# Stress Recognition from Heterogeneous Data

Bo Zhang, Yann Morère, Loïc Sieler, Cécile Langlet, Benoît Bolmont, and Guy Bourhis
University of Lorraine, Metz, France
Email: {bo.zhang, yann.morere, loic.sieler, cecile.langlet, benoit.bolmont, guy.bourhis}@univ-lorraine.fr

***Abstract*—The assessment of the stress of an individual attracts the attentions of the researchers since it helps to provide individualized assistance in managing this emotional state. This paper investigates the potential of stress recognition using heterogeneous data, where not only the physiological signals but also the Reaction Time (RT) is used to recognize different stress levels. To acquire the data related to mental stress of an individual, we design the experiments with two different stressors: 'Stroop test' and acoustic induction. We develop the classifier based on the Support Vector Machines (SVM) for the stress recognition given the physiological signals. Three physiological signals, Electrodermal Activity (EDA), Electrocardiography (ECG) and Electromyography (EMG), are registered and analyzed. An overall high recognition accuracy of the SVM classifier is obtained. During the experiments, RT task appears. RTs are registered and their statistical analysis shows a generally good discrimination between the period of low stress and the period of high stress. Results indicate that the data from heterogeneous sources, such as physiological signal and cognitive reaction can be adopted for stress recognition.**

***Index Terms*—stress recognition, heterogeneous data, physiological signal, reaction time, Stroop test, acoustic induction**

## I. Introduction

In modern society, the stress of the individual has been found to be a common problem. In 2007, the research indicated that the stress was the second most common work-related health problem in the European Union [1]. Continuous stress can lead to various mental and physical problems [2] and especially for the persons who always face emergency situations (e.g., fireman): it may alter their actions and put them in danger, so that it is meaningful to provide the assessment of the stress of the individual. Based on this idea, we proposed the Psypocket project which is aimed at making a portable device able to analyze accurately the emotional state of the individual based on physiological, psychological and behavioural modifications. It should then offer solutions for feedback to regulate this state. The system adopts the data from heterogeneous sources, such as physiological signal, cognitive reaction and behavioural reaction, for stress recognition. Besides, in this project, we would like to analyze the effects of various stressors that can elicit the mental stress and build the psychophysiological expertise for stress recognition, i.e. finding out for one kind of stressor, which signal is the best indicator to recognize the stress state and the best corresponding characteristic features of this signal for stress recognition. In this paper, we present the feasibility of stress recognition from heterogeneous data, which is the essential part of the research of our project.

Traditionally, to assess the individual affective state, people are asked to fill in the standardized questionnaire (e.g., Perceived Stress Questionnaire [3]) which helps to quantify the stress. However, in 2001, R. Picard *et al.* [4] proposed that the ability to recognize emotion should be an important part of machine intelligence and developed a machine's ability to recognize human affective state given the physiological signals, which opened a new gate to assess the individual affective state. After that, the researchers began to investigate the potential of physiological signals for stress recognition. P. Rani *et al.* [5] presented online stress detection by monitoring the Heart Rate Variability (HRV) of a human. They chose playing video games to generate mental stress and fuzzy logic for stress detection. R. Picard and J. Healey [6] collected and analyzed physiological signals during real world driving tasks to determine a driver's relative stress level. Their proposed methods based on linear discriminant function distinguished three levels of driver stress with high accuracy. In the context of human computer interaction, J. Zhai *et al.* [7] presented their research of stress recognition using four physiological signals when the user was interacting with the computer. A computer-based "Paced Stroop Test" was designed to elicit emotional stress and the classification accuracies of different learning algorithms were compared. Based on these discussions, several stress recognition systems were proposed. In 2003, E. Jovanov *et al.* [8] proposed a distributed wireless sensor system, which quantified stress levels based on measures of HRV. The system iCalm [9], using a wearable sensor and network architecture, could provide the long-term monitoring of autonomic nervous system, by registering the Electrocardiography (ECG) and Electrodermal Activity (EDA). The system INTREPID [10] estimated the subjects' levels of apprehension in real time by classifying features extracted from biosignals.

