ASSOCIATIONS OF PSYCHOLOGICAL SELF-ASSESSMENTS AND HRV IN LONG-TERM MEASUREMENTS AT HOME

K. Antila, M. van Gils, J. Merilahti and I. Korhonen

VTT Information Technology, Tampere, Finland

kari.antila@vtt.fi

Abstract: Psychological self-assessments and heart rate variability analysis are popular methods of estimating subject's mental load and his/her load on the autonomic nervous system, thus the level of mental stress. The aim of the study was to test a recent heart rate variability analysis method against self-assessments. Long-term measurements carried out in everyday life ensured a sufficient amount data (12 subjects, 35 variables and approximately 300 measurements per subject/variable). Significant ($p<0.05$) correlations between data from the two sources were found ($\rho<0.359$). Associations within self-assessment variables were studied with Principal Factor Analysis and the most powerful of the resulting variables (feature vectors) were retained. The distributions of these new variables in space were studied with a clustering algorithm which concluded in a division into two groups. Based on the characteristics of the values assigned to the groups, they were named as bad (40% of grouped points) and good (60%) days/evenings. The same division was applied to heart rate variability-related variables which showed significantly higher relative measurement time spent in stress on days marked as bad (mean 60%, std 19%) when compared to good (mean 52%, std 17%).

Introduction

Work-related mental stress is a degenerating human and economical problem especially in industrialized countries. Studies carried out in Europe and other countries suggest that 50%-60% of all lost working days are somehow related to stress [1]. Surveys indicate that stress-related symptoms are the second largest category of health problems faced by European workers exceeded only by musculoskeletal complications [2]. The International Labour Organization (ILO) estimates that the costs of stress and related mental problems equal 3%-4% of the GNP in the 15 EU states (in the year 2000) [3]. The reflecting consequences in other aspects of life can be obscure and unforeseen. The problem is well recognized, yet diagnosing and treating the condition is far from trivial. Therefore viable tools for predicting, detecting and controlling detrimental stress are needed.

Enquiries, such as Bergen Burnout Indicator (BBI) [4] and Derogatis Stress Profile (DSP) [5], are currently popular methods of monitoring and screening stress levels. During enquiries the subject assesses his/her mood and survival in everyday life etc. by answering to a standard set of questions. The results can be ranked and mapped to a distribution of a general population. However, because of the inconvenience and adaptation associated with questionnaires, they cannot be repeated with a high resolution.

Heart rate variability (HRV) is used routinely in estimating the state of the autonomic nervous system (ANS) [6]. Activity in the sympathetic and parasympathetic parts of ANS is generally known to be in connection with changes in mental stress levels. Still reliable and unobtrusive measurement of HRV in everyday life has been difficult. Originally developed for electrocardiographic (ECG) recordings, HRV analysis techniques can now employed in exploring data collected with modern heart rate meters such as Suunto t6 [7] and Polar S810i [8].

The aim of the study was to test recently developed, HRV analysis based methods for monitoring the mental stress against psychological self-assessments as reference.

Materials and Methods

The material is based on a study [9] where 12 healthy male volunteers of ages 36-47 were recorded over a period of approximately ten weeks. Several physiological variables including R-to-R heartbeat intervals (RRI) were measured while awake daily. In addition, a behavioural diary (DRY) with 12 different variables (Table 1) was filled-in two times a day, days (d) and evenings (e).

Table 1: Collected DRY variables.

Variable	Scale
mental strive	1-7 (7 for the strongest feeling)
physical strive	1-7
management	1-7
anger	1-7
anxiety	1-7
melancholy	1-7
fatigue	1-7
busyness	1-7
happiness	1-7
coffee or tea	cups per period (day or evening)
cigarettes	n. of cigarettes per period
alcohol	n. of alcohol doses (4 cl) per period

Some statistics of collected DRY entries are summarized in Table 2.

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Table 2: DRY Variable statistics with the number of entries (N), mean and standard deviation (std). *Based on two smokers. **Based on 11 subjects who use alcohol.

