2013 Humaine Association Conference on Affective Computing and Intelligent Interaction

Wearable Physiological Sensors Reflect Mental Stress State in Office-Like Situations

Jacqueline Wijsman
Factulty of Electrical Engineering,
Mathematics and Computer Science
University of Twente
Enschede, The Netherlands
Body Area Networks
Holst Centre/imec
Eindhoven, The Netherlands
Email: Jacqueline.Wijsman@imec-nl.nl

Bernard Grundlehner
Hao Liu and Julien Penders
Body Area Networks
Holst Centre/imec
Eindhoven, The Netherlands

Hermie Hermens
Factulty of Electrical Engineering,
Mathematics and Computer Science
University of Twente
Enschede, The Netherlands

***Abstract*—Timely mental stress detection can help to prevent stress-related health problems. The aim of this study was to identify those physiological signals and features suitable for detecting mental stress in office-like situations. Electrocardiogram (ECG), respiration, skin conductance and surface electromyogram (sEMG) of the upper trapezius muscle were measured with a wearable system during three distinctive stress tests. The protocol contained stress tests that were designed to represent office-like situations. Generalized Estimating Equations were used to classify the data into rest and stress conditions. We reached an average classification rate of 74.5%. This approach may be used for continuous stress measurement in daily office life to detect mental stress at an early stage.**

I. Introduction

Stress is a major and increasing problem in today's society. Stress, depression and anxiety together are the second most frequently occurring work-related health problems in Europe. Of sickness absences of one month or more, 25% is caused by stress, depression or anxiety [1]. In the US, 30-40% of employees report their job as stressful and the number of lost work days due to anxiety, stress, and neurotic disorders is four times higher than other nonfatal injuries and illnesses [2].

Stress activates the Sympathetic Nervous System (SNS) [3]. Activation of the SNS induces various reactions in the body, including increases of sweat production, heart rate and muscle activation [4], [5]. Chronic mental stress results in chronic SNS activation and this can cause health problems such as hypertension, cardiovascular diseases, increased likelihood of infections and depression [3], [6], [7].

Stress-related health problems could be prevented by detecting stress at an early stage, but stress needs to be assessed in an objective and quantitative way. One approach to detect mental stress is by measuring relevant physiological parameters, such as muscle tone, heart rate, heart rate variability, skin conductance and eye pupil diameter; see for example [8]–[11]. Combinations of several features from these physiological parameters differentiate between stressful and non-stressful situations; see for example [11]–[16]. These studies all measure signals in 'stressful' situations such as the Stroop test, mental arithmetic, movie and sound fragments, and car driving. We think daily office work stress often involves solving problems under time pressure and working in a team, trying to beat competitors. We tried to mimic these stressors with our newly developed test protocol that consists of problem solving puzzle tasks and a memory task done in team effort.

Previously, we reported on the reaction of the trapezius muscle surface electromyography (sEMG) signal, from now on referred to as electromyography (EMG), on our protocol [17]. In our study, we collected four physiological signals that can be measured noninvasively and with small, wearable sensors: electrocardiogram (ECG), skin conductance (SC), respiration and EMG of the trapezius muscles. The goal of the current study was to identify those physiological signals and features that show the most distinct reaction to the various mental stress situations in our protocol.

Many studies apply statistics to their data to investigate significant differences between the various conditions of their protocols. However, we use classification to actually classify the data points into one of the conditions. This approach is more relevant for stress detection on an individual basis in the future. It is relevant to know if an *individual* using a stress detection system is stressed, rather than knowing if there are differences between a group of stressed persons and a group of non-stressed persons.

The main contributions of this paper are as follows: (i) we propose a set of nine physiological features, from four different physiological signals, contributing to the stress response; (ii) we demonstrate the possibility to classify mental stress from rest conditions using these features; and (iii) we show evidences that the four physiological signals all contribute to the identification of stress in a robust manner.