Generally speaking, these existing systems only use the physiological signals for stress recognition. However, it should be mentioned that the physiological signals are not the only source of data to quantify the reactions of an individual. Intuitively, we can observe that the personal cognitive reactions or behaviors may differ when an individual deals with various situations. For example, B. Bolmont *et al.* [11] presented that the climbers' mood

Manuscript received June 13, 2016; revised September 20, 2016.



doi: 10.18178/joig.4.2.116-121

states may change when they are exposed to high altitude and their performance in Reaction Time (RT) differs as well. This gives us the idea that not only physiological signals, but also cognitive and behavioral reactions are possible to be adopted to recognize if an individual is under mental stress. However the existing systems pay little attention to use these actions for stress recognition. In this paper, we discuss the feasibility of stress recognition using physiological signals and RT. Another contribution is that concerning about the acquisition of the data related to the mental stress, we designed the experiments using various kinds of stressors to elicit the stress. The effects of different stressors were analyzed whereas in the researches of stress recognition given physiological data, usually only one stressor was used and the result of recognition is only based on the data related to this stressor.

The rest of the paper is organized as follows: Section 2 describes our experiments and Section 3 explains our methodology of stress recognition. The results of recognition are presented and discussed in the Section 4.

## II. Experiment

To acquire the physiological signals related to the mental stress, we proposed two different experiments. The experimental protocol is aimed at eliciting the stress of the participating subject at the pre-determined period. The first experiment used 'Stroop test' to elicit the stress. The Stroop test [12] asks the subject to name the font color of the word when the color and the meaning of the words differ (e.g., the word “yellow” printed in green ink instead of yellow ink). This test has been used as an effective physiological stressor for stress recognition by many authors like Zhai and Barreto [7]. The second experiment used acoustic induction to elicit the stress. Music was found to be effective to arouse positive and negative emotion in the research of Kim and Andr é [13]. They observed the physiological changes in music listening. This gave us the idea that acoustic induction could be a stress stimulus in the controlled laboratory environment. The details of these two experiments are explained in the following paragraphs. Nine students from University of Lorraine participated in our experiments and they were divided into two groups. The first group of four male students participated in the experiment of Stroop test and the second group of five female students participated in the experiment of acoustic induction.

An experimental platform was designed for data acquisition. A screen was placed in front of the subject for the Stroop test and a joystick was placed between them. The joystick can be manipulated to point in four directions by the subject and a button is equipped on the top of the joystick. Two LEDs were put below the screen for RT test. The BIOPACTM System, consisted of the physiological sensors and amplifiers, was used to register the physiological signals. Three physiological sensors were used: EDA, ECG and Electromyography (EMG). The electrodes of the EDA sensor were attached to the index finger of the left hand and the two-lead ECG signal was register with the ECG sensor on the chest. The EMG sensor was placed on the trapezius muscle (shoulder). The BIOPACTM System collected all three physiological signals and digitized these signals at a common sampling rate of 2000 Hz. During the experiment, the subject sat in the chair, wore a headset and held the joystick.

The experiment of Stroop test consists of three sections (Fig. 1). It begins with Section 1 composed of 100 consecutive RT trials. In one RT trial, when the LEDs (originally turned off) are lighted up with the white color, the subject should press the button on the top of the joystick to respond. The RT, which is the time interval between the moment when LEDs are lighted up and the moment that the subject clicks the button, is calculated and registered. Section 2 and Section 3 are the sections for Stroop test and each section is consisted of 300 consecutive Stroop trials. We designed a computer-based interacting environment for the Stroop test. In one Stroop trial, a graphic user interface is shown on the screen. A word is written in the center of the interface with four buttons surrounding it (Fig. 2). The word is the name of a color in French and the buttons are also labeled with different colors' names in French. The subject should choose the button with the label that matched the font color of that word. The choice of the button is realized by using the joystick. When the joystick is manipulated to point in one direction, its corresponding button is chosen. For example, when the joystick is pushed to point forward, the button above the word is chosen. If the answer is not right, the subject will hear a buzz in the headset. Moreover, if the subject does not respond in 2.5 seconds, the screen will change to the next trial automatically. The Stroop trials of Section 2 are the trials without interference, which means that the word is printed in the color denoted by its name (e.g., word “jaune” (yellow) printed in yellow ink). The Stroop trials of Section 3 are the trials with interference, where the word is printed in the color not denoted by its name (e.g., word “jaune” printed in green ink instead of yellow ink). Besides, RT trials appear randomly in Section 2 and Section 3. When one section is finished, the subject is firstly asked to fill in the Self-Assessment Manikin (SAM) [14] so that we can acquire his self-assessment stress state. Then the subject is asked to relax for one minute before the test of next section.

