Physiological Signals for Stress Measurements

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***Abstract*—The aim of this paper is to give a brief overview about the physiological parameters and sensors that could be used to perform stress detection. Stress is considered one of the most serious social problem in today's society, in particular work-related stress. An unhealthy level of stress is a direct cause of diseases and disorders, such as difficulty in concentration and decision, chronic fatigue, depression, emotional problems, anxiety, irritability and insomnia. Stress has a high social cost due to medical treatments, lost productivity and absenteeism. Hence the need to have accurate measurements of stress level to apply mechanisms for prevention and treatment.**

***Keywords*—stress measurement, physiological signals, well-being.**

I. Introduction

Stress is a response of the organism to the stimuli of the environment [1]. Such stimuli, that can be physical, biological and psychosocial, are called stressors and constitute the set of modification requests. There are two form of stress: the eustress [2], [3], a positive form of stress that helps the individual to face and overcome the various challenges in his/her life, and the distress [4] that represents the negative aspect of stress, i.e. when stressors exceed the tolerability limits, causing difficulties such as physical and psychological disorders.

Human well-being depends on the ability to maintain a balance (homeostasis) and to respond to stress [5]. For this reasons, accurate measurements are important to have a qualitative and quantitative assessment of stress levels and the correlation between mind and body.

The main physiological parameters that could be used to perform stress detection are:

- the cardiovascular system activity that is frequently measured through blood volume pulse (BVP) and electrocardiography (ECG) signals, as well as through blood pressure (BP);
- the respiratory system activity that is strongly related to the cardiovascular system activity. The performed measures refer usually to the respiratory rate and the respiratory variability;
- the electrodermal activity (EDA) sensors that measure changes in the electrical conductivity of the skin surface;
- the muscle activity that is measured through electromyography (EMG). The EMG detects the electric potentials caused by the voluntary contraction of the muscle;
- the electroencephalography (EEG) signals. In particular, research focuses on dry EEG sensors that do not require skin preparation.

All these parameters are in some manner linked to the activity of the autonomic nervous system that can be subdivided in two parts: the parasympathetic and sympathetic system. The parasympathetic component is active during rest state. For example, it favors the contractility of the stomach for digestion, lowers the tone of the muscles and reduces the heart rate and blood pressure. The sympathetic system is linked instead to the fight or flight functions. It is active during physical activity, during work, or during moments of emotional stress. For example, the sympathetic system increases the heart rate and the blood pressure, blocks the gastrointestinal system and increases muscle strength.

II. Cardiovascular System Activity

The cardiovascular system is the set of organs and vessels responsible for the circulation of blood in the organism. The cardiovascular system activity can be measured through the blood volume pulse (BVP) and the electrocardiography (ECG) signals. The BVP is related to the change in volume of blood that flows into peripheral vessels and generally is measured through a photoplethysmographic (PPG) sensor. The PPG sensor finds the cyclical changes in the pressure tone in the capillaries that represent the heartbeat, illuminating the skin and measuring changes in light absorption [6]. A great advantage of this kind of sensor is that they have low invasiveness, but they are quite sensitive to motion. The ECG gives a more accurate measure of the cardiovascular activity, but the electrodes must be placed in direct contact with the user skin. Therefore, this solution could be less comfortable. The ECG is the recording of the electrical activity of the cardiac cells on the body surface. In particular, the periodicity of the cardiac rhythm is scanned with the R wave, in correspondence to which the EEG reaches its maximum value, Fig 1. A frequently used heart rate feature is the heart rate variability (HRV). HRV describes the time variation between consecutive heartbeats and it is an accurate measure of the sympathetic and parasympathetic nervous systems activity. The rhythm of the heartbeat indeed has a natural fluctuation caused by the exercised control of the sympathetic and parasympathetic systems. Once the exact intervals between the heartbeats are computed, it is possible to draw the so-called tachogram: a diagram that expresses the R-R interval between a heartbeat and the following in function of the heartbeat number, the so called RR time series, Fig. 2.

HRV can be mainly evaluated in two manners. The first is the analysis in the time domain, while the second is in the frequency domain. The analysis in the time domain uses

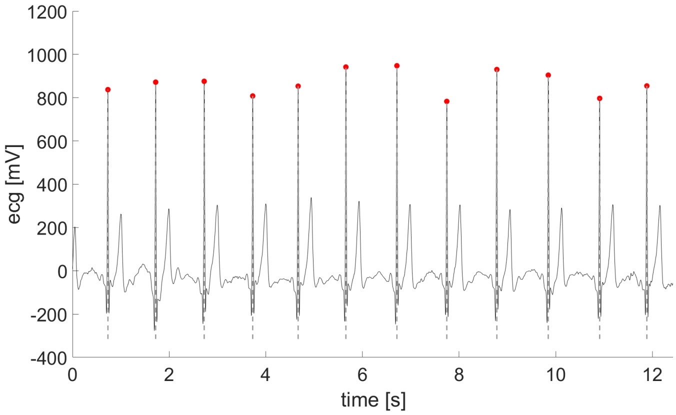

Fig. 1: ECG signal. The red dots correspond to the R wave, in correspondence to which the EEG reaches its maximum value.

