the subjects.
Annex 2: Plot of the electrode weights learnt from the training data set of subject 7, for the 3 pairs of filters, generated by the CSP.

I. Band pass 4 to 8 Hz: theta waves

![Filter 1](image1)
![Filter 2](image2)
![Filter 3](image3)

![Filter 4](image4)
![Filter 5](image5)
![Filter 6](image6)

II. Band pass 8 to 12 Hz: alpha waves

![Filter 1](image7)
![Filter 2](image8)
![Filter 3](image9)

![Filter 4](image10)
![Filter 5](image11)
![Filter 6](image12)