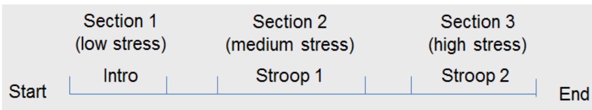



Figure 1. Schedule of the Stroop test experiment.

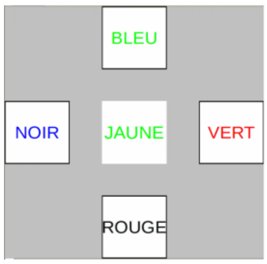



Figure 2. Illustration of Stroop trial.

The experiment of acoustic induction also consists of three sections (Fig. 3) and each section is consisted of 100 consecutive RT trials. The experiment begins with Section 1. During this section, there is no sound in the headset. In Section 2, the subject hears the positive ambient sounds in the headset, such as agreeable music and applause, and in Section 3, the subject hears the negative ambient sounds, for example horrible shrieking. In this experiment, the subject is also asked to fill in the SAM and then relax for one minute when one section is finished.

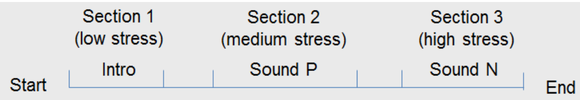



Figure 3. Schedule of the experiment of acoustic induction.

## III. Methodology

Our system is aimed at using heterogeneous data for stress recognition. For the moment, physiological signals (ECG, EMG and EDA) and RT are used as the inputs of the system.

### A. *Stress Recognition Using Physiological Signals*

The overall structure of stress recognition given physiological signals is illustrated in Fig. 4. After the preprocessing, the raw time-series of physiological signals were transformed into features, since standard classification algorithms can not be directly applied to the raw time-series signals. Then these informative features were used as the inputs for classification. We chose Support Vector Machines (SVM) for classification and the outputs of the SVM are the stress levels.


Figure 4. Block diagram of the stress recognition using physiological signals.

#### 1) *Preprocessing*

At first, the physiological signals were filtered to avoid artifacts. The EMG signal was firstly filtered with a notch filter of 50Hz to filter out power line noise and a low-pass filter where the cutoff frequency is 500Hz. Since EMG recordings of trapezius muscle are often contaminated by the ECG signal [15], we added a 30Hz high-pass Butterworth filter to EMG for ECG contamination removal. It should be mentioned that the ECG signal requires addition preprocessing, since we need to generate informative features from HRV [13] for classification. To obtain HRV from continuous ECG signal, Pan-Tompkins algorithm [16] was used which detects the QRS complex of ECG to determine the R peak interval and the interpolated HRV time series with a re-sampling frequency of 8Hz were used for feature extraction.

#### 2) *Feature extraction*

The informative features were generated from the filtered EMG, EDA and HRV signals. These signals were divided into the segments with predefined size (called windows) and informative features are generated for each window. Informative features are the statistical features which are originally used to analyze affective physiological state [4] and they can be computed in an online way which is an advantage for real-time recognition. Let the physiological signal be designated by x and $x_n$ represent the value of the n-th sample of the signal in the window, where n=1, …, N. Table I lists the informative features that are used in our research where AD is short for absolute difference. The features were max-min normalized to the range of [0, 1], as shown in (1):

$$\bar{y} = \frac{y - \min(y)}{\max(y) - \min(y)} \tag{1}$$

where *y* denotes one informative feature. These max-min normalized features were the inputs of SVM classifier.