II. Methods

A. Experimental protocol

The experimental protocol is only discussed briefly here. For a detailed description of the protocol, and a validation that

978-0-7695-5048-0/13 $26.00 © 2013 IEEE
DOI 10.1109/ACII.2013.105

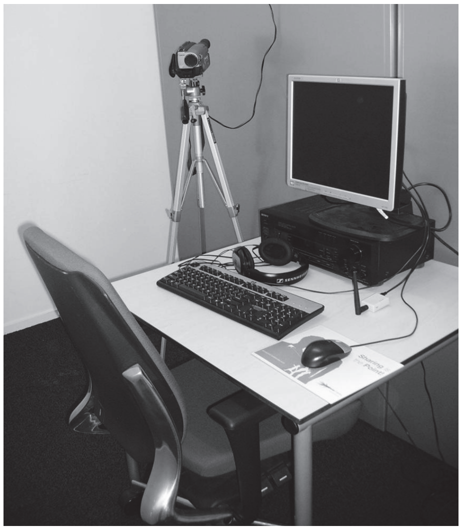

Fig. 1. Experiment room

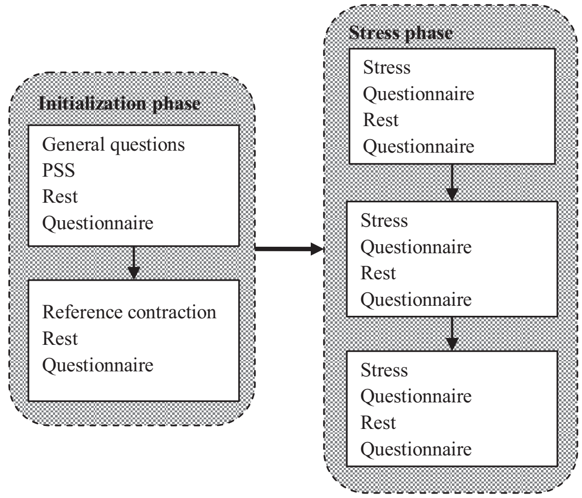

Fig. 2. Schematic overview of the procedure of the stress experiment. The procedure starts with an initialization phase. The stress phase consists of three different stress conditions, with rest periods and self-report questionnaires scheduled in between. PSS: Perceived Stress Scale

stress was actually induced, based on questionnaire answers, the reader is referred to [17].

A total number of 30 subjects were recruited for the experiment. Subjects had to be aged 18 or older and English-speaking. Subjects with muscle disease, cardiac problems or mental disorders such as depression or anxiety were excluded. The ages of the subjects ranged from 19 to 53 (mean = 33.1; SD = 7.9); 25 subjects were male and 5 were female. All subjects were right-handed. Although there are some indications that women and men react differently to stress (e.g. [18]), the subject group was too small to investigate the differences between men and women. Therefore the subject group was analyzed as a whole.

The test was performed via a PC in a quiet room with as few distractions as possible (Fig. 1). The subject had a mouse and keyboard available for completing the questions and tests involved in the protocol. The sounds involved in the protocol were played through headphones. A video camera was set up in the room to suggest that the subject would be videotaped during the protocol.

We developed an experimental protocol to study physiological responses to stress situations similar to stressors encountered in daily office life. The experimental protocol is illustrated in Fig. 2.

In the initialization phase of the protocol, the subject answered some general questions and completed the perceived stress scale (PSS) questionnaire [19]. Then a rest period was scheduled and the subject completed the first self-report questionnaire. In this questionnaire, the subject indicated his/her emotional state on visual analogue scales (VAS) by answering 10 questions about 10 different discrete emotions. The scales ranged from ‘not at all’ to ‘extremely’. One of the emotions was ‘stressed’. Then the subject performed a reference contraction of the shoulder muscles, followed by another rest period and questionnaire.

In the stress phase, every subject was exposed to three different stress conditions: a calculation task (the Norinder test [20], 2:30 min), a logical puzzle task (3:00 min) and a memory task (approximately 5:00 min). All three tasks were done under time pressure and with distracting news fragments that were played through headphones. Social pressure was induced in the memory task by telling the subjects that their performance would be included in a group result and published to colleagues afterwards. To invoke extra stress, the subject was recorded on video during the memory task as well. It was told that this was done for analysis after the experiment. The order of the three tests was randomized among the subjects to minimize crossover effects. Two-minute resting periods were scheduled in between the stress conditions to let the subject return to baseline physiological and psychological states. The subject heard classical music during these periods. There was some physical activity involved in the rest periods that consisted of typing numbers on the keyboard. This activity was similar to the expected activity during the stress conditions. Self-report questionnaires had to be completed both before and after each stress and rest condition. The results of these self-reports were used to validate that we actually induced stress with our protocol; for details see [17].

