ELEKTROTEHNIŠKI VESTNIK 81(5): 263-271, 2014
REVIEW SCIENTIFIC PAPER

Stress-sensors classification and stress-analysis algorithms review

Mikhail Sysoev, Urban Sedlar, Andrej Kos, Matevž Pogačnik

Laboratory for Telecommunications, Faculty of Electrical Engineering, University of Ljubljana, Tržaška 25, 1000 Ljubljana, Slovenija
Email: mikhail.sysoev@ltfe.org

Abstract. A prolonged exposure to stress can lead to mental disorders and psychosomatic diseases, e.g declining of health. This survey reviews sensors, human-body parameters and context information correlated with the stress level, and investigates various stress analysis methods. Sensors for stress determination are classified and divided into four groups with regard to the physiological and physical parameters of the human-body, context information, expert assessment and questionnaires. The work to be done in future in the field of stress recognition is discussed.

Keywords: stress, psychological parameters, user's context, sensors classification, algorithms, machine learning

Pregled senzorjev in algoritmov za določanje stopnje stresa

Daljša izpostavljenost stresu lahko vodi k psihičnim motnjam in nastanku psihosomatskih bolezni oz. poslabšanju zdravstvenega stanja. V članku smo se zato posvetili pregledu senzorjev, identifikaciji parametrov človeškega telesa in pregledu kontekstualnih informacij, ter njihovi korelaciji z različnimi nivoji stresa. Poleg tega smo raziskali različne metode za določanje stopnje stresa. Predstavljena je klasifikacija senzorjev za določanje stresa v štiri razrede, z upoštevanjem fizioloških in psiholoških parametrov človeškega telesa, kontekstualnih informacij, analize ekspertov in z uporabo vprašalnikov. Obravnavane so tudi možnosti nadaljnjega razvoja in raziskav na področju identifikacije stresa.

1 INTRODUCTION

The recent decades are characterized by a constant increase in the proportion of the mental-health problems in the structure of public health. According to WHO, mental disorders are responsible for 13% of the global amount of disease. 10% of the adults at any moment have a particular mental disorder and 25% of the disorders can develop throughout life [1].

The stress is associated with numerous disturbances in the mental and physical health. The chronic or severe damaging stress combines with anxiety, tension and depressive mood, which are essential preconditions for depression, e.g. the most common result of the chronic stress [2, 3, 4].

The stress can contribute to illness directly, through its physiological effects, or indirectly, through maladaptive health behaviors (for example, smoking, poor eating habits or lack of sleep) [5].

Received 1 July 2014
Accepted 30 September 2014

The systematic stress also leads to overstrain of catecholamine mechanisms, and since cortisol enhances the effects of adrenalin and noradrenalin, a stable hypertonicity of vessels is then formed. All this results in particular chronic diseases affecting the cardiovascular system, kidney tissue, liver, muscle or bone skeleton. Probably, the chronic or severe damaging stress gradually destroys physical health, and increases the probability of malignant-tumors occurrence [6-12].

With the widespread of mobile phones (according to [13], in 2013 there were 6.8 billion active mobile numbers in the world) and the wide availability of low-cost wearable biophysiological sensors we can now measure how the environment and our experiences affect our physiology [14] as and also to improve the quality of our life by better understanding of our emotional condition and the stress in the daily life and by preventing the increase in the stress levels and emergence of health impacts.

2 PHYSIOLOGICAL AND PHYSICAL BODY PARAMETERS

Physiological and physical responses/reactions of the human body to the stress are used to assess the stress level.

The galvanic skin response (GSR) (also known as electrodermal activity (EDA)) is one of the most convenient and reliable ways of stress determination, the usage of which we met in a large number of studies. The stress causes increasing sweating which results in increased skin conductivity [15], [16]. Distributions of the EDA peak height and the skin conductance response

(SCR) peak rate carry information about the stress level of a person [15].

The heart rate (HR) and electrocardiogram (ECG) are also frequently used to determine the stress, because of their high correlation with the stress level [17]. For example, the decrease in the ECG amplitude is an indicator of the stress in a healthy person [18]. The heart-rate variability (HRV) parameter can not be an efficient indicator of the job stress [19] without additional information, like the context. According to [20], the blood pressure increases under the stress. The electromyogram (EMG) and brain waves are rarely used to determine the stress, this is primarily due to the impracticality of using the sensor data. However, EMG was used in [21] in conjunction with other sensors to determine the stress of drivers in real life. The skin temperature (ST) is a parameter mainly used in conjunction with other parameters to determine the stress. According to [23], the decrease in the body temperature indicates the appearance of the stress.

Respiration is also used in conjunction with other parameters. It is not very popular because of the need to wear a flexible belt around the chest to sense the data [23]. But with appearance of smart T-shirts, like OMsignal Smart T-Shirts which can measure respiration and other body parameters, this disadvantage is no longer a problem.

The sleep quality is a very important parameter. In [24], sleepiness was rather related to the average sleep quality than to the sleep quantity. In [19], the authors evaluated the sleep quality and job stress among the white-collar workers. Their results suggest that the job stress disrupts the night sleep that causes daytime sympathetic predominance.

In some studies, for example in [25], medical analysis of the cortisol level was used as an expert assessment of the stress. The increase in the level of cortisol indicates the stress [20].

