Sensor-based Identification of Human Stress Levels

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***Abstract*—In this work we present a mobile stress recognition system based on an existing activity recognition system using a hip-worn inertial measurement unit and a chest belt. Integrating activity knowledge, the prediction of different human stress levels in a mobile environment can be enabled while the state of the art is focussed on stress recognition in static environments. Our system has been implemented on an Android mobile phone and evaluated for different Bayesian networks as classifiers. Our implementation is able to operate in real-time with a stress inference rate of 1 Hz.**

The results of this work indicate that the implemented system is able to differentiate between the states 'No Stress' and 'Stress' in a mobile context. A more detailed distinction of stress in five substates has not been possible in a reliable way to date. With our results, the proposed system can serve as a basis for further improvements with larger data sets and for in-situ testing during disaster assessment.

***Keywords*-context; inference; stress; activity recognition; Bayesian**

I. Introduction

Stress is of high importance for personal health and well-being. In the last years, it also gained more attention in public. Interestingly, we all know and use the term 'stress' in our daily life for different situations. The individual perception of stress varies from person to person with remarkably few people sharing the same definition. Nevertheless there is a common aspect in all formulations because any demand upon our adaptability causes the stress phenomenon.

While there are different stress definitions (e.g. systemic or psychological stress, cf. [1]), our work follows the definition of Selye [2]: "Stress is a state manifested by a syndrome which consists of all the non-specifically induced changes in a biologic system". Hence, stress has no particular cause while the elements of its form are the visible changes due to stress. To put it differently: looking at non-specific, by many different agents induced bodily changes gives a picture of stress, caused by the *General Adaptation Syndrome (GAS)*. The intensity of the GAS manifestations allows to deduce the stress intensity. [2].

While in the last years, many approaches have been brought up to deduce the activity of persons from sensor measurements in real-time (e.g. [3], [4]), unobtrusive real-time stress recognition has not been addressed adequately. In particular for users in demanding and/or dangerous situations however, such knowledge would add important value. For instance the mission control in disaster relief missions could benefit from knowing when to replace a team and force them to rest, so they do not run into bigger risks for themselves.

The objective of this paper is the presentation of an approach to measure a user's stress level based on a wireless chest belt and an activity recognition system together with a prototype which allows the inference of six stress levels on an Android operated mobile phone. The results of our experiments are encouraging to show that the recognition of stress is feasible, but still needs further work to reach the required standards of reliability.

The organisation of this paper is as follows: the next section will explain the underlying theory of our recognition approach and report on the state of the art in activity recognition. In section III we explain how we recorded reference data to train our classifier and to evaluate our results, before section IV explains the details of the developed classifier. The evaluation of our prototype in the explained environment and a conclusion close this paper.

II. Related Work

This section will first give the theoretical background for measuring physical manifestations of stress, before it relates our approach with the state of the art.

A. Psychophysiological Measuring

The processes taking place in the human body manifest themselves to a large degree in measurable events [5]. All these measurable, so called deductive, phenomena are called *bio-signals* if they can be quantified directly at the body surface. For instance the measurement of change of the chest during respiration or the voltage fluctuation at the cranium (due to brain activity) are bio-signals. Derived functional dimensions, like respiration frequency or depth, are referred to as *psychophysiological parameters*. The following bio-signals are particularly relevant for stress recognition:

1) Electro Dermal Activity (EDA): The electro dermal reaction measures describe skin conductance and potential deflection while showing direct correlations to psychological processes. The skin conductance is measured as an exosomatic measure by applying an electric potential to the biological system. In particular the *skin conductance response (SCR)* develops as a reaction to particular stimuli. The form of the reaction development is not completely uniform especially concerning the increase and decrease times.

2) Cardiovascular Activity: As the cardiovascular system shows distinct reactions in conjunction with a lot of psychological processes including, for instance, activation and stress. The cardiovascular system provides a number of relevant psychophysiological parameters including heart rate, blood pressure and peripheral vasomotion.