The entire experimental protocol was implemented in a MATLAB interface. Once the interface was started, the whole experiment proceeded automatically for about 40 minutes, until the subject finished the last questionnaire. Automated event marking allowed accurate mapping of the various conditions on the recorded signals.

B. Physiological Recordings

The physiological signals were recorded with a wireless body sensor network based on the body area network platform developed within the Human++ program in Holst Centre/imec

[21]. The body sensor network facilitated synchronization of all sensors and accurate mapping of the different phases of the test protocol on the signals. Signals were recorded on a micro SD card. One-lead ECG and respiration were recorded at a sampling frequency of 250 Hz using a wireless chest belt. A wireless hand sensor recorded SC with a sampling frequency of 100 Hz. Bipolar EMG signals were measured from the upper trapezius muscles of both shoulders. Two electrodes were placed on the trapezius muscles in the position as described by SENIAM [22]. A reference electrode was placed on the spinous process of vertebra C7. The electrodes were connected to wireless EMG sensor nodes recording at 1000 Hz. More details about the procedure of EMG recording can be found in [17].

C. Signal Processing and Feature Extraction

An overview and description of the features that were calculated from the measured signals is shown in Table I. The features were chosen based on literature on stress detection from physiological signals (see for example [11], [13]–[15], [17]). All signal processing was done using MATLAB.

LF, HF, and LFHF were calculated after applying a Hann window on the interpolated heart rate signal. For details on the calculation of SCdiff2 and OPD, see [13]. RespFreq was determined as the main frequency component of the power spectral density of the respiration signal. EMG features were calculated from the signals of the left shoulder. The subject gave all PC input during the protocol using the right hand. The left arm did not move at all during the entire protocol and therefore no movement interference was expected in the EMG signals from the left side. Details on the calculation of the EMG related features can be found in [17].

Because large variability in physiology between the subjects is expected, the feature values were normalized first. The following procedure was followed. All features were calculated over a sliding window of 120s that moved over the signals. The length of the window was equal to the length of the shortest condition: the two-minute rest condition. For most of the features, the window moved in steps of 1s. We believed that a smaller step size would not have led to more accurate results, because we assume that stress levels are not changing within fractions of seconds. For heart rate (HR) and standard deviation of interbeat intervals (SDNN) the window moved from beat to beat. For every position of the window, one value was calculated for each feature for that particular time window. The obtained feature values were normalized by calculating the z-score as follows:

$$z = \frac{(x - \bar{x})}{s} \tag{1}$$

With x being the original feature value, z the normalized value, and $\bar{x}$ and s the mean and standard deviation of the feature values over the entire recording, respectively.

After this normalization step, we chose to analyze one average value per rest or stress condition and not to investigate the variability of the feature values *during* the various conditions. For rest conditions, we used the normalized value for the 120s time window exactly overlapping the rest condition. The stress conditions all lasted longer than 120s. We assumed that stress would build up during the stress conditions and therefore used the normalized feature values calculated over the last 120s of these conditions for our analysis.

D. Analysis Methods

A total of 19 features were extracted from four physiological signals. It was expected that some of these features would show high correlations, since they are based on the same physiological processes. This introduces redundancy in the dataset and multicollinearity among the features. A selection was made based on the correlations and prior knowledge from a literature study to reduce the number of features and construct a non-redundant feature set for further analysis. Selecting this subset of features also reduced the number of features that needed to be calculated from the data. In a future application of a stress monitoring system this will save processing time and power.

Generalized Estimating Equations (GEE) analysis was applied to the feature subset. We combined the results of the three different stress conditions and therefore our dependent variable is binomial; it has only two states: ‘rest’ and ‘stress’. GEE was chosen because of the repeated measures nature of our dataset. A GEE model with binomial distribution and logit link function was chosen. The order of the three stress tests was randomized, so an exchangeable working correlation matrix was chosen. The analysis was performed using software package “IBM SPSS Statistics 20”.

Manual backward feature selection was used to select the best features for differentiation between the rest and stress conditions. The selection was based on significance of the Wald Chi-Square tests of the coefficients. In every step, the parameter with the largest significance value was removed from the model. While selecting features, the goodness-of-fit statistic (Corrected Quasi Likelihood under Independence Model Criterion) was monitored. This statistic should become smaller after every step.

