EEG Signals to Measure Mental Stress

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Abstract. Stress is originated from brain, neurological signals are important to measure mental stress. In this paper, a survey of physiological studies to measure mental stress is presented. Methods and individual technique from previous studies are summarised. The concepts of stress from its origin to detection are discussed.

Keywords: EEG, Mental Stress, Neurological Signals

1. Introduction

Stress is a physiological and psychological response to threatening situations which need adjustment in homeostatic imbalance caused by a general alarm in homeostasis. Normally, the alarm occurs when there is a discrepancy between what it should be and what it is[1]. Pioneering effort on stress was made by Hans Selye who introduced the term 'stress' in medical studies by presenting a general adaptation syndrome (GAS) [2].

The stress response can be measured and evaluated in terms of perceptual, behavioural and physical responses. Psychological questionnaires are commonly used to infer stress in terms of behavioral changes. Progress in science and technology has granted methods which can be used to take the objective measurement of stress using neurophysiological signals that include neurological signals.

Neurological studies employ some stressors (stressful stimuli) in order to evoke mental stress. According to [3], two types of stressors exist: systemic and processive as shown in table A.The former are immediate threatening conditions for homeostasis such as injuries[4]. In human physiological studies, processive stressor is used. Its conditions do not directly create alarm in the homeostatic system. Processive stressors test the subject psychologically and psychosocially through substantial cognitive processing. Various experimental settings have been adopted in previous studies in order to evoke cognitive demands such as mental arithmetic, decision making, memory retention, high workload,and multiple tasks solutions. Most common experiments are Colour-Stroop Task [5], Montreal Imaging Stress Task and basic arithmetic questions under time limits [6].

Brain activates many neuropeptide-secreting systems in response to stress. In result to this activation, adrenal corticosteroid hormones are released, which are known as "stress hormones". The brain continuously gets feedback from these hormones.Corticosteroid hormones function in a binary fashion. They serve as a master switch by targeting many genes in the neurons and network response control that underlies behavioral adaptation. Corticosteroids penetrate into every part through circulation, which assists the brain to synchronize with body function that is gear towards coping with stress, revival and adaptation. There is a consensus that amygdala, a group of nuclei residing in temporal lobes has a central role in regulating stress effects on memory [7]. Amygdala has a pivotal role in processing memories as it is believed that emotional and unpleasant experiences are well remembered. Acute and chronic stress creates functional changes in amygdale along with changes in other regions of brain such as hippocampus and prefrontal cortex. Amygdala undergoes totally different pattern of functional and structural changes induced by stress that are totally different from pattern observed in other regions of the brain.

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Table 1: Stressor types

Type	Threats	Example
Systemic stressor	Threatens to homeostatic system directly	Physical threat
Processive stressor	Does not threaten homeostatic system immediately	Psychological or physiological threat

2. Neurological Methods

In selecting a neurophysiological method, the most important factor is that it should be non-invasive. Other factors include rich in spatial and temporal resolution, specificity and coverage. Various neural recording methods are illustrated in figure 1. Among these methods, single-unit activity (SUA), multi-unit activity (MUA), local field potential (LFP) and electrocorticography (ECoG) provide high resolution in temporal and spatial axis and high specificity. Unfortunately, they have limited coverage and these are invasive methods.Functional magnetic resonance imaging (fMRI), electroencephalography (EEG) and magnetoencephalography (MEG) are non-invasive methods. fMRI has high spatial resolution but very low temporal resolution, whereas EEG and MEG have higher temporal resolution[8].