The heart rate (HR) is defined as the number of heart beats per minute. It is the most used indicator for the cardiovascular activity in the field of psychophysiology and hence also an important factor for stress recognition. Heart rate variabilities accompany nearly any change in physical or psychological requirements. Under activation conditions an increase of the heart rate up to 2.5 times is possible [6]. An important characteristic of tonic changes is the heart rate variability. It can be assumed that, for instance under alertness supporting conditions, the variability decreases with the increase of the heart rate reflecting the more precise central-nervous heart rate control under exertion. Another point which has to be considered is the age of the subject as it influences both, the heart rate and the heart rate variability.

Electrical Muscle Activity As psychophysiological arousal directly relates to muscle tension, the registration of the electrical muscle activity represents a major psychophysiological method. The corresponding bio-potential is recorded using electromyography.

3) Temperature: When talking about temperature as a physiological signal of the body, it is important to differentiate between *core* and *body temperature* which are commonly referred to as the inner temperature of the organism and the *skin temperature*. The latter is much more dependent on the environmental temperature and hence more difficult to interpret. For instance, the temperature change of the skin during the so called emotional rubescence, which might be caused by stress, is at most 1°C, normally only around some tenths of °C [5].

4) Respiration: The respiratory activity is commonly registered in psychophysiological examinations, but rarely serves as an independent measurement for bodily reactions as it is subject to deliberate control. In general its recording is meant to identify interference signals caused by respiration in the elevation of the ECG, EDA and others.

B. State of the Art Stress Recognition Approaches

In the related work, stress recognition is mainly considered in the fields of human computer interaction [7], [8], real-time security systems [9] or affective state detection of drivers [10]–[12]. In all these research areas the stress recognition is intended to help the system reacting on the affective state of the user. Hence, they concentrate on stress recognition in static environments where the subjects remain in a sitting position. Therefore, most of the used sensing modules are not wearable or practicable in a mobile environment. Others, like the *BodyMedia SenseWear Armband* lack the possibility of real-time signal transmission and thus cannot be used for real-time classification.

The range of physiopsychological reactions, the so called signals, is very broad. In theory, a complete recording of all of them would be available, but in practice, only a subset of the possible measurements are used in the related work to identify the human stress level. The selection thereby depends on the situation and requirements under which the recognition system has to operate. For instance, the prerequisite of using minimal invasive measurements methods [8] rules out obtrusive methods like electromyography. The following table gives an overview about the signals used in the state of the art.

Reaction system	Signal	Related work
Cardiovascular system	ECG	[10], [11], [13]
	Heart rate	[7], [9], [14], [15]
	Blood volume	[8]
Electro dermal system	SCR / GSR	[7]–[11], [15]
	Skin temperature	[7], [8], [13]
Respiratory system	Respiration	[10], [11], [13]
Muscular system	EMG	[10], [11]
Eye	EOG	[13]
	Pupil diameter	[8]
	Eye movement	[7]
	Eyelid movement	[16]
Electric brain activity	EEG	[13]
Others	Mouth openness	[7]
	Facial Expression	[16]
	Gaze	[16]

Table I
BIO-SIGNALS USED FOR STRESS AND EMOTION RECOGNITION.

Challenges for stress recognition can be caused by day-to-day variabilities (e.g. caused by different moods) and real-time recognition with fast response times even in high-dimensional feature spaces. There are different approaches to this problem in the related work using Fisher Projection or Sequential Floating Forward Search [17].

The stress levels are recognised in so called *classifiers* which take as input features calculated from the signals. From training data the classifiers are adapted (“learning”) to the specific use case. The following classifiers have been used in the related work: Support vector machine (SVM [8], [11], Adaptive Neuro-Fuzzy Inference System (ANFIS) [11], k-nearest neighbors (kNN) [9], [15], [17], Discriminant Function Analysis (DFA) [15], Marquardt Backpropagation Algorithm (MBP) [15], Fisher Discriminant Analysis (FDA) [9], Fuzzy logic [14], Decision Tree [8], Naïve Bayes [8], Bayesian networks [16], and Dynamic Influence Diagram [7].