As a training set, 80% of the stress cases and 80% of the rest cases were selected randomly. The other 20% of the stress and rest cases were used as the test set. This splitting procedure was done five times to check if the results obtained with different training and test sets would be consistent.

Using the coefficients obtained by the GEE analysis, the odds of certain normalized feature values to be measured during a stress condition were calculated, using:

$$odds = e^{\sum_{k=1}^{n} B_k \cdot x_k} \tag{2}$$

n is the number of features, B_k is the coefficient for feature k and x_k is the normalized feature value of feature k. The probability p was then calculated from the odds as follows:

$$p = \frac{odds}{1 + odds} \tag{3}$$

TABLE I

OVERVIEW OF FEATURES EXTRACTED FROM THE MEASURED SIGNALS

Number	Feature	Extracted from	Abbreviation	Meaning
1	Heart rate	ECG	HR	Mean heart rate
2	Standard deviation interbeat intervals	ECG	SDNN	Mean standard deviation of the interbeat intervals
3	Low frequency heart rate variability	ECG	LF	Heart rate variability in the 0.04–0.15 Hz band
4	High frequency heart rate variability	ECG	HF	Heart rate variability in the 0.15–0.4 Hz band
5	LF/HF ratio heart rate variability	ECG	LFHF	Ratio of the low and high frequency of heart rate variability
6	Skin conductance level	SC	SCL	Mean level of skin conductance
7	Skin conductance response rate	SC	SCRR	Mean number of skin conductance responses per second
8	Skin conductance second difference power	SC	SCdiff2	Signal power in the second difference of the skin conductance signal
9	Ohmic perturbation duration skin conductance	SC	OPD	Relative time of responsiveness of the skin conductance signal
10	Respiration frequency	Resp	RespFreq	Mean respiration frequency
11	RMS of the respiration signal	Resp	RMSResp	Root mean square value of the respiration signal for estimating tidal volume changes
12	RMS of the EMG signal	EMG	RMSEMG	Normalized root mean square value as percentage of the EMG reference contraction
13	Static load	EMG	Static	10th percentile of rank ordered EMG RMS values
14	Median load	EMG	Median	50th percentile of rank ordered EMG RMS values
15	Peak load	EMG	Peak	90th percentile of rank ordered EMG RMS values
16	Gaps/min	EMG	Gaprate	Average number of EMG gaps per minute
17	Relative time with gaps	EMG	Gaptime	Percentage of time in which EMG gaps occurred
18	Mean EMG frequency	EMG	MNF	Mean frequency of the magnitude of the EMG frequency spectrum
19	Median EMG frequency	EMG	MDF	Frequency at which the surface on the left side equals that of the right side of the magnitude of the EMG frequency spectrum

ECG: electrocardiogram, SC: skin conductance, Resp: respiration, EMG: electromyography.

So the outcome of the GEE procedure was a probability between 0 and 1 for each case of being a stress condition. With a cutoff value of 0.5, cases were classified into rest or stress conditions.

III. RESULTS

A. Population

A number of subjects were excluded from analysis because of poor signal quality (1 poor respiration signal, 5 poor SC signals, 5 poor EMG signals; 9 subjects excluded), incomplete data due to failing sensor nodes (2 subjects), or distractions due to other people being present in the room during the experiment (1 subject). Exclusion of these subjects left 18 full recordings of good quality.

B. Feature Selection

The absolute correlation values among the 19 normalized features are shown in Fig. 3. High correlations were found for some features. For example, SDNN, LF, and HF correlate strongly as do RMSEMG, static, median, and peak load of the EMG signal. MNF and MDF are also highly correlated.

Based on these correlations and on prior knowledge, a subset of 9 features was chosen that did not include absolute correlation values higher than 0.6 between features:

HR Does not correlate strongly to any other feature and has shown to react to stress in many other studies (see for example [18]).