The characteristics of the voice (tone, speech rate) and facial expressions are studied in the research of the emotional state of humans [26]. Gestures and poses of people, pupil dilation and blink rate are used to determine the emotional state. For example, enhanced high pupil spatial distribution of sight is highly correlated with the stress level, while the average eye-closure speed has less dependence on the stress (coefficient Cor. Prior -0,5-0,6). These methods are used, for example, to verify persons (security systems and access control), in advertising to evaluate the expression that advertising makes on consumers, but it is not very practical in everyday life. In this paper, our aim is not to consider the "physical manifestations of stress" in detail, but to investigate what extent they are covered in scientific papers [26-28].

The above stress determination methods are either used separately or in combination with each other. In [29], a higher accuracy was obtained by using more sensors (accelerometer (ACC), ECG, GSR) than by excluding any of them.

Unfortunately, the measuring results alone tell us almost nothing. In order to understand what's going on, we need to know the context of the other events during the day/week/... For example, if our heart rhythm accelerates, does it come from the stress or were we running? Or, are we using a fitness tracker or an application that encourages us to sports after we had a party until 4 a.m. We will not be happy if the phone or tracker offers us to get up early and run a five km distance [30]. The context is very important for understanding what happens. In [31] a solution is presented for measuring the chronic stress solely on the user context.

3 SUBJECTIVE (USER CONTEXT)

In [32], one of three tracker owners stops wearing his devices for six months. The success is defined by the degree of a long-term impact on the user health and happiness of these devices and services. Gathering and processing the contextual data in order to get more information in the context of what events are going on are interesting to study.

The tomorrow's apps will use the sensors already embedded in our smartphones, wearable devices, and personal computers to understand our current context and figure out how they can enhance our experience — on a device or in the real world [30]. Table 1 provides an overview of the already applied contextual information with a link to the measured parameters and data processing methods.

Based on self-reports, different contextual information from smartphones, computers, video cameras, microphones, light sensors, accelerometer data, GPS and other sensors, stress-recognition systems are developed and in correlation with the basic stress-assessment methods they give a high accuracy results (see Chapter 4 Analysis methods). At the same time it is very important to obtain the contextual information noninvasively/unobtrusively, with a minimal user participation, not to require the user to a large number of additional actions, or to minimise them.

In [31] the authors evaluated the user ability to estimate his/her current stress by using a questionnaire, and researchers observed that an average user is able to make a good assessment. In this study, too, various contextual information from smartphones and user computers, such as the location, external noise, computer and telephone activity, was gathered.

Questionnaires (self-reports) are used quite often for the currently relevant user evaluation of the condition. In [21], drivers completed a questionnaire about the stress level during driving along a route. Sometimes questionnaires are used as a method of objective evaluation of the stress presence [26].