III. Groundtruth Experiment

To create a working classifier, the most adequate sensors have to be chosen and data have to be recorded to train the classifier. For the recorded data, also the groundtruth, i.e. in our case the actual stress level at the moment in time, has to be recorded. The following section will detail our choice of sensors and the experiment which enables us to record bio-signals for stress with groundtruth.

A. Used Sensors

One of our targets is the recognition of stress in mobile environments. Therefore we need sensors to measure bio-signals, but moreover also sensors for the activities.

1) Zephyr BioHarness BT: For the bio-signals, we have chosen the Zephyr BioHarness BT. It is a compact electronic module attached to a lightweight Smart Fabric strap, which incorporates electrocardiogram, breathing, temperature and skin conductance level sensors. Besides the raw signals also derived values are available. Used derived values given by the sensor are the heart rate and RR-interval, which are calculated from the ECG, and the breathing rate, which is calculated from the raw signal. The specifications for all directly measured and inferred signals are given in Table II.

	Unit	Range	Frequency (Hz)
ECG	Bits	0-1024	250
Heart Rate	BPM	25-240	1
RR-Interval	ms	-	18
Breathing Sensor	Bits	0-4095	18
Breathing Rate	BPM	3-70	1
Temperature	°C	10-60	1

Table II
RECEIVED SENSOR DATA FROM THE ZEPHYR BIOHARNESS BT.

2) Activity Recognition System: The *activity recognition system (ARS)* [3] used is capable of predicting the current activity of a person based on the sensor data provided by an IMU with high reliability. It distinguishes between 7 different states: *Sitting*, *Standing*, *Walking*, *Running*, *Jumping*, *Falling*, and *Lying*.

The ARS receives raw data with a frequency of 100 Hz and yields a recognition delay of about $20ms$ for an inference rate of $4Hz$. Ported to Android, the system gives a delay of $1s$ at an inference rate of $2Hz$.

B. Stroop Colour Test

The methods for eliciting stress are the basis for the generation of the training data. In this work, regarding mental as well as physical stress, a multicomponent stress test is used, incorporating both psychological and physiological aspects.

The Stroop *Colour Word Test (CWT)* is a well known method in the field of psychology for putting cognitive load on a subject [18], named after J.R. Stroop [19]. It describes the fact that people are faster in recognizing a written word than a symbol with the same meaning. An example of a Stroop CWT is illustrated in Figure 1.

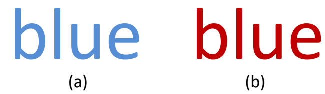

Figure 1. Example for the Colour Word Test. If a person is asked to name the colour in which the words are written, it takes remarkably longer in the incongruent case (b) than in the congruent case (a).

The CWT is a reliable test to study stress responses [18] and accordingly it has already been successfully applied as an elicitation method in the related work, e.g. in [8]. In order to induce different levels or intensities of stress, the CWT is implemented in this work as a game to challenge the test person in different difficulties. Each level extends the preceding one by a new component intended to increase the difficulty of the test and hence the perceived stress.

The first level represents a standard CWT without any modifications as described above. In the second level the CWT is extended with a pacing timer of five seconds to put time pressure on the test subject. Then in the next stage the possible answers, the test person can choose, are presented in different colours instead of just black. This is causing additional distraction and thus more stress. On the fourth level a task variation is added by randomly asking the test person to either name the font colour of the word or the word itself. Finally on the last level the time pressure is increased by reducing the limit for an answer to three seconds.