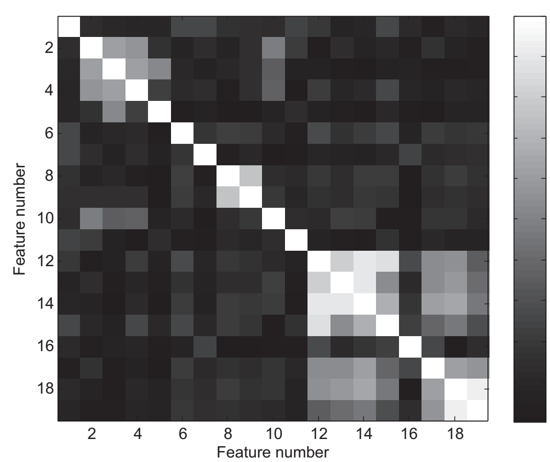

Fig. 3. Absolute correlation values among the features. The feature numbers correspond to the numbers in Table I.

SDNN Was chosen from the cluster SDNN, LF, HF, LFHF. SDNN showed promising results in earlier research [13].

SCL Does not correlate strongly with other features, so this feature is included by itself.

SCRR Does not correlate strongly with other features, so this feature is included by itself.

TABLE II
GEE COEFFICIENTS C1–C5 FOR THE SELECTED FEATURES

Feature	C1	C2	C3	C4	C5
HR	0.376	0.277	-0.221*	0.121	0.615
SCL	0.817*	0.871*	0.884*	0.411*	0.959*
SCdiff2	1.391*	1.406*	0.641*	0.638*	1.177*
RespFreq	1.122*	0.813*	0.525*	-0.126*	1.360*
Gaptime	-1.163*	-1.090*	-0.086	0.183*	-0.895*
Intercept	-0.151	-0.021	-0.045	0.082*	-0.135

* $p<0.05$ Wald Chi-Square test

TABLE III
CLASSIFICATION RESULTS FROM GEE ON THE TEST SETS

	Set 1	Set 2	Set 3	Set 4	Set 5	Average (%)
Rest	100.0	81.8	63.6	63.6	90.9	80.0
Stress	63.6	81.8	63.6	63.6	72.7	69.1
Overall	81.8	81.8	63.6	63.6	81.8	74.5

SCdiff2 Correlated strongly with OPD; SCdiff2 was chosen arbitrarily from the two.

RespFreq Does not correlate strongly with other features, and might be indicative of stress.

Peak Was chosen from RMS, Static, Median, Peak; Peak load gave the best result from this subset in our earlier analysis on EMG signals [17].

Gaptime Showed promising results in our earlier analysis [17].

MNF Showed a slightly better result than MDF in our earlier analysis [17].

C. Generalized Estimating Equations

We used a manual backward feature selection procedure to select the best features for GEE. Four features (Peak, SCRR, SDNN, MNF) were removed from the analysis. Removing the fifth feature (HR), caused the goodness-of-fit statistic to increase, so we decided to keep HR in the model. The five selected features and their coefficients for the different training sets are listed in Table II. The coefficients of SCL and SCdiff2 are all positive and significant. Also the HR and RespFreq coefficients are positive for four out of five training sets. These results confirm the expectations that raised from literature, suggesting that all four features are positively related to stress. The coefficients of Gaptime are negative in four out of five training sets. This indicates that a decrease in Gaptime corresponds to an increase in stress level, as was expected.

Using the calculated probabilities for each case, each condition was classified in a rest or in a stress condition. The classification results for the five test sets (22 cases in each set) are shown in Table III. There were some variations in the results among the different test sets. On average, 80.0% of the rest cases and 69.1% of the stress cases were classified correctly. Overall, 74.5% of the test set cases were classified in the correct condition.

IV. DISCUSSION

The goal of this study was to identify those physiological features that show distinct reactions to mental stress in office-like situations. We measured ECG, respiration, SC and EMG signals during stress and rest conditions. We selected nine non-correlating features from these four signals. Using GEE, we reduced the feature set to five features and on average 74.5% of the cases of the test set were classified correctly into a rest or stress condition. We were able to reduce the feature set to five features, which is an advantage, as especially in small datasets it is preferred to use as few features as possible to avoid the curse of dimensionality. Also, calculating fewer features saves processing time and power, which is relevant for a future wearable low-power stress management system.

The five features selected for GEE were spread over the four different signals, which shows that all signals contain information about stress. This observation points to the benefit of multi-signal data collection and analysis. Apparently, all signals contributed to the global stress reaction and together facilitated robust stress detection.