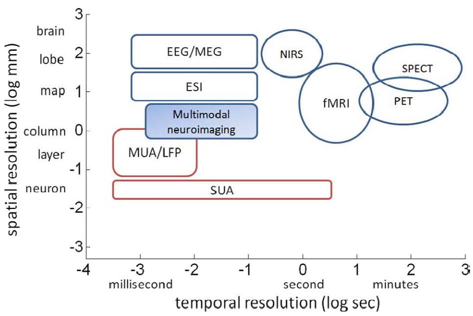

Fig. 1: Spatial and temporal resolution of various experimental techniques [8]

EEG is an important method for studying the transient dynamics of the human brain's large-scale neuronal circuits. In EEG, electrodes are placed at the head skin to make a good contact with scalp and register the electrical potentials due to neuronal activity [9]. EEG provides good observational data of variability in mental status because of its high temporal resolution. EEG waveform (amplitude and frequency) depends on the conscious level of the person. Table B summarises that spectral analysis of EEG can be split into several frequency bands.

EEG shows a good correlation with the mental stress in terms of suppression of alpha waves[10] and improvement of theta waves[11]. Alpha waves are more active in occipital and frontal regions of the brain[12]. These waves are associated with idleness of the brain. So in no stress condition, when the brain is doing no activity, alpha waves are dominant. In stressful situations, the power of alpha waves falls down showing the change in response under stress. Beta waves show varying behavior in different frequencies in different parts of the brain and power in theta waves increases under stress or mental tasks [11]. Table B includes the activities of EEG signals in sress.

Table 2: EEG waveforms representation

Signal	Frequency	Amplitude	Activity
Delta (δ)	Less than 4 Hz	20 – 200 µV	Increased power during difficult conditions [11]
Theta (θ)	4 - 8 Hz	Around 20 µV	Power increases during the stress [11]
Alpha (α)	8 - 12 Hz	20 – 200 µV	Power suppresses during the stress [13]
Beta (β)	13 – 31 Hz	5 – 10 µV	Power varies according to task difficulty [11]

3. Analysis Techniques

In this section, analysis techniques will be discussed to extract required information of stress from raw EEG data.

3.1. Pre-Processing

EEG signals are very sensitive to artifacts, whose source are not the brain. Possible sources of artifact in EEG signals include either technical reasons or person's own behavioral and physical activities. The former may include power lines noise (50/60 Hz); broken EEG electrodes or leads; excessive electrodes gel or dried electrodes; impedance fluctuation; EEG equipment in terms of electromagnetic noise. Person's own behavioral and physical activities related to electrical activity generated by heart, blinking and movement of eyes, stretching of muscles or body movement and sweating and so on. These artifacts can be inspected manually by expert eyes, but automatic artifacts detection is encouraged in automated system designs, otherwise artifacts can corrupt the results. Out of these artifacts, power lines noises can be eliminated by applying a 50/60 Hz notch filter. A wide range of artifact removal methods exists, including [12, 14]:

- *Rejection method:* In this method, contaminated signal is discarded. Its performance depends upon detection accuracy. Its drawback is that contaminated signal has to be removed and hence, results in loss of information [14].
- *Subtraction method:* This method assumes that contaminated EEG signal is a linear combination of original EEG signal and noisy signal. So, the original signal can be retrieved by subtracting noise from contaminated signal. Subtraction method is applied for removing the artifacts produced by eye movement [14].
- *Simple amplitude threshold:* This method defines negative and positive amplitude thresholds. Data out of this range is considered artefact [12].
- *Min-max threshold:* This method defines a minimum or maximum allowed amplitude difference for a particular time length [12].
- *Gradient Criterion:* An artefact threshold is defined based on point-to-point changes in voltage relative to intersample time [12].
- *Joint Probability:* This is relatively a new method that finds the probability of occurrence of a given value of point in time in a specific channel and segment relative to global probability of occurrence of such value [12].
- *Independent component analysis (ICA):* ICA performs blind source separation to split components that have statistical difference. ICA recovers N linearly mixed source signals $s = \{s_1(t), \ldots, s_N(t)\}$, after multiplying by A, an unknown matrix, $x(i) = \{x_1(t), \ldots, x_N(t)\} = As(i)$, with as little assumption about A or the source signal as possible[12].