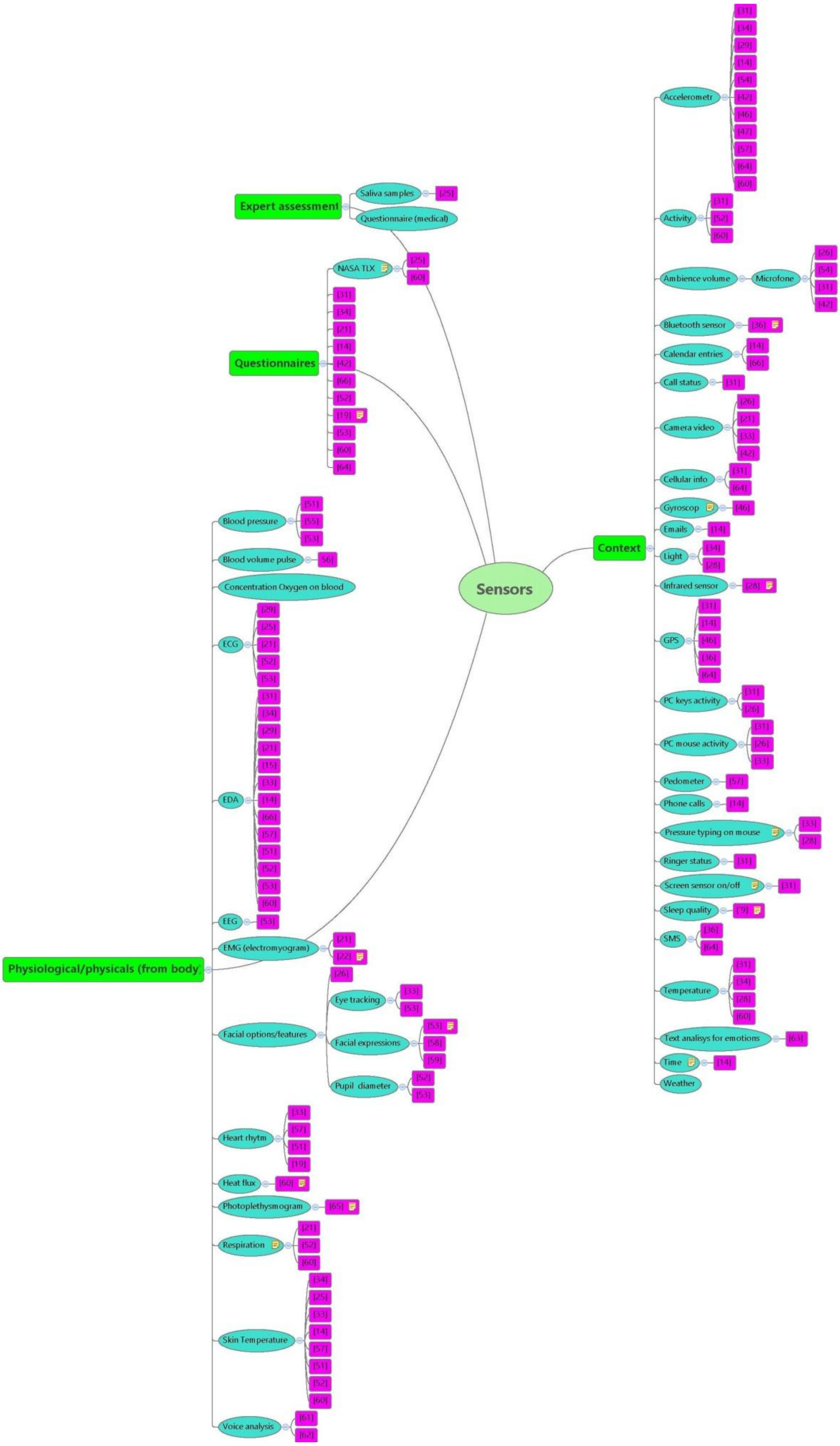

Figure 1. Sensors classification on few groups: data gathered from the body (physical and physiological parameters) and from the environment (context) with links to papers (larger picture https://yadi.sk/d/xGfwEhMqTuWPP)

A system for determining the stress level in [33] included the physical appearance (facial expression, eye and head movements) extracted from video via visual sensors, physiological conditions and behavioral data from the user interaction activities with the computer, and performance measures.

In [14], events/calendar appointments, reading e-mail were used. The users were able to make notes about their condition to be able to remember and understand what situation caused their stress. It was noted that in conjunction with the contextual information, the system had a higher accuracy compared to using the data only from the sensors.

In [34], the data was collected from the working calendar of the scheduled appointments, time and place. The users assessed their current emotional state in simple self-reports and used this data for stress recognition. In [29], an investigation was made of how events (sitting, standing, and walking) affect the stress level. In [35], communication (phone calls, SMS), device usage (key presses), users context (calendar appointments), location (GPS), and environmental sensors (microphone, Bluetooth-environmental sensing) are used as the contextual information.

In [36], the authors determined the number of people near the user phone, as the contextual information, by detecting the Bluetooth-smartphones, and found differences in the social behavior during the stress and stress-less times.

The context as a subjective factor is not used in all studies. In some studies, only physiological and physical factors and different analysis methods are compared to improve the result accuracy [25], [15].

Fig. 1 presents sensors classification. Sensors are divided into two major and two minor groups. (I) The body parameters: physiological and physical parameters measured with a variety of sensors. (II)The context: the contextual information used to characterize the situation of an entity. An entity is a person, place, or object that is considered to be relevant to the interaction between a user and an application, including the user and application themselves [37]. (III) The medical (expert) assessment: expert evaluation of the stress presence was made in a small number of studies examined by us. (IV) Questionnaires: they are used to obtain a feedback from the users as well as self-reports with a subjective evaluation of the current stress state.

4 ANALYSIS METHODS

In different systems analysis for stress recognition, various methods from the decision tree and self-report questionnaires to the machine-learning algorithms are applied. They are of a particular interest for researches because they enable to partially or fully automate the complex processes and can find also a connection invisible for humans, due to a large amount of the input data and implicit correlations. The most commonly used algorithms are the support vector machine (SVM), hidden Markov model (HMM), k-nearest neighbors (k-NN), Decision Tree, Bayesian network (BN) and their modifications. The main features of each of these algorithms are described below.

4.1 SVM

SVM is one of the fastest methods of finding the decision function. The method finds the maximum width separating the hyperplane between two classes of the maximum width which allows further implementing of a more confident classification and reduces the empirical classification error [40]. In case of the multi-class decision, the rule based on a binary decomposition by scheme "One-vs-Rest" is often used on practice. Unlike most other methods the advantage of the method is a small data set which is sufficient because in classifying a multiple samples they are not all used, but only a small portion of them located at the boundaries. The method is sensitive to the noise. In practice, normalization of the input data is desired in order to present large deviations from the middle values to affect the classifier. This classifier is well suited for linearly separable samples. If samples are not linearly separable, the data get lost.

Examples of the software implementations are SVMLight, LIBSVM and LIBLINEAR, all in C ++.

4.2 Desicion tree

The Decision Tree is a way of representing the hierarchical structure of the classification rules such as " IF ... THEN ...», having the form of a tree. The larger the tree the more it is exposed to overfitting. The tree that takes into account all the possible signs is usually overfitting. Classification is performed by a simple but fast enough movement through the tree. The algorithm is simple to understand and interpret by people.

Examples of the software implementations are WEKA, J48 Decision Tree.

4.3 Bayesian Classifier

For the classified objects the likelihood function of each class was calculated and on its basis their posterior probability was determined. An object belongs to a class for which the posterior probability is maximised. The advantage of the Bayesian classifier is a small amount of the training data needed to estimate the parameters required for classification. The data set has to be a short as there is no adjustment mode to the specific data distribution and the data collides with the effect of overfitting. The bayesian classifier based on the Bayes formula is used. The classifier contains a trained data set for each class and each input sequence is compared with these sets by a particular algorithm and the most likely class is then selected. To build a classifier, it is necessary to restore the density distribution by a trained data set (there are three main approaches to the recovery likelihood function: parametric, non-parametric distributions, and combined).

Examples of the software implementations are jBNC - Bayesian Network Classifier Toolbox.