In Table III, we can see that the rest cases are more often classified correctly than the stress cases. It seems more difficult to detect stress from physiological signals than to identify that someone is at rest. A possible explanation can be found in the subjective stress levels that subjects indicated during the study. Subjects reported low stress levels during the rest conditions, whereas during the stress conditions the reported stress levels covered a larger range. This means that not all subjects indicated high stress levels during the stress conditions. So although on group level, the stress conditions were perceived more stressful than the rest conditions (see validation of protocol in [17]), this did not hold for every single case. In future work, the individual subjective stress levels should be taken into account in the analysis of the physiological data to get to more personalized stress estimations.

Compared to other papers on classification of mental stress situations, our classification results were relatively low. Classification accuracies of other studies we found range from 80% [16] to 97.4% [14]. However, most other studies only used one type of stressor in their protocols and therefore they were able to tune their algorithms to detect the specific reaction induced by that stressor. In our study, three different stressors were used that were all included in the analysis. Still, an accuracy of 74.5% was achieved in differentiating these three mental stress conditions from rest conditions. A similar study like ours was done by Choi et al. [12]. Their protocol consisted of five different stress conditions, interleaved with deep breathing relaxation periods. They used four features extracted from skin conductance, respiration and heart rate in a logistic model to classify between rest and stress conditions. Choi et al. obtained a classification accuracy of 81%. We reached similar classification accuracy for some of our test sets.

The study presented in this paper has the following limitations. Our normalization method worked well for this analysis and we obtained good classification results. However, this method of normalization is not practical for real-time use of the system, because it needs a signal of several minutes including both rest and stress conditions. Clearly, it is preferable to have only a short calibration measurement that is sufficient for normalization of all future recordings. A special protocol could be developed to achieve that. Such a protocol should include baseline recording and also a stressor to be able to normalize for the reactivity to stress.

The entire protocol was performed in a controlled environment. To facilitate future use of a stress measurement system, recordings should be made in uncontrolled, real-life environments. In uncontrolled environments, many factors other than stress influence physiology. This complicates the data analysis. We need to be able to distinguish between changes in physiology due to stress and changes due to other factors. Creating context awareness by monitoring environmental factors and activity will be needed to deal with these factors and to be able to identify stress levels from the physiological signals.

The classification approach we took fits the context of long-term, real-time, continuous stress monitoring, which will be needed for many of the future applications of stress measurement. We want to be able to determine if a person is stressed or not, at any point in time. This information can be used in systems giving personal feedback about stress levels. We think that GEE is a useful method to achieve this goal. It is relatively straightforward to calculate a probability from a set of feature values, once the coefficients are determined. In combination with the sliding window, the calculated probabilities might be used as a continuous measure of stress level on a scale from 0 to 1. Of course, this hypothesis will need to be validated first.

In the future, we will continue towards developing methods for long-term physiological monitoring with real-time stress level calculation. A small and non-obtrusive sensor system can be used on a regular, or even daily, basis to monitor stress levels, for example in office environments. When the stress level can be calculated in real-time, direct feedback can be given to the user to help him/her regulate his/her stress level by keeping it in an optimal range.

V. Conclusions

We recorded ECG, SC, respiration and EMG signals during a protocol designed to include realistic office-like stress situations. We used these signals for multimodal stress detection. We achieved a classification rate of 74.5% using GEE. We still need to overcome the physiological differences among users and add context awareness and activity monitoring to compensate for factors other than stress influencing the physiology. In the end, this method can be used for long-term, real-time, continuous stress monitoring on an individual basis using a small and non-obtrusive sensor system. Such a system could detect mental stress at an early stage and therefore contribute to stress prevention at work, for example.

References

[1] European Commission, *Health and safety at work in Europe - A statistical portrait*. Luxembourg: Publications Office of the European Union, 2010.

[2] National Institute for Occupational Safety and Health, "Stress...at work," U.S. Department of Health and Human Services; Public Health Service; Centers for Disease Control and Prevention, 1999.

[3] C. Tsigos and G. P. Chrousos, "Hypothalamic-pituitary-adrenal axis, neuroendocrine factors and stress," *J Psychosom Res*, vol. 53, pp. 865–871, 2002.

[4] K. Griffiths, M. Mackey, and B. Adamson, "The impact of a computerized work environment on professional occupational groups and behavioural and physiological risk factors for musculoskeletal symptoms: A literature review," *J Occup Rehabil*, vol. 17, pp. 743–765, 2007.