TABLE I. Informative Features for Stress Recognition Given Physiological Signal

| Informative Feature | Formula |
|---|---|
| Sample mean: $\mu_x$ | $\mu_x = \frac{1}{N}\sum_{n=1}^{N} x_n$ |
| Standard deviation: $\sigma_x$ | $\sigma_x = (\frac{1}{N-1}\sum_{n=1}^{N}(x_n - \mu_x)^2)^{\frac{1}{2}}$ |
| First AD: $\delta_x$ | $\delta_x = \frac{1}{N-1}\sum_{n=1}^{N-1}\lvert x_{n+1} - x_n\rvert$ |
| Second AD: $\gamma_x$ | $\gamma_x = \frac{1}{N-2}\sum_{n=1}^{N-2}\lvert x_{n+2} - x_n\rvert$ |
| Normalized first AD: $\bar{\delta}_x$ | $\bar{x}_n = \frac{x_n - \mu_x}{\sigma_x}$ |
| | $\bar{\delta}_x = \frac{1}{N-1}\sum_{n=1}^{N-1}\lvert \bar{x}_{n+1} - \bar{x}_n\rvert$ |
| Normalized second AD: $\bar{\gamma}_x$ | $\bar{\gamma}_x = \frac{1}{N-2}\sum_{n=1}^{N-2}\lvert \bar{x}_{n+2} - \bar{x}_n\rvert$ |

#### 3) *SVM classification*

SVM [17] is a supervised learning method used for pattern recognition. SVM considers that every data is a point in its feature space and it is possible to find a linear or non-linear discriminant function in high dimensional feature space to separate the data points that related to different classes. To ensure the classification accuracy, SVM needs the distance of the discriminant function from the nearest feature vector set to be maximal and these nearest feature vectors are called support vectors. It needs the data points that have been labeled in different classes to determine several parameters of SVM in training process. Once these parameters are determined, SVM can be used to label the rest data in different classes. In this paper, we used SVM with a usual Gaussian kernel [18] for the classification of different stress levels based on the informative features derived from physiological signals. The trained SVM can be used to predict the unknown stress level given physiological signals.

### B. *Stress Recognition Using RT*

We analyzed the registered RT of RT trial to find out if the difference of RT exists when the subject is under different stress levels. For each subject, we computed the mean, the median and the standard deviation (std) of the RT of one hundred RT trials in each section of our experiments. Then the Confidence Interval (CI) with 95% confidence level of the RT for each section was compared.

## IV. RESULTS

During the experiments, the physiological signals (ECG, EMG and EDA) of the subject were registered. In each section, they were divided into one minute 50% overlapping segments. Each of these segments was designed to represent a period of low stress (Section 1), medium stress (Section 2) and high stress (Section 3). Different stress levels are confirmed by SAM. Six informative features were calculated for each segment. After the max-min normalization stage, the informative features were used as the inputs of SVM classifier. The classification accuracy of SVM was evaluated using the 5-fold cross validation method [18]. Meanwhile, we registered the RTs of RT trials in each section and evaluated its ability of recognition using the statistical analysis.

### A. *The Experiment of Stroop Test*

To begin with, we analyzed the performance of SVM classifier for stress recognition given the physiological signals. The inputs of SVM classifier were firstly the informative features generated from the segments of Section 1 and Section 3 and the output were two stress levels: low stress and high stress. The SVM classifier was trained with the mean value of the segment and all six informative features respectively for each physiological signal and the classification accuracies are listed in Table II. We note that the classification accuracies of the HRV for the subject 3 were not computed since his ECG signal of the Section 1 was not registered in the experiment.