4.4 k-NN

The nearest-neighbor algorithm is a metric classification algorithm based on assessment of the similarity of objects. It is easy to implement. The object assigned to the class is most commonly among its k-nearest neighbors. The method of the k-nearest neighbors is based on explicit storage of all learning objects. The neighbors are taken on the basis of a set of objects the classes of which are already known. Excluding the noise and uninformative objects from the data set provides several advantages: improved classification quality, reduced amount of the stored data and decreased classification time. On the other hand, increasing its value increases the classification accuracy, but the border between the classes becomes less distinct clear. In practice, heuristic methods for selecting the k-parameter give good results, for example, cross-validation. Its main drawback is the high computational complexity, which increases quadratically with the increasing number of records in the dataset.

4.5 HMM

The Hidden Markov Model is a statistical model used to solve the classification problem of the hidden variables based on observetion. In the hidden Markov model, each state with a given probability corresponds to the observed state. It is actively used for speech recognition, machine translation and stress recognition, as well as gesture recognition.

An examples of the software implementation is Jahmm.

4.6 Other methods

As there has been no much research done in the context of comparing different analysis techniques, different algorithms for stress determinination [29], [41], [42], are probably the area of future interest for researchs. Besides the above algorithms, the following over are also often used: neural networks [43], fuzzy techniques [44], linear discriminate analysis (LDA) [25] and [21], Hidden Conditional Random Fields (HCRF) [26]. It would be very interesting to analyse various modifications of algorithms, for example:

- the relevance vector machine (RVM) method is a method that unlike SVM determines the probability with which an object belongs to certain class. If SVM says "x belongs to class A", then RVM says "x belongs to class A with probability p and belongs to class B with probability 1 -p".
- Dynamic Bayesian network (DBN) [33] method is an extension of the usual BN metod. It examines and modeles the finite sequence of sets of random variables rather than only one set in BN.
- the layered HMM (LHMM) algorithm requires less training data compared with HMM. Subcomponents are trained separately on a small amount of data. Another advantage of this algorithm is that the layers may be trained independently. For the same amount of the training data the LHMMs accuracy is significantly higher compared to HMMs [45], and LHMM is more robust to changes in the environment than HMM.

A combination of different algorithms used to find the most optimal computational techniques is also interesting. In [53] the authors used the genetic algorithm (GA) to select subsets of features to optimise stress classifications by SVM and got a better result compared to when GA is not used.

4.7 Computation Accuracy

The accuracy of a particular calculation method depends on the properties of the whole system, used sensors, data-collection methods, type of contextual information, etc. The accuracy of some calculation methods vary from one study to another. Table 1 presents an overview and evaluation factors for the computation methods used in stress recognition.

The human behavior and reaction to various situations in life can change: some events that have caused stress before, do no longer cause it now or in future as people can get used to them and experience them in a more relaxed way. Also, with the development of the society, new types of contextual information and/or methods may appear. As the value of some factors may be reduced the factors correlated with the stress level need to be revised to exclude the ineffective then to economise with the computing resources, and new factors should be found to improve the accuracy and computational efficiency. In machine learning, objects attributes do not play a less important role than the classification algorithms: no matter how good the algorithm is, if the factors/features are not good, we can't build an efficient and accurate system.

We also need to understand how else of the impact of individual features (aka factor) influence on the computation accuracy, resource consumption and spend of the smartphone battery.

The result on overfitting and the quantity of the training data are checked on a small amount of testing and training samples.

Another method used to test the algorithm accuracy is cross-validation [29], [53]. All the received data is divided into k-parts, which are then used for training, and the remaining part k-part is used as a testing sample. The procedure is repeated k-times, thus each k-part is used as a training sample. As a result, algorithm accuracy is assessed with the most uniform data distribution minimising the effects of too much "good" training or testing samples

Table 1: Analysis methods, sensors and context and individual studies

Analysis methods	Sensors and questionnaires	Context information
HMM	EDA; questionnaires (self assessment of stress, 7-point Likert scale by NASA TLX); ST	User mobile location (GPS); Ambient audio features; User physical activity; user phone status; PC keys pressed; PC mouse clicks; light sensor; ACC
Min-max algorithm	EDA; ST; questionnaires (self-report about stress)	Temperature; ACC; light; events from digital calendar
J48 Decision Tree, SVM, Bayesian network	EDA; ECG; (HRV and ect.)	ACC; posture (seating, walking, standing)
SVM (with linear kernel), LDA, k-NN	ECG; questionnaires (Nasa TLX); ST; saliva samples	No context
Wilcoxon test	EDA; ST; questionnaires (emotion reaction)	ACC; GPS; e-mail; events from digital calendar; user's phone calls
Bayesian network, naive Bayes	EDA; ECG; HR; ST; respiration data; questionnaires (Nasa TLX); body heat flux	Activites: sitting, walking, bicycling; temperature; from ACC: step counter, lying down, sleep, physical activity, energy expenditure
linear correlation analysis, SVM, k-NN, (Principal component analysis) PCA	EDA; questionnaires (general health, mood and stress)	ACC; from mobile phone usage (call, sms, location and screen on/off)

Fig. 2 presents an overview of the stress-recognition algorithms.

5 Stress-recognition system design

The result of collecting the contextual information, its classification and process is a feedback system with the user. It can be prompts, visualization, change of certain applications, etc. It is very important for the user to be able to access visualization of the chronic-stress occurrences in order to help him/her recognize the ongoing stress situations [31]. It is important to give the feedback from the system (e.g., visualization).

In this section, we pay attention to important points in the design of the stress-recognition system.