[5] E. Marieb, *Human anatomy and physiology*, 6th ed. San Fransisco: Pearson Benjamin Cummings, 2004, ch. The autonomic nervous system, pp. 531–553.

[6] A. Steptoe, "Invited review: The links between stress and illness," *J Psychosom Res*, vol. 35, no. 6, pp. 633 – 644, 1991.

[7] C. Schubert, M. Lambertz, R. Nelesen, W. Bardwell, J.-B. Choi, and J. Dimsdale, "Effects of stress on heart rate complexity–a comparison between short-term and chronic stress," *Biol Psychol*, vol. 80, no. 3, pp. 325 – 332, 2009.

[8] N. Hjortskov, D. Rissén, A. Blangsted, N. Fallentin, U. Lundberg, and K. Søgaard, "The effect of mental stress on heart rate variability and blood pressure during computer work," *Eur J Appl Physiol*, vol. 92, pp. 84–89, 2004.

[9] U. Lundberg, R. Kadefors, B. Melin, G. Palmerud, P. Hassmen, M. Engstrom, and I. E. Dohns, "Psychophysiological stress and EMG activity of the trapezius muscle." *Int J Behav Med*, vol. 1, no. 4, pp. 354–370, 1994.

[10] M. L. Peters, G. L. Godaert, R. E. Ballieux, M. van Vliet, J. J. Willemsen, F. C. Sweep, and C. J. Heijnen, "Cardiovascular and endocrine responses to experimental stress: effects of mental effort and controllability." *Psychoneuroendocrinology*, vol. 23, no. 1, pp. 1–17, 1998.

[11] J. Zhai and A. Barreto, "Stress detection in computer users based on digital signal processing of noninvasive physiological variables." in *IEEE Engineering in Medicine and Biology Society*, vol. 1, 2006, pp. 1355–1358.

[12] J. Choi, B. Ahmed, and R. Gutierrez-Osuna, "Development and evaluation of an ambulatory stress monitor based on wearable sensors," *IEEE Transactions on Information Technology in Biomedicine*, vol. 16, no. 2, pp. 279 –286, 2012.

[13] B. Grundlehner, L. Brown, J. Penders, and B. Gyselinckx, "The design and analysis of a real-time, continuous arousal monitor," in *Proc. Sixth Int. Workshop Wearable and Implantable Body Sensor Networks BSN*, 2009, pp. 156–161.

[14] J. Healey and R. Picard, "Detecting stress during real-world driving tasks using physiological sensors," *IEEE Transactions on Intelligent Transportation Systems*, vol. 6, no. 2, pp. 156 – 166, 2005.

[15] C. Setz, B. Arnrich, J. Schumm, R. L. Marca, G. Trster, and U. Ehlert, "Discriminating stress from cognitive load using a wearable EDA device." *IEEE Trans Inf Technol Biomed*, vol. 14, no. 2, pp. 410–417, 2010.

[16] J. Zhai, A. B. Barreto, C. Chin, and C. Li, "Realization of stress detection using psychophysiological signals for improvement of human-computer interactions," in *Proc. IEEE SoutheastCon*, 2005, pp. 415–420.

[17] J. Wijsman, B. Grundlehner, J. Penders, and H. Hermens, "Trapezius muscle EMG as predictor of mental stress," *Trans. Embedded Computing Syst., Special Issue: Wireless Health 2010*, vol. 12, no. 4, 2013, in press.

[18] G. Krantz, M. Forsman, and U. Lundberg, "Consistency in physiological stress responses and electromyographic activity during induced stress exposure in women and men." *Integr Psychol Behav Sci*, vol. 39, no. 2, pp. 105–118, 2004.

[19] S. Cohen, T. Kamarck, and R. Mermelstein, "A global measure of perceived stress," *J Health Soc Behav*, vol. 24, pp. 385–396, 1983.

[20] M. Loeb, D. H. Holding, and M. A. Baker, "Noise stress and circadian arousal in self-paced computation," *Motivation and Emotion*, vol. 6, pp. 43–48, 1982.

[21] L. Brown, B. Grundlehner, J. van de Molengraft, J. Penders, and B. Gyselinckx, "Body area network for monitoring autonomic nervous system responses," in *Pervasive Computing Technologies for Healthcare*, 2009.

[22] SENIAM, "Recommendations for sensor locations in shoulder or neck muscles," http://www.seniam.org/, 1999.