Variable	N	mean	std
mental strive	618	2.65	1.23
physical strive	617	2.81	1.45
management	610	4.90	1.12
anger	617	1.94	1.08
anxiety	615	1.90	1.03
melancholy	606	1.70	0.95
fatigue	615	2.70	1.33
busyness	615	2.80	1.43
happiness	613	4.70	1.07
coffee or tea	587	3.07	7.36
cigarettes*	109	2.11	5.00
alcohol**	504	0.51	1.44

The RRI data were analyzed with *Wellness Analysis* software v. 1.3 [10] by Firstbeat Technologies, Jyväskylä, Finland (FBT). All HRV analysis in the study was done with the software.

The software is designed to detect various physical states from the RRI series or ECG signal input. The analysis begins with pre-processing steps: heartbeat extraction, artefact filtering and interpolation to equidistant time series. After pre-processing the signal is segmented according to features extracted from the series. The physical state of every segment is detected by ruling out recognizable physical states such as recovery from physical exercise, physical exercise, light physical activity and changes in posture. This is done with the help of individual physiological parameters such as heart rate limits, the level of usual physical activity, sex, age, weight, height, etc. The remaining segments are tested first for *relaxation* and then for *stress* (of ANS) and the rest are classified to an undifferentiated state. The algorithm is also capable of estimating the intensity of *relaxation* or *stress* in respective segments.

The algorithm output contains a total of 35 variables, seven of which were selected, on the basis of the recommendation from the software maker, for further analysis (Table 3).

Table 3: Selected FBT variables.

Variable	Explanation
relaxation time (RT)	time (min) spent relaxing
stress time (ST)	time (min) spent in stress
relax. percentage (R%)	% of time in relaxation
stress percentage (S%)	% of time in stress
avg HR	average heart rate (bpm)
max HR	max heart rate (bpm)
min HR	min heart rate (bpm)

Spearman Rank Order correlations between DRY and FBT variables were computed to find possible one-to-one dependencies between DRY and FBT variables. Correlations were computed first on data normalized by dividing every value with its subject mean and subsequently pooling over all subjects. Another set of correlations was obtained by averaging all subject wise computed correlations.

Further, Principal Factor Analysis (PFA) [11] was performed for the set of DRY variables. The PFA is a convenient method for both searching dominant features in the studied variable set and performing data reduction. The method builds a new set of feature vectors of the studied variables with similar statistical variability and estimates their power in explaining the overall variance.

After the analysis, the distribution of PFA variables in space was studied. The particular point of interest was if the values of PFA variables form natural groupings. These were searched with SPSS v. 12.0.1 [12] TwoStep Clustering algorithm. The algorithm is capable of determining the best number of successive clusters when an appropriate distance measure (here log-likelihood) and a clustering criterion (Schwarz's Bayesian Criterion) are chosen. Based on the clustering, PFA values can be classified and characterized by typical values observed within the class. Since PFA values can be mapped to the initial dates of the DRY entries, a study of possible weekly rhythms is possible.

Finally, the TwoStep Clustering based classification of PFA variables were applied to FBT variables computed for corresponding dates (measurements). After the classification, differences in the values of FBT variables in separate groups were computed using the Mann-Whitney test where $p<0.05$ was considered significant.

Results

The highest and the most significant correlations on pooled data are summarized in Table 4 and Table 5.

Table 4: Correlation coefficients on pooled data between DRY variables and stress-related FBT variables. Only signifigant values ($p<0.05$) are included.

DRY variable	RT	ST	R%	S%
ment. str. (d) ρ	-	0.158	-	-
p (2-tailed)	-	0.001	-	-
N	-	422	-	-
phys. str. (d) ρ	-0.169	-	-	-
p (2-tailed)	0.001	-	-	-
N	420	-	-	-
busyness (d) ρ	-	0.134	-0.128	-
p (2-tailed)	-	0.006	0.008	-
N	-	422	422	-

Results show several small but significant correlations in daytime DRY entries and relaxation/stress-related FBT variables. *Mental strive* appears to be positively correlated with *stress* while *physical strive* is in negative dependence with *relaxation*. *Busyness* seems to be slightly correlated with both.