To consume the smallest possible amount of energy in order to save the battery, cloud computing is used (the increased amount of the transmitted data also reduces the computational load that can faster the battery plant performance and reduce the usage memory of the smartphone). The ability to store data and upload it to the user smartphone on a network server for storing and processing.

Easy expandable systems are used when new devices appear or sources of data are expanded to be able to quickly add, for example, new contextual data into the system.

In [27], the accuracies of 95% and 70% were achieved for the subject-dependent and subject-independent classification. This suggests that the physiological responses to stress of individual persons differs and should be considered in designing systems for a wide range of users, and the approach should be determined individually.

The system has to be highly accurate, it may need calibration, because every user has his/her own individual characteristics (GSR, HR, respiration). Calibration and preparation for work, and work of the system itself should be simple and understandable to the user to avoid cause inconvenience or hardship while using it.

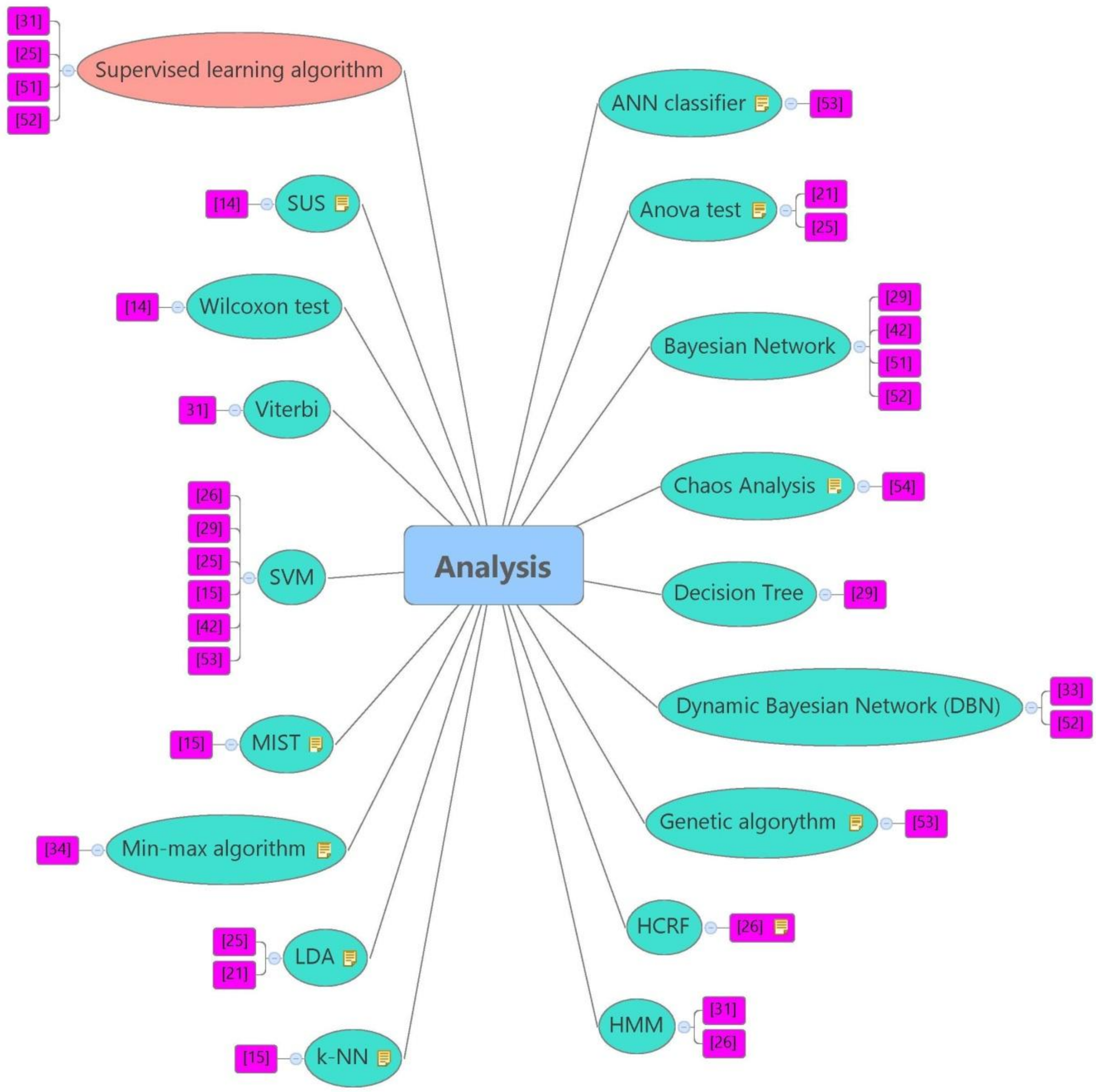

Figure 2 Stress-analysis methods with links to the relevant papers using these methods

6 CONCLUSION

Each of the considered body parameters is correlated with stress. Some of them are used as separate parameters (GSR and HR) and some in conjunction with others to determine the stress (e.g. ST, EMG). But based only on one or few parameters, the stress can't be defined; an additional information, like the context is needed. The contextual information is very important to interpreted the data received from sensors and to understand what is going on. The contextual data have to be collected from smartphones because we always carry them with us, and from computers because we spend a lot of time working on them and the context should be gathered non-invasively. Also, we explored different single and combined algorithms for stress analysis. Sensors were classified to allow for stress analysis and it is shown that the physical and psychological body response to stress have already been well-studied compared to the correlation context and stress. In our future works, it would be interesting to gather a lot of diverse contextual data and find the features, that mostly correlate with the stress level and compare the accuracy of the systems working with the context and without it. Our next step will be retrieving the possible contextual information, methods of its consumption and we will extend the classification of context information.