In addition, physical load has been put on a test subject. The recorded activities are used as the ground truth for the physical stress. With an increasing physical load, for instance '*Running*' is more exhausting than '*Walking*', also the physical stress increases. Hence the activity trace defines the physical stress which is put on a person. Being able to record the physical stress during a certain sequence of activities and the mental stress in a static, in this case sitting, situation, it is possible to combine these two methods. This way, the differences, for instance due to additional mental stress, can be detected. This is the basis for recognizing stress in a mobile and versatile environment.

IV. Classifier Design

This section presents the training dataset and the resulting classifier, a *Bayesian network (BN)*.

A. Training Dataset

The training dataset serves as an input for the learning of the stress classifier and hence has a huge influence on its quality. The data set has been recorded with the experiments described above. Fifteen subjects participated in the study, aged between 24 – 57, 5 female and 10 male. Only five subjects participated in the combined part. According to the presented stress elicitation methods, three different experiments for data acquisition were conducted. First, a mental stress test using the adapted CWT, second a physical stress test and third a combined stress test. Overall 550 minutes of data have been recorded during the study. The data have been labelled manually according to the self-assessed stress of the test person after the experiment. Detail can be found at http://www.kn-s.dlr.de/activity/.

B. Bayesian Network

In this work a *Bayesian network (BN)* is used as a classifier to identify the stress level of a person. It has to differentiate between six stress levels varying from *”no stress”*, level 0, to *”very high stress”*, level 5. Bayesian networks have been used as they can handle uncertain and missing data - such as from mobile sensors. Furthermore also the used activity recognition system relies on a Bayesian network for classification. Hence its output is given as a probability distribution, which can be easily integrated into stress recognition with BNs.

Based on the recorded dataset, a Bayesian network has to be learnt. Every feature is represented by a discrete random variable, just like stress (with its six stress levels as states). The first step is to choose the features which have to be deduced from the recorded raw data.

1) Random Variables: The objective is to find a set of random variables which determines the different stress states as good as possible. The points which then have to be considered are the sensitivity to stress, the computational complexity of calculating the feature and the available data provided by the sensors. The used sensors, the Xsens MTx IMU and the Zephyr BioHarness BT, provide the following signals: Heart Rate, Breathing Rate, Temperature, and RR-Interval. Table III presents the features selected for our work.

Feature	**Definition**
Signal: Heart Rate	
Norm. absolute value	x_{hr}
Mean	$\overline{x_{hr}}$
Standard deviation	$\sigma_{x_{hr}}$
Mean first difference	$\sum_{i=0}^{N} x_{norm_i} - x_{norm_{i-1}}$
Signal: Breathing Rate	
Norm. absolute value	x_{br}
Mean	$\overline{x_{br}}$
Standard deviation	$\sigma_{x_{br}}$
Mean first difference	$\sum_{i=0}^{N} x_{norm_i} - x_{norm_{i-1}}$
Signal: Temperature	
Norm. absolute value	x_{temp}
Mean [3]	$\overline{x_{temp}}$
Standard deviation	$\sigma_{x_{temp}}$
Mean first difference	$\sum_{i=0}^{N} x_{norm_i} - x_{norm_{i-1}}$
Signal: RR-Interval	
RMSSD	$\sqrt{\frac{1}{N}\sum_{n=1}^{N}(RR_n - RR_{n+1})^2}$
pRR50	$\frac{NN_{50}}{NN_{total}}$
SDRR	$\sqrt{\frac{1}{N-1}\sum_{n=1}^{N}\left(RR_n - \overline{RR} - \overline{RR}\right)^2}$
SDSD	$\sqrt{\frac{1}{N-1}\sum_{n=1}^{N}\left(\lvert RR_n - RR_{n+1}\rvert - \overline{RR_{diff}}\right)^2}$

Table III
THE SET OF FEATURES STEMMING FROM THE CHEST BELT WHICH ARE USED IN THIS WORK.