TABLE II. CLASSIFICATION ACCURACIES OF THE EXPERIMENT OF STROOP TEST FOR LOW STRESS VS. HIGH STRESS

| Inputs of SVM | No. of subject | | | |
|---|---|---|---|---|
| | 1 | 2 | 3 | 4 |
| mean of EDA | 100.0% | 96.6% | 100.0% | 78.6% |
| all 6 features of EDA | 100.0% | 100.0% | 100.0% | 100.0% |
| mean of EMG | 78.5% | 46.6% | 78.5% | 64.3% |
| all 6 features of EMG | 100.0% | 100.0% | 100.0% | 85.7% |
| mean of HRV | 85.7% | 76.6% | no | 85.7% |
| all 6 features of HRV | 100.0% | 100.0% | no | 100.0% |

Similarly, we trained the SVM classifier with the informative features generated from the segments of Section 2 and Section 3 to see the performance of recognition for the medium and high stress levels. The classification accuracies are listed in Table III. Based on the results of Table II and Table III, we can note that the proposed SVM classifier is quite efficient for the stress recognition given physiological signals and a better performance is able to be obtained for the discrimination between the period of low stress and the period of high stress. The improvement of the classification accuracy can be observed when all 6 informative features were used to train the SVM classifier compared with the case where the input of SVM is only the mean value of the segment. Besides, it can be found that generally, the EDA signal bring in a better recognition performance compared with other physiological signals.

TABLE III. CLASSIFICATION ACCURACIES OF THE EXPERIMENT OF STROOP TEST FOR MEDIUM STRESS VS. HIGH STRESS

| Inputs of SVM | No. of subject | | | |
|---|---|---|---|---|
| | 1 | 2 | 3 | 4 |
| mean of EDA | 97.0% | 78.5% | 79.4% | 79.4% |
| all 6 features of EDA | 97.0% | 92.8% | 79.4% | 100.0% |
| mean of EMG | 61.7% | 64.3% | 61.8% | 55.9% |
| all 6 features of EMG | 94.1% | 97.1% | 97.0% | 82.4% |
| mean of HRV | 67.6% | 70.0% | 73.0% | 91.1% |
| all 6 features of HRV | 97% | 100.0% | 100.0% | 97.0% |

Then, we discussed the ability of stress recognition when RT was taken into consideration. For each section of the experiment, the statistical indexes of the RTs of RT trials such as mean, median, std and CI were computed (see Table IV). As can be seen, except the subject 3, the CI can be well distinguished for Section 1 and Section 3 which means that it is able to discriminate the period of low stress and the period of high stress with RT. However, the same results are not found when comparing the CI of Section 2 and the CI of Section 3.

TABLE IV. STATISTICAL INDEXES OF RT (EXPERIMENT OF STROOP TEST)

subject 1

| | Section 1 | Section 2 | Section 3 |
|---|---|---|---|
| mean (ms) | 225.39 | 273.90 | 248.43 |
| median (ms) | 215.50 | 238.00 | 230.25 |
| std (ms) | 34.57 | 101.01 | 79.01 |
| CI (ms) | [218.42, 232.36] | [253.75, 294.04] | [232.75, 264.10] |

subject 2

| | Section 1 | Section 2 | Section 3 |
|---|---|---|---|
| mean (ms) | 233.79 | 289.51 | 304.66 |
| median (ms) | 233.50 | 257.50 | 262.25 |
| std (ms) | 34.33 | 114.02 | 112.60 |
| CI (ms) | [226.98, 240.60] | [266.65, 312.37] | [282.32, 327.00] |

subject 3

| | Section 1 | Section 2 | Section 3 |
|---|---|---|---|
| mean (ms) | 236.30 | 237.19 | 231.95 |
| median (ms) | 230.00 | 236.00 | 228.50 |
| std (ms) | 28.69 | 30.28 | 32.00 |
| CI (ms) | [230.60, 241.99] | [231.18, 243.20] | [225.60, 238.29] |

subject 4

| | Section 1 | Section 2 | Section 3 |
|---|---|---|---|
| mean (ms) | 307.76 | 322.31 | 358.77 |
| median (ms) | 280.25 | 283.25 | 345.25 |
| std (ms) | 103.33 | 113.06 | 129.16 |
| CI (ms) | [287.04, 328.48] | [299.64, 344.98] | [333.14, 384.40] |