REFERENCES

[1] Improving health systems and services for mental health. *World Health Organization*, p.102, 2009.

[2] Aguilera, G.; Kiss, A.; Liu, Y. et al. Negative regulation of corticotropin releasing factor expression and limitation of stress response. Stress, 10(2), pp. 153–161, 2007.

[3] Korosi, A.; Baram, T.Z. The central corticotropin releasing factor system during development and adulthood. *Eur. J. Pharmacol*, 583 (2–3), pp. 204–214, 2008.

[4] Owens, M.J.; Nemeroff, C.B. Physiology and pharmacology of corticotropin-releasing factor. *Pharmacol. Review*, 43, pp. 425–473, 1991.

[5] Glanz, K. and Schwartz, M. Stress, coping, and health behavior. *Health behavior and health education: Theory, research, and practice*, pp. 211–236, 2008.

[6] Stress and mental health: contemporary issues and prospects for the future / W.R.Avisen, I.H.Gotlib (Eds.). *NY: Plenum Press*, p.340, 1994.

[7] Hochberg, Z.; Feil, R.; Constancia, M. et al. Child health, developmental plasticity and epigenetic programming. *Endocrine Rev*. 32(2), pp. 159–224, 2011.

[8] Bauer, M.E. Stress, glucocorticoids and ageing of the immune system. *Stress*, 8(1), pp. 69–83, 2005.

[9] Carrasco, G.A.; Van de Kar, L.D. Neuroendocrine pharmacology of stress. *Eur. J. Pharmacol*, 463(1-3), pp. 235–272, 2003.

[10] De Kloet, E.R. Hormones and the stressed brain. *Ann. NY Acad. Sci*, 1018, pp. 1–15, 2004.

[11] Reiche, E.M.; Nunes, S.O.; Morimoto, H.K. Stress, depression, the immune system, and cancer. *Lancet Oncol*., 5(10), pp. 617–625, 2004.

[12] Valenti, G. Neuroendocrine hypothesis of aging: the role of corticoadrenal steroids. *J. Endocrinol. Invest*., 27(6), pp. 62–63, 2004.

[13] ITU statistics. [Online]. Available: http://www.itu.int/ITU-D/ict/statistics, 2013.

[14] Ayzenberg, Y. and Picard, R. W. FEEL: A System for Frequent Event and Electrodermal Activity Labeling. *Biomedical and Health Informatics, IEEE Journal*, *18*, pp. 266-277, January 2014.

[15] Setz, C.; Arnrich, B.; Schumm J.; La Marca, R.; Troster, G. Discriminating stress from cognitive load using a wearable EDA device. *IEEE Trans. Infor. Technol. Biomed*. 14, pp. 410–417, 2010.

[16] Dawson, M.E.; Schell, A.M.; Filion, D.L. The Electrodermal System. In *Handbook of Psychophysiology*; Cacioppo, J.T., Tassinary, L.G., Berntson, G.G., Eds.; Cambridge University. Press: New York, NY, USA; pp. 200–223, 2000.

[17] Bonoris, P.E. et al., Significance of changes in R wave amplitude during treadmill stress testing: angiographic correlation, *The American Journal of Cardiology*, 41, pp. 846–851, 1978.

[18] Task force of the European Society of Cardiology, the North American Society of Pacing, and Electrophysiology. Heart rate variability: Standards of measurement, physio-logical interpretation, and clinical use. *European Heart Journal*, March 17(2), pp.1043–1065, 1996.

[19] Kageyama, T.; Nishikido, N.; Kobayashi, T.; Kurokawa, Y.; Kaneko, T.; Kabuto, M. Self-reported sleep quality, job stress, and daytime autonomic activities assessed in terms of short-term heart rate variability among male white-collar workers. *Industrial Health*, 36, pp. 263–272, 1998.

[20] Pickering, T.; Devereux, R.; James, G. et al. Environmental influences on blood pressure and the role of job strain. *Supplement: Official Journal of the International Society of Hypertension*, 14, pp. 179–185, 1996.

[21] Healey, J.A.; Picard, R.W. Detecting Stress During Real-world driving tasks using physiological sensors. *IEEE Trans. Intel. Transport. Syst*., pp. 156–166, 2005.

[22] Dharmawan, Z. Analysis of computer games player stress level using EEG data, Master of Science Thesis Report, Faculty of Electrical Engineering, Mathematics and Computer Science, Delft University of Technology, Netherlands, 2007.

[23] Reisman, S. Measurement of stress. *Bioengineering conference 1997, Proceedings of the IEEE 23rd* Northeast, pp. 21-23, 1997.

[24] Pilcher, J.; Ginter, D.; Sadowsky, B. Sleep quality versus sleep quantity: relationships between sleep and measures of health, well-being and sleepiness in college students. *Journal of Psychosomatic Research*, 429(6), pp. 583-596, 1997.

[25] Cinaz, B.; Arnrich, B.; La Marca, R.; Tröster, G. Monitoring of mental workload levels during an everyday life office-work scenario. *Accepted for Personal and Ubiquitous Computing Journal*, 2011.

[26] Hoque, M.E.; McDuff, D.J.; Picard, R.W. Exploring temporal patterns towards classifying frustrated and delighted smiles. *IEEE Trans. Affect. Comput*., 3, pp.323–334, 2012.