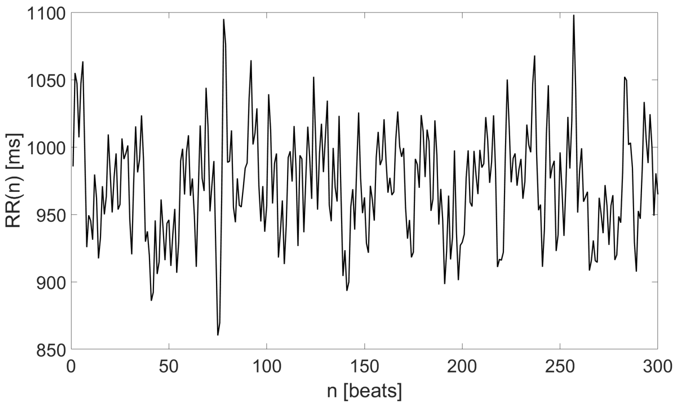

Fig. 2: An example of an RR series.

statistical operations applied on the R-R interval. The most frequently used are:

- The standard deviation of normal-to-normal intervals (SDNN) (measured in ms)
- The root mean square of the successive differences (RMSSD) (measured in ms)

Low value of SDNN and RMSSD indicates a prevalence of the sympathetic system. In general, SDNN and RMSSD are measured in an interval of $5\,\mathrm{min}$.

The analysis in the frequency domain (spectral analysis) gives instead some value, among which:

- The low-frequency (LF) power (0.04-$0.15\,\mathrm{Hz}$);
- The high-frequency (HF) power (0.15-$0.40\,\mathrm{Hz}$);
- The low-frequency high frequency ratio (LF/HF);

The LF band is considered as an index of the activation of the sympathetic system, while the HF as an index of the activation of the parasympathetic system. The LF/HF ratio is used to investigate the balance between the two systems. Fig. 3 shows an example of a Power Spectral Density (PSD) of an RR time series during rest and during a mental arithmetic task. It can be noticed how the LF peak increases during the stressful task and consequently the LF/HF ratio increases.

Generally, when the body is not under stress conditions, the heart rate is irregular and there is a natural variation

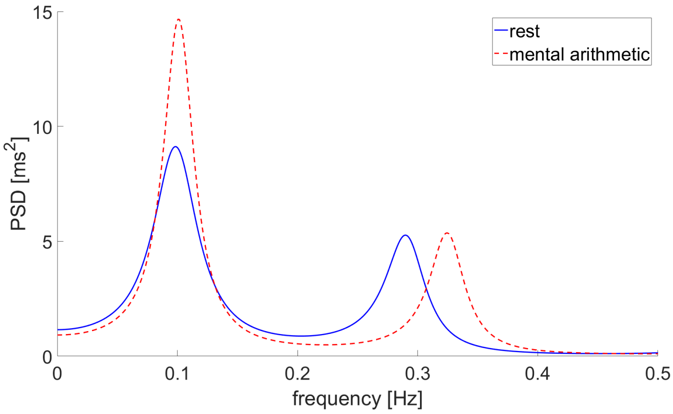

Fig. 3: Comparison between a PSD of an RR time series during rest and during mental arithmetic. It can be clearly noticed how the LF/HF ratio increases during the stressful task.

between an R-R interval and the following. When the activity of the sympathetic system is prevailing, this natural variation is reduced: as soon as the sympathetic activity increases, the parasympathetic effect on the heart rate decreases. This behavior determines a more stable rhythm. On the contrary, when the parasympathetic activity is very high, an increase of the HRV occurs.

Another parameter used to measure the cardiovascular system activity is the blood pressure (BP). BP is defined as the force exerted by blood on the walls of blood vessels as it flows inside them. BP is determined from factors such as force impressed by cardiac thrust, quantity of pumped blood to each heart contraction and resistance opposed by arteries.

BP is directly correlated to the sympathetic system: during a fight-or-flight response, BP rises due to increase in heart rate and to contraction of blood vessels.