Normalized Absolute Value: The normalized absolute value x of the heart rate x_{hr}, the breathing rate x_{br} and the temperature x_{temp} are used as features. Because the absolute values are very much person dependent, a baseline normalization $x_{baseline}$ is used to get the current value relative to a state of rest.

Mean Value: The mean values of the heart rate, the breathing rate and the temperature are used for different window lengths depending on the speed in which a stress stimulus shows in the reaction of the respective system.

Standard deviation: The standard deviation σ_x indicates in what extend the signals in the window N vary from the mean.The same window sizes as for the mean value $\overline{x}$ are used. Thereby the same window sizes as for the mean value $\overline{x}$ are used.

RMSSD: The *square root of the mean squared differences of successive NN intervals (RMSSD)* [20]. is calculated with a window size of 1024 samples in order to have enough heart beats in one interval to get a reliable estimation. With the used sampling rate of $18Hz$, the window includes the heart beats in $56.9s$.

pNN50: The *pNN50* is defined as the percentage of NN-intervals which are greater than $50ms$, NN_{50}, regarding the total number of NN-intervals NN_{total} in a window [20]. For pNN50, the same window size as for the RMSSD is applied.

SDNN: The *standard deviation of the NN interval (SDNN)* is a variable to describe the heart rate variation [20], which is very simple to calculate.

SDSD: The *standard deviation of differences (SDSD)* between adjacent NN-intervals is an indicator for the heart rate variability due to cycles shorter than $5min$ [20]. The window size N is the same as the one used for the RMSSD.

Previous Activity: The previous activities have a huge influence on the momentary measurement. An exhausting activity, in the past minutes for instance, will result, in a higher heart- and breathing rate. In order to be able to link that change to its cause, it is necessary to have the information about the preceding activity. In this work only the directly preceding activity is considered.

Features Related to the Current Activity: There are three features considered related to the current activity. The current activity itself, its probability and the time it is already ongoing. All three values are given by the ARS and can be used directly without additional calculations.

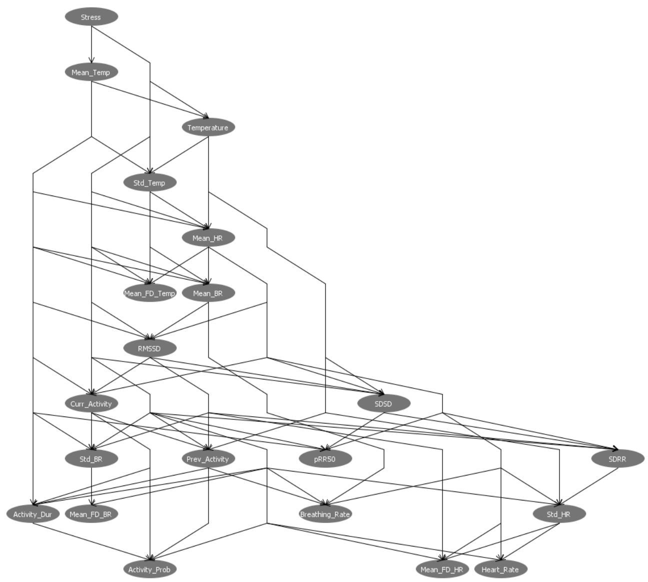

Figure 2. Bayesian network learnt with continuous transitions for complete stress.

2) Bayesian network for stress classification: After a discretization (clustering) of the calculated feature values, a Bayesian network is learnt based on the training data. Therefore the *local Repeated Hill Climber Algorithm* [21] has been used.

The resulting network, including mental stress, physical stress and resting phases, can be found in Figure 2. The originating dataset contains 29531 instances, of which 26578 are used for learning the Bayesian network and 2953 are used for evaluating the found model.

V. Evaluation

The Bayesian network learnt from our training data has been evaluated offline with the test data set, but also live with new test subjects. The results will be shown in the following section.