[27] Kim, J. and André, E. Emotion Recognition Based on Physiological Changes in Music Listening. *IEEE Trans. Pattern Analysis and Machine Intelligence*, 30(12), pp. 2067-2083, 2008.

[28] Kwok-Fai Lui, A.; Wong, Ka-Fai; Sin Chun Ng, and Law, Ka-Hing. Development of a mental stress relaxation tool based on guided imagery and Microsoft Kinect. *Distributed Smart Cameras (ICDSC), 2012 Sixth International Conference on*, 2012.

[29] Sun, F.-T.; Kuo, C.; Cheng, H.-T.; Buthpitiya, S.; Collins, P.; Griss, M. Activity-aware mental stress detection using physiological sensors. *Silicon Valley Campus*., 23, pp. 1–20, 2010.

[30] By Andy Hickl, CEO, A.R.O. [Online]. Available: http://recode.net/2014/05/07/tracking-is-dead-the-next-wave-of-wearables-is-context/. 7th May 2014.

[31] Peternel, K.; Pogačnik, M.; Tavčar, R.; Kos, A. A Presence-BasedContext-Aware Chronic Stress Recognition System. *Sensors*, 12, pp. 15888–15906, 2012.

[32] Ledger, D. and McCaffrey, D. How the Science of Human Behavior Change Offers the Secret to Long-Term Engagement. [Online]. Available: http://endeavourpartners.net/assets/Wearables-and-the-Science-of-Human-Behavior-Change-EP4.pdf. 2014.

[33] Liao, W. et al. A real-time human stress monitoring system using dynamic Bayesian network. *Proc. 2005 IEEE CS Conf. Computer Vision and Pattern Recognition*, p. 70, 2005.

[34] Kocielnik, R., Sidorova, N., Maggi, F., Westerink, J., and Ouwerkerk, M. Smart technologies for long-term stress monitoring at work. In *Proceedings of the 26th IEEE international Symposium on Computer-Based Medical Systems. CBMS. IEEE*. 2013.

[35] Froehlich, J.; Chen, M. and Consolvo, S. My Experience: A system for in situ tracing and capturing of user feedback on mobile phones. In *Proc. MobiSys '07: Proc. 5th Int. Conf. Mobile Syst., Appl. Service*, 2007, pp. 50–57.

[36] Bauer, G.; Lukowicz, P. Can Smartphones Detect Stress-Related Changes in the Behaviour of Individuals. In *Proceedings of Pervasive Computing and Communications Workshops*, Lugano, Switzerland, pp. 423–426, 19-23 March 2012.

[37] Dey, A.K.; Abowd, G.D. Towards a Better Understanding of Context and Context-Awareness. In *Proceedings of CHI Workshop*, Hague, The Netherlands, 3 April 2000.

[38] Grings, W. W. Recording of electrodermal phenomena. Methods in physilogical psychology (Bioelectric recording techniques. Part C: Receptor and effector processes, 1(1), pp. 273–296, 1974.

[39] Ekman, P. The Argument and Evidence about Universals in Facial Expressions of Emotion. *Handbook of Social Psychophysiology, John Wiley & Sons*, pp. 143-164, 1989.

[40] Hastie, T.; Tibshirani, R.; Friedman, J. *The Elements of Statistical Learning, 2nd edition*. - Springer, p. 533, 2009.

[41] Sharma, N. and Gedeon T. Objective measures, sensors and computational techniques for stress recognition and classification: A survey. *Computer Methods and Programs in Biomedicine*, 108(3), pp. 1287-1301, 2012.

[42] Das, B.; Seelye, A. M.; Thomas, B. L.; Cook, D. J.; Holder, L. B. and Schmitter-Edgecombe, M. Using smart phones for context-aware prompting in smart environments. In *Proc. IEEE Int. Workshop Consumer eHealth Platforms, Services and Applications (CeHPSA)*, Las Vegas, NV, 2012.

[43] Fukuoka, Y.; Ishida, A. Chronic stress evaluation using neural networks. *IEEE Engineering in Medicine and Biology Magazine*, 19, pp. 34–38, 2000.

[44] Kumar, M. et al. Fuzzy evaluation of heart rate signals for mental stress assessment. *IEEE Transactions on Fuzzy Systems*, 15, pp. 791–808, 2007.

[45] Oliver, N.; Garg, A.; Horvitz E. Layered representations for learning and inferring office activity from multiple sensory channels. *Computer Vision and Image Understanding*, 96(2), pp. 163–180, 2004.

[46] Baron-Cohen, S.; Ring, H.A.; Bullmore, E.T.; Wheelright, S.; Ashwin, C. and Williams, S.C.R. The Amygdala Theory of Autism. *Neuroscience and Behavioual Reviews*, 24(3), pp. 355-364, 2000.

[47] Howard, M.A.; Cowell, P.E.; Boucher, J.; Brooks, P.; Mayes, A.; Farrant, A. and Roberts, N. Convergent Neuroanatomical and Behavioural Evidence of an Amygdala Hypothesis of Autism. *Neuroreport*, 11, pp. 2931-2935, 2000.

[48] Kang, D.; Ha, K. and Lee J. A context aware system for personalized services using wearable biological signal sensors. In *Proc. Int. Conf. Control, Automation Syst., ICCAS*, pp. 888–891, 2008.

[49] Baron-Cohen, S.; Ring, H.A.; Bullmore, E.T.; Wheelright, S.; Ashwin, C. and Williams, S.C.R. The Amygdala Theory of Autism. *Neuroscience and Behavioual Rev*., 24, pp. 355-364, 2000.