Researchers have been focused on non-invasive continuous measurements of arterial blood pressure. One of them is the Volume Clamp Method [7]. In this method, BP is measured using a finger cuff with variable pressure. A plethysmograph, installed inside the finger cuff, measures the blood volume changes, which are compared with a set-point value corresponding to a zero transmural pressure, i.e. the condition in which the wall of the blood vessel does not accumulates pressure and the pressure inside the artery is the same as that on the outside. Thus, a pneumatic servo system acts on the pressure exerted by the finger cuff in order to keep a zero transmural pressure. In this manner, the pressure applied to the finger cuff follows continually the endovasal pressure, giving a non-invasive continuous measurement of BP.

III. Respiratory System Activity

Breathing frequency is an important indicator for stress assessment. In general, anxiety and stress give a faster and shallower breathing [8] and the respiratory rate, i.e. the number of breaths in a minute, increases with the physical or cognitive workload [9]. Moreover, mental stress and sustained attention tasks are proved to reduce respiratory variability [10].

Respiration is also strongly coupled with the cardiovascular system activity [11]. The interaction between these two systems can be clearly noticed in the variation in heart rate that occurs during the breathing cycle, the so called respiratory sinus arrhythmia (RSA). The RSA is a meaningful indicator of the parasympathetic activity of the autonomic nervous system [12].

There are different approaches for respiration monitoring, but generally they can be distinguished in contact and non-contact measurements [13]. Contact approaches usually measure parameters such as breathing sounds, airflow and chest or abdominal movements. In this latter case, the respiratory signal (Fig. 4) can be acquired, for example, through a piezoresistive sensor applied on an elastic band or a t-shirt at the chest or abdomen level. Respiratory signals can also

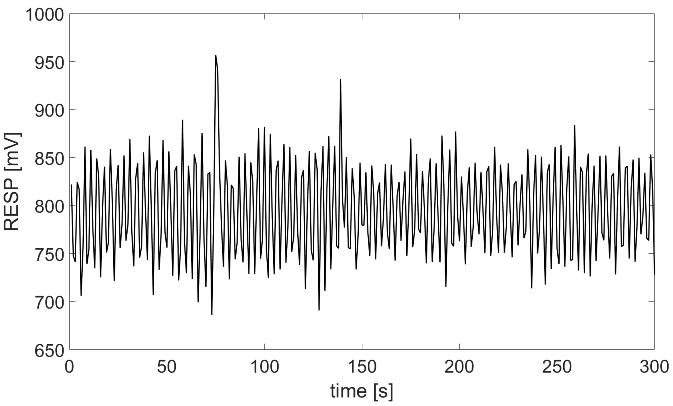

Fig. 4: An example of a respiratory signal acquired by a piezoresistive sensor.

be derived measuring the fluctuations in the ECG [14]. Non-contact approaches for respiration monitoring rely instead on cameras [15] or on thermal sensors [16].

IV. Electrodermal Activity

Electrodermal activity (EDA), also known as Galvanic Skin Response (GSR), is a measure of the continuous variations in the electrical characteristics of the skin. EDA refers to all the electrical phenomena (active and passive) of the skin. EDA increases when there is a sudden event, an increasing in the mental workload and in correspondence of both positive and negative emotional states. A common index used to quantify EDA is Skin Conductance (SC). SC varies with skin humidity and it is measured placing two electrodes on the skin, usually on two nearby fingers. The measurement is obtained applying a weak electric current through the electrodes, which generate a voltage from which it is possible to compute the conductance in microSiemens (µS). SC is a good index of "arousal", because the eccrine sweat glands depend exclusively by the sympathetic system [17].

SC can be split in two main components [18]:

- the skin conductance level (SCL), which is the tonic level, i.e. the basic level in absence of external stimuli. It is an index of the general state of activation of the nervous system. The more the individual is keyed up and nervous, the more is the skin sweating and consequently the conductance rises up;
- the skin conductance response (SCR), i.e. rapid phasics components. SCR changes in function of emotional, sensorial or ideational events and acts in the short period.

Fig. 5 shows an example of a raw SC signal decomposed in its phasic and tonic components, using the cvxEDA algorithm [19]. It can be clearly noticed how the SCR components is significantly higher and how the SCL rises up during the mental arithmetic task with respect to rest condition.