A. Offline Evaluation

	S_0	S_1	S_2	S_3	S_4	S_5
Precision	0.971	0.783	0.832	0.871	0.858	0.827
Recall	0.977	0.844	0.858	0.823	0.826	0.848

Table IV
COMPARISON OF PRECISION, RECALL AND CORRECTLY CLASSIFIED INSTANCES FOR THE LEARNT BAYESIAN NETWORK FROM FIGURE 2. S_i THEREBY REPRESENTS STRESS LEVEL $i, 0 \leq i \leq 5$.

The results of the evaluation with a random 10% test split (2953 data instances) are presented as precision and recall in Table IV. '*Stress 0*' has the best results for precision and recall compared to the other stress states. The learnt network has a overall classification accuracy of 90.35%, .

The different stress levels can be very well differentiated from each other. Looking at the precision and recall for the different classes the worst value is 78.3%. Considering a binary class distribution with only '*No Stress*' and '*Stress*', in each case a considerably better result can be achieved.

B. Online Evaluation

Online evaluation has 2 objectives. Time consumption, memory and CPU usage have to be evaluated, as well as the prediction accuracy on live data.

1) Performance: The SRS is intended to work on mobile devices, in particular the *Samsung Galaxy S2 (SGS2)*. This evaluation is based on the SGS2 with Android 2.3.3 Gingerbread. CPU and memory usage are determined using the *Task Manager*. Results are given in Table V.

	Used CPU	Used RAM
ARS	45%	$27MB$
SRS without ARS	28%	$15MB$
SRS with ARS	65%	$36MB$

Table V
OVERVIEW OF CPU AND RAM USAGE OF THE *stress recognition system (SRS)* WITH AND WITH OUT ACTIVITY RECOGNITION.

In total, stress recognition needs $500ms$ to infer the current status. Thereby, it takes $331ms$ to compute all feature values and $169ms$ for the actual inference. Hence the current system is capable of operating in real-time with an inference rate of at least $1Hz$ on the SGS2.

2) Online Classification Results: For online classification, a test person conducts the mental stress test only. The features related to activity are set to *Sitting* to avoid extra complexity due to the influence of physical stress. The test person is asked to relax for five minutes before conducting the test. During that time, the stress is inferred already to examine the sensitivity of the SRS to non-stress. The recorded stress level is then compared with the self-assessed stress level of the person which serves as the groundtruth. The resulting confusion matrix is shown in Table VI.

true class → ↓ predicted	S_0	S_1	S_2	S_3	S_4	S_5
S_0	156	15	0	0	2	0
S_1	0	3	0	0	0	0
S_2	0	1	56	37	7	28
S_3	1	12	30	66	53	3
S_4	0	0	0	17	32	86
S_5	14	21	93	62	88	63

Table VI
CONFUSION MATRIX OF ONLINE EVALUATION OF THE BN LEARNT WITH CONTINUOUS TRANSITIONS FOR COMPLETE STRESS. S_i THEREBY REPRESENTS STRESS LEVEL $i, 0 \leq i \leq 5$.

Only a classification accuracy of 39.7% is reached. Looking at the confusion matrix, it is apparent that '*Stress 0*' is very well recognized, with a precision of 0.902 and a recall of 0.912. However, the boundaries between the further classes, '*Stress 1*' to "*Stress 4*", are blurred and no clear distinction is possible.

VI. Conclusion

The objective of this work is the development of an unobtrusive, real-time capable, mobile stress recognition system. We have realised an Android app connecting an activity recognition system and a Bluetooth chest belt. It measures psychophysiological parameters and infers stress levels with a frequency of $1Hz$. While the main targets have been met, the stress recognition yields room for improvement.

Only the distinction between "No Stress" and "Stress" is reliably possible in the current version. The big difference between offline and online evaluation results reveal problems with the used dataset, possibly explained by an overfitting due to the split of the data set which led to misleading results in the offline evaluation. Moreover, the quantity and diversity of the data set have to extended.

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