[50] Howard, M.A.; Cowell, P.E.; Boucher, J.; Brooks, P.; Mayes, A.; Farrant, A. and Roberts, N. Convergent Neuroanatomical and Behavioural Evidence of an Amygdala Hypothesis of Autism. *Neuroreport*, 11, pp. 2931-2935, 1994.

[51] Sharma, T.; Kapoor, B. Intelligent data analysis algorithms on biofeedback signals for estimating emotions. *Optimization, Reliabilty, and Information Technology (ICROIT), 2014 International Conference on*, pp.335-340, 6-8 Feb. 2014.

[52] Frank, K.; Robertson, P.; Gross, M.; Wiesner, K. Sensor-based identification of human stress levels. *Pervasive Computing and Communications Workshops (PERCOM Workshops), 2013 IEEE International Conference on*, pp.127-132, 18-22 March 2013.

[53] Sharma, N.; Gedeon, T. Modeling Stress Recognition in Typical Virtual Environments. In *Int. Conf. on Pervasive Computing Technologies for Healthcare*, 2013

[54] Iso, T.; Kawasaki, N. and Kurakake, S. Personal Context Extractor with Multiple Sensor on a Cell Phone. *The 7th IFIPInternational Conference on Mobile and Wireless CommunicationsNetworks*, September 2005

[55] Pickering, T. et al. Environmental influences on blood pressure and the role of job strain. *Journal of Hypertension*. Supplement: Official Journal of the International Society of Hypertension 14, pp. 179–185, 1996.

[56] Zhai, J.: Barreto, A. Stress recognition using non-invasive technology. In *Proceedings of the 19th International Florida Artificial Intelligence Research Society Conference FLAIRS*, pp. 395–400, 2006.

[57] Sanches, P.; Höök, K.; Vaara, E.K.; Weymann, C.; Bylund, M.; Ferreira, P.; Peira, N. and Sjölinder, M. Mind the body!: Designing a mobile stress management application encouraging personal reflection. In *Conference on Designing Interactive Systems*, pp. 47-56, 2010.

[58] Dinges, D.F. et al. Optical computer recognition of facial expressions associated with stress induced by performance demands. *Aviation, Space, and Environmental Medicine,* 76, pp. 172–182, 2005.

[59] Lerner, J.S. et al., Facial expressions of emotion reveal neuroendocrine and cardiovascular stress responses. Biological Psychiatry, 61, pp. 253–260, 2007.

[60] Hong, H.; Ramos, J. and Dey, A.K. Understanding physiological responses to stressors during physical activity. In *Proceedings of the 2012 ACM Conference on Ubiquitous Computing*, pp. 270-279, 2012.

[61] Hansen, J.; Patil, S. Speech under stress: analysis, modeling and recognition. Speaker Classification, pp. 108–137, 2007.

[62] Rothkrantz, L.J.M. et al. Voice stress analysis. *Lecture Notes in Computer Science,* pp. 449–456, 2004.

[63] Tromp, E. and Pechenizkiy, M. Senticorr: Multilingual sentiment analysis of personal correspondence. In *Proc. of IEEE ICDM 2011 Workshops*. IEEE Press, 2011.

[64] Sano, A.; Picard, R.W. Stress recognition using wearable sensors and mobile phones. *The 5th biannual Humaine Association Conference on Affective Computing and Intelligent Interaction (ACII 2013)*, pp. 671-676, 2-5 September 2013.

[65] Mokhayeri, F.; Akbarzadeh-T, M.R. and Toosizadeh, S. Mental stress detection using physiological signals based on soft computing techniques. In 2011 18th Iranian Conference of Biomedical Engineering (ICBME), pp. 232-237, 2011.

[66] Bakker, J.; Pechenizkiy, M.; Sidorova, N. What's Your Current Stress Level? Detection of Stress Patterns from GSR data. In Proceedings of the 2011 IEEE 11th International Conference on Data Mining Workshops, ICDMW '11, Vancouver, BC, Canada, pp. 573–580, 11–14 December 2011.

Mikhail Sysoev graduated in 2010 from St. Petersburg State University of Aerospace Instrumentation. He currently works towards his Ph.D. degree at the Faculty of Electrical Engineering, University of Ljubljana. His main research interests include stress-recognition systems and machine-learning algorithms.

Urban Sedlar received his Ph.D. from the Faculty of Electrical Engineering, University of Ljubljana, in 2010. He is currently working as a researcher at the Laboratory for Telecommunications at the same faculty. His research focuses on internet systems and web technologies, QoE in fixed and wireless networks, converged multimedia service architectures, and applications in IoT systems.

Andrej Kos received his Ph.D. in 2003. Currently he is an associate professor and deputy head of the Laboratory for Telecommunications both at the Faculty of Electrical Engineering, University of Ljubljana. He has specialized in modeling and design of high-speed networks and services. Currently, his main interest is in Internet of Things with multimedia applications and quality of service in broadband networks.

Matevž Pogačnik graduated in 1997 and received his Ph.D. degree in 2004 in the field of telecommunication and informatics from Faculty of Electrical Engineering, the University of Ljubljana. His research and scientific work are focused on development of interactive multimedia services for different devices with a special emphasis on development of systems for user-adapted content choice (personalization). Lately he's been involved in development of interactive services on all devices in the fields of e-learning and IPTV systems using different interaction modalities. He has participated in numerous European projects in the field of interactive digital television, e-learning, e-tourism and P2P systems. He is also a member of the international organization IEEE.