### B. The Experiment of Acoustic Induction

Similar to the discussion of the experiment of Stroop test, firstly, the performance of SVM classifier for the stress recognition given physiological signals was analyzed. Table V shows the classification accuracies of the SVM classifier to recognize two stress levels: low stress and high stress, where the informative features were generated from the segments of Section 1 and Section 3. The performance of the SVM classifier to recognize the medium stress and high stress levels was also analyzed where the features were generated from the segments of the Section 2 and Section 3 (see Table VI). The results of recognition show that our SVM classifier can recognize different stress levels elicited by acoustic induction based on the features derived from physiological signals. Classification accuracy can be improved when SVM classifier is trained with all 6 informative features compared with training with the mean value of the segment. The same improvement is found in the experiment of Stroop test. However, contrasted with the experiment of Stroop test, the EDA signal does not bring in a better recognition performance than others physiological signals.

TABLE V. CLASSIFICATION ACCURACIES OF THE EXPERIMENT OF ACOUSTIC INDUCTION FOR LOW STRESS VS. HIGH STRESS

| Inputs of SVM | No. of subject | | | | |
|---|---|---|---|---|---|
| | 1 | 2 | 3 | 4 | 5 |
| mean of EDA | 71.4% | 85.7% | 92.8% | 64.3 % | 57.1% |
| all 6 features of EDA | 100.0% | 85.7% | 100.0% | 85.7% | 64.2% |
| mean of EMG | 100.0% | 71.4% | 92.8% | 71.4% | 78.5% |
| all 6 features of EMG | 100.0% | 100.0% | 100.0% | 71.4% | 78.5% |
| mean of HRV | 92.8% | 50.0% | 85.7% | 78.5% | 100.0% |
| all 6 features of HRV | 92.8% | 83.3% | 100.0% | 78.5% | 100.0% |

TABLE VI. CLASSIFICATION ACCURACIES OF THE EXPERIMENT OF ACOUSTIC INDUCTION FOR MEDIUM STRESS VS. HIGH STRESS

| Inputs of SVM | No. of subject | | | | |
|---|---|---|---|---|---|
| | 1 | 2 | 3 | 4 | 5 |
| mean of EDA | 78.6% | 64.2% | 42.8% | 42.9 % | 50.0% |
| all 6 features of EDA | 92.8% | 71.4% | 100.0% | 85.7% | 78.5% |
| mean of EMG | 100.0% | 100.0% | 64.2% | 35.7% | 92.8% |
| all 6 features of EMG | 100.0% | 100.0% | 92.8% | 100.0% | 92.8% |
| mean of HRV | 64.2% | 100.0% | 64.2% | 85.7% | 78.5% |
| all 6 features of HRV | 78.5% | 100.0% | 85.7% | 85.7% | 78.5% |

Secondly, we analyzed the ability of stress recognition using RT. Table VII lists the statistical indexes of the RTs of RT trials for each section of the experiment. Among the five subjects, a good discrimination can be found between the CI of Section 1 and the CI of Section 3 for the subject 1, subject 4 and subject 5. For the other two subjects, even though the CI does not show a good discrimination, we can observe that the std of Section 3 is always greater than the std of Section 1. Besides, similar to the experiment of Stroop test, the CI of Section 2 can not be well distinguished from the CI of Section 3 for five subjects.