3.2. Feature Extraction

Feature extraction is the step after pre-processing of EEG signals. It determines the features or feature vectors that are best representative of a pattern vector. A feature is an exclusivere presentation of a pattern segment. The advantage of feature extraction is to reduce dimensional space, which is essential to satisfy the software and hardware complexity, data processing cost and storage size. Features selection is done on signal's statistical properties or syntactic description.

Short time Fourier transform (STFT) is a frequently used feature extraction technique in which separation of stationary signals is performed into small fragments [15].Comparing with STFT, Fourier transform (FT), in which a finite length signal is expressed as the sum of infinite duration frequency components, does not provide the accurate location of an event in the frequency domain along the time scale. Moreover, FT is not suitable for non-stationary signals analysis.

The drawback of STFT is its finite length window. Narrow length window can increase the time resolution but reduces the frequency resolution[15]. Equation (1) is the mathematical representation of STFT, where $x(t)$is analyzed signal and *w*(.) represents the time window function.

$$STFT_x^{(w)}(t,f) = \int_{-\infty}^{\infty} [x(t)w^*(t-t')].\, e^{-j2\pi ft}dt \tag{1}$$

Wavelet transform (WT) solves the resolution problem of STFT. It replaces the sinusoidal component of FT by translation and dilation of a window function called wavelet [15]. Wavelets are ideally suitable for the analysis of sudden short duration signal changes [16]. Equation (2) provides mathematical representation of continuous wavelet transform (CWT), which is the part of WT.

$$CWT(a,b) = \int_{-\infty}^{\infty} x(t)\psi_{a,b}^{*}(t)dt \tag{2}$$

Here a and b are scaling factors, asterisk in the superscript represents the complex conjugate of function $\psi_{a,b}(t)$which is called the wavelet. It can be obtained by scaling the wavelet at b time and a scale shown in equation (3).

$$\psi_{a,b}(t) = \frac{1}{\sqrt{|a|}}\psi\left(\frac{t-b}{a}\right) \tag{3}$$

After features have been extracted from the raw data, they will be classified into different categories.

3.3. Classification

The classification can be assisted by linear discriminant analysis (LDA) [17], support vector machines (SVM) [18], neural networks (NN) [19], Bayes rule [20], and so on. LDA divides data into hyperplane representing the different classes. It has very low computational requirements, so it is simple to use and provides good results. However, LDA is hard to dear with nonlinear EEG data due to its linear nature [21].

A discrimination based on hyperplane can also be used in SVM. The hyperplane in SVM maximizes the marginal distance, which is believed to enhance the generalization competence [21].

The inspiration of NN is designed as the structure of actual brain modeling. NNs assemble independent processing units which are connected with each other in stages that generate a very simple function of their total inputs.

Bayes rule is used to design Bayes classifier which computes a postriori probability of a feature vector to belong to a particular class. Bayes classification locates a feature vector into a class where it belongs to with the highest probability. Table C below summarizes some advantages and disadvantages of these classifiers.

Table 3: Classifiers

Classifier	Advantages	Disadvantages
SVM	maximized margins between the nearest training points.	Linear decision boundaries
NN	Nonlinear decision boundaries	Acts as a black box, no inside information
Bayes	Simple in calculation	Requires complete information of the basic probability distribution
LDA	Low computational requirements	Linear decision boundaries

4. Conclusion

EEG signals are rich in temporal resolution and can successfully be used to measure mental stress. This survey supplies information on EEG signals to be used in psychological studies to measure mental stress. The relation of stress with the brain is discussed. Analytical techniques used in previous studies to measure stress using EEG signals are included. Various classification techniques are reivewed, in which LDA and SVM are linear classifiers, so their performance with EEG signals is limited since EEG signals have nonlinear behavior. Moreover, NN provides nonlinear solution, but information in its internal processing units is not available.

5. References

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