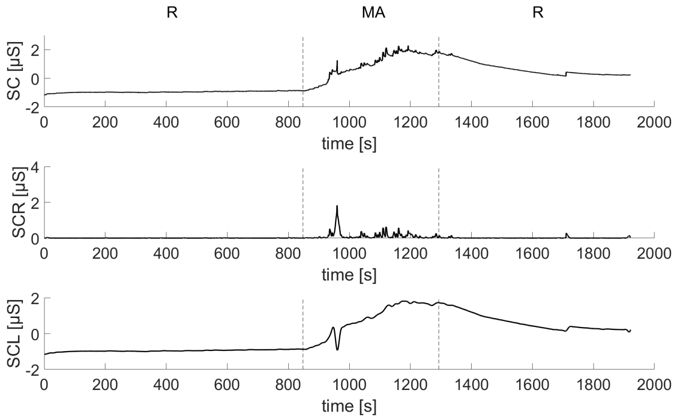

Fig. 5: Raw SC signal (top) and its estimated phasic (middle) and tonic (bottom) components during rest (R), mental arithmetic (MA) and rest again.

V. Muscle Activity

The electrical activity produced by skeletal muscles can be measured using an electromyograph, which measures the level of discharge of the motor nerve fibers that innervate the muscle. The EMG signals provide information concerning muscle tone. The most frequently monitored muscles are the trapezius and the forearm muscles, because these muscles reflect more than others the overall degree of tension in the organism.

Under acute stress, EMG signals show higher amplitudes, in particular in the upper trapezius muscle groups [20]. Moreover, in the frequency domain analysis, significant increases of the lower frequency contents were observed during stress in the EMG signals [21].

Also facial muscle activity can provide useful information regarding the emotional status, because emotions are usually related to facial expression. In this case, one of the main problems is related to the uncomfortableness that can be experienced wearing the electrodes on the face.

VI. Cerebral Activity

The use of the electroencephalography for stress detection is an emerging field. The development of wireless and dry EEG systems makes possible to use this technology to study human brain activity in a generic environment without mechanical restrictions. The main problem in the use of this technology for stress detection is that an exploratory phase is required to identify the recording sites, frequencies and frequency pairs. Moreover some problems are related to motion artifacts that can corrupt the signals.

In EEG-based stress assessment algorithms, power features are the most commonly used [22]. EEG power spectrum can be subdivided essentially in 4 bands:

- delta (δ): 0.5-4 Hz
- theta (θ): 4-8 Hz
- alpha (α): 8-12 Hz
- beta (β): 12-30 Hz

Delta waves have the greatest amplitude and are related to deep sleep. They are very common in infants and younger children. These waves are mainly related to involuntary bodily activities, such as heart rate or digestion. The rhythm of theta waves is dominant in newborns. Theta waves are usually associated with drowsiness in adults and teens and with states of emotional tension and hypnosis. Alpha waves predominantly originate from the occipital lobe and they are dominant during relaxation with closed eyes. Alpha waves are characteristic of waking conditions and mental rest. Beta waves are dominant in open-eye subjects who are engaged in brain activities. Therefore they are usually present during active concentration or anxious thinking. In particular, regarding stress measurements, a stressful situation usually coincides with a suppression of α waves and boost of β waves [23], Fig. 6.

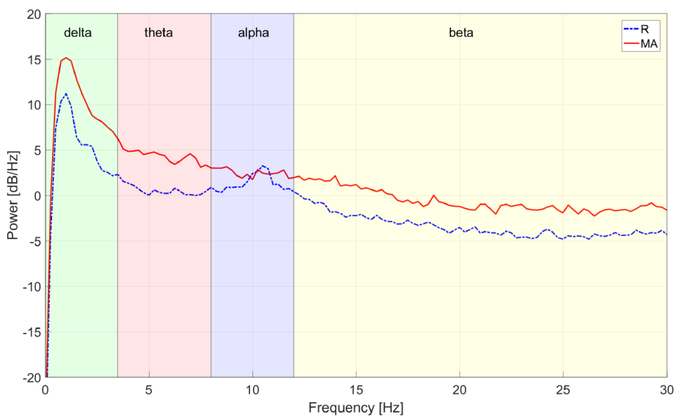

Fig. 6: PSD of an EEG channel during rest (R) and mental arithmetic (MA).

VII. Conclusion

In this paper, we presented the main physiological parameters used for stress detection. To monitor these parameters, researchers are focusing in particular on wearable devices. These devices, that can be accessories or clothes, can guarantee the collection of data without having to reside in a specific place and ensure a certain freedom of movement. The general trend goes to the reduction of invasiveness of such systems, in order to make their use suitable for a real-life scenario and accepted by the various users.

Another emerging field in this area is the developing of machine learning algorithms to perform automatic stress detection [24]. Such algorithms exploit the features provided by the different physiological parameters to make a more reliable estimate of the stress status of a person.

Stress detection based on physiological sensors can open new interesting horizons in the design of technologies and applications [25] with the aim to reduce the perceived stress level and enhance the comfort of various products and solutions.

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