TABLE VII. STATISTICAL INDEXES OF RT (EXPERIMENT OF ACOUSTIC INDUCTION)

subject 1

| | Section 1 | Section 2 | Section 3 |
|---|---|---|---|
| mean (ms) | 255.67 | 307.42 | 329.72 |
| median (ms) | 252.50 | 293.50 | 318.25 |
| std (ms) | 37.39 | 77.04 | 81.88 |
| CI (ms) | [248.21, 263.13] | [291.98, 322.87] | [313.31, 346.14] |

subject 2

| | Section 1 | Section 2 | Section 3 |
|---|---|---|---|
| mean (ms) | 269.33 | 266.68 | 280.90 |
| median (ms) | 262.25 | 257.00 | 257.50 |
| std (ms) | 50.47 | 44.26 | 88.75 |
| CI (ms) | [257.31, 279.34] | [257.85, 275.51] | [263.28, 298.51] |

subject 3

| | Section 1 | Section 2 | Section 3 |
|---|---|---|---|
| mean (ms) | 248.09 | 255.13 | 252.14 |
| median (ms) | 240.25 | 247.00 | 234.50 |
| std (ms) | 33.86 | 37.70 | 50.16 |
| CI (ms) | [241.23, 254.95] | [247.49, 262.77] | [242.19, 262.09] |

subject 4

| | Section 1 | Section 2 | Section 3 |
|---|---|---|---|
| mean (ms) | 274.65 | 290.44 | 330.91 |
| median (ms) | 252.50 | 270.75 | 299.00 |
| std (ms) | 61.29 | 96.52 | 119.90 |
| CI (ms) | [262.43, 286.88] | [270.88, 309.99] | [306.74, 355.07] |

subject 5

| | Section 1 | Section 2 | Section 3 |
|---|---|---|---|
| mean (ms) | 235.88 | 271.69 | 279.70 |
| median (ms) | 220.50 | 228.00 | 267.00 |
| std (ms) | 61.08 | 138.12 | 98.39 |
| CI (ms) | [223.70, 247.07] | [244.28, 299.10] | [260.18, 299.22] |

## V. CONCLUSION

In this paper, we discuss the feasibility of stress recognition from heterogeneous data. Not only physiological signals, but also reaction time is adopted to recognize different stress levels. The proposed SVM classifier obtains an overall high accuracy of recognition given physiological signals. Statistical analysis of reaction time shows a good discrimination between the period of low stress and the period of high stress. The results of our research reinforce the belief that it is likely to adopt the data from heterogeneous sources (physiological signals, cognitive reactions, etc.) for stress recognition. As our research is still in progress, in the future, we will discuss the feasibility of embedded system which would realize the complete data processing.

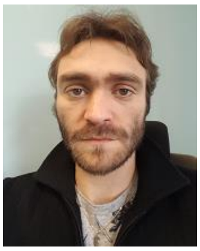
## REFERENCES

[1] European Foundation for the Improvement of Living and Working Conditions, Work-related stress, 2007.

[2] T. Chandola, E. Brunner, and M. Marmot, “Chronic stress at work and the metabolic syndrome: Prospective study,” *Bmj*, vol. 332, no. 7540, pp. 521-525, 2006.
[3] S. Cohen, T. Kamarck, and R. Mermelstein, “A global measure of perceived stress,” *Journal of Health and Social Behavior*, pp. 385-396, 1983.
[4] R. W. Picard, E. Vyzas, and J. Healey, “Toward machine emotional intelligence: Analysis of affective physiological state,” *IEEE Trans. Pattern Analysis and Machine Intelligence*, vol. 23, pp. 1175-1191, 2001.
[5] P. Rani, J. Sims, R. Brackin, and N. Sarkar, “Online stress detection using psychophysiological signals for implicit human-robot cooperation,” *Robotica*, vol. 20, pp. 673-685, 2002.
[6] J. A. Healey and R. W. Picard, “Detecting stress during real-world driving tasks using physiological sensors,” *IEEE Trans. on Intelligent Transportation Systems*, vol. 6, pp. 156-166, 2005.
[7] J. Zhai and A. Barreto, “Stress recognition using non-invasive technology,” in *Proc. FLAIRS Conference*, 2006, pp. 395-401.
[8] E. Jovanov, A. O. D. Lords, D. Raskovic, P. G. Cox, R. Adhami, and F. Andrasik, “Stress monitoring using a distributed wireless intelligent sensor system,” *Engineering in Medicine and Biology Magazine, IEEE*, vol. 22, no. 3, pp. 49-55, 2003.
[9] R. R. Fletcher, K. Dobson, M. S. Goodwin, H. Eydgahi, O. Wilder-Smith, D. Fernholz, and R. W. Picard, “iCalm: Wearable sensor and network architecture for wirelessly communicating and logging autonomic activity,” *IEEE Trans. Information Technology in Biomedicine*, vol. 14, no. 2, pp. 215-223, 2010.
[10] N. S. Katertsidis, C. D. Katsis, and D. Fotiadis, “INTREPID, a biosignal-based system for the monitoring of patients with anxiety disorders,” in *Proc. 9th International Conference on Information Technology and Applications in Biomedicine, IEEE*, 2009, pp. 1-6.
[11] B. Bolmont, F. Thullier, and J. H. Abraini, “Relationships between mood states and performances in reaction time, psychomotor ability, and mental efficiency during a 31-day gradual decompression in a hypobaric chamber from sea level to 8848 m equivalent altitude,” *Physiology & Behavior*, vol. 71, no. 5, pp. 469-476, 2000.
[12] J. R. Stroop, “Studies of interference in serial verbal reactions,” *Journal of Experimental Psychology*, vol. 18, no. 6, p. 643, 1935.
[13] J. Kim and E. André, “Emotion recognition based on physiological changes in music listening,” *IEEE Trans. Pattern Analysis and Machine Intelligence*, vol. 30, no. 12, pp. 2067-2083, 2008.
[14] P. J. Lang, “Behavioral treatment and bio-behavioral assessment: Computer applications,” 1980.
[15] R. J. Marker and K. S. Maluf, “Effects of electrocardiography contamination and comparison of ECG removal methods on upper trapezius electromyography recordings,” *Journal of Electromyography and Kinesiology*, vol. 24, no. 6, pp. 902-909, 2014.
[16] J. Pan and W. J. Tompkins, “A real-time QRS detection algorithm,” *IEEE Trans. Biomedical Engineering*, no. 3, pp. 230-236, 1985.
[17] V. N. Vapnik and V. Vapnik, *Statistical Learning Theory*, New York: Wiley, 1998.
[18] C. C. Chang and C. J. Lin, “LIBSVM: A library for support vector machines,” *ACM Transactions on Intelligent Systems and Technology (TIST)*, vol. 2, no. 3, p. 27, 2011.

**Bo Zhang** received the master degree in information, system and technology from the University of Paris-Sud, France, in 2013. He is now a PhD student at LCOMS (Laboratoire de Conception, Optimisation et Modélisation des Systèmes), University of Lorraine, France. His current research interests include stress recognition, physiological signal processing and pattern classification.

**Yann Morère** is assistant professor at LCOMS (Laboratoire de Conception, d'Optimisation et de Modélisation des Systèmes) at the University of Lorraine since 2001. His scientific areas include signal processing, aid to navigation, analysis of wheelchair driving and the processing of data from physiological signals.



**Loïc Sieler** received the PhD. Degree in "Robotic Vision System" from Blaise Pascal University (France), in 2011. He is currently assistant professor at Lorraine University (France). His research interests are the FPGA design of dedicated and adaptative architectures to address the problem of computing time which are common in: transmission, computing vision and data processing.

**Cécile Langlet** obtained her PhD in Life sciences and Health in 2000 from the University of Sciences and Technology in Lille (France). She is currently assistant professor at Lorraine University (France). Her main research interests are in neurophysiology and psychophysiology and affective neurosciences.

**Benoît Bolmont** obtained his PH.D in Neuroscience and Behavior in 2000 from the University Henri Poincare of Nancy (France). He is currently Professor at Lorraine University (France). His research interests are in the area of affective neurosciences and psychophysiology. His research focuses on relationships between Action and Emotion.

**Guy Bourhis** obtained his PhD in Biomedical Engineering in 1985 from the INPL Nancy (France). He is currently professor at Lorraine University (France). His main research interests are in the area of rehabilitation engineering, smart wheelchairs and human-machine interaction.