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Table 5: Correlation coefficients on pooled data between DRY and HR level-related FBTvariables.

DRY variable	avg HR	max HR	min HR
phys. strive (d) ρ	0.359	0.193	0.152
p (2-tailed)	0.000	0.000	0.002
N	420	420	420
phys. strive (e) ρ	0.223	0.215	-
p (2-tailed)	0.000	0.000	-
N	463	463	-
busyness (d) ρ	0.143	-	-
p (2-tailed)	0.003	-	-
N	422	-	-

A relatively strong connection was found between *physical strive* and elevated *HR* levels. Also daytime *busyness* correlates positively with *average HR*. Notable correlations were also found with *mental strive*, *physical strive* and *busyness* when compared to estimated energy consumption. The outcome of subject wise computed and averaged correlations are presented in Table 6.

Table 6: The subject wise computed and averaged correlations.

DRY variable	RT	ST	R%	S%
ment. str. (d)	-	0.228	-	-
phys. str. (d)	-0.114	-	-0.174	-0.185
busyness (d)	-0.157	0.132	-0.224	-
busyness (e)	-0.206	0.133	-0.234	-
cigarettes (d)	-0.317	0.443	-0.319	0.423
cigarettes (e)	-0.193	0.387	-0.224	0.362

The PFA was performed only on the DRY variables. Day and evening were considered separately, making the total number of variables 24. *Cigarettes* were excluded because of the small number of recorded entries, so the number of variables fed to the PFA was 22.

After the PFA, the seven most powerful variables (feature vectors, factors) were retained (Table 7).

Table 7: The seven most powerful PFA variables (#), percetage of variance explained and their composition of DRY variables.

#	%	PFA variable composition
1	29	anxiety (d) + anxiety (e) + melancholy (d) + melancholy (e) + anger (d) + anger (e)
2	11	management (d) + management (e) + happiness (d) + happiness (e)
3	9	fatigue (d) + fatigue (e) + business (d) + physical strive (d)
4	6	physical strive (e) + mental strive (e) + business (e)
5	5	coffee or tea (e)
6	5	alcohol (d) + alcohol (e)
7	5	coffee or tea (d) + mental strive (d)

The selected seven variables explain 71% of overall variance. The power of every PFA variable in explaining the overall variance is presented Figure 1.

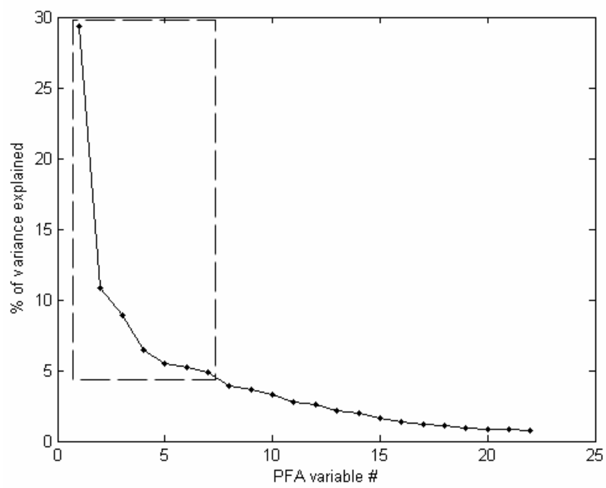

Figure 1: The percentage of variance explained by extracted PFA variables. The seven selected variables are marked with a dashed box.

The seven selected variables (1-7) are distinguishable with the first variable clearly the most powerful one. These new variables were named (Table 8) according to the nature of their composition of DRY variables (Table 7).

Since the PFA variables correspond to the DRY variables filled in a daily schedule, the study of weekly rhythms in PFA variables is quite straightforward. One rather clear rhythm can be seen in *negative feelings* (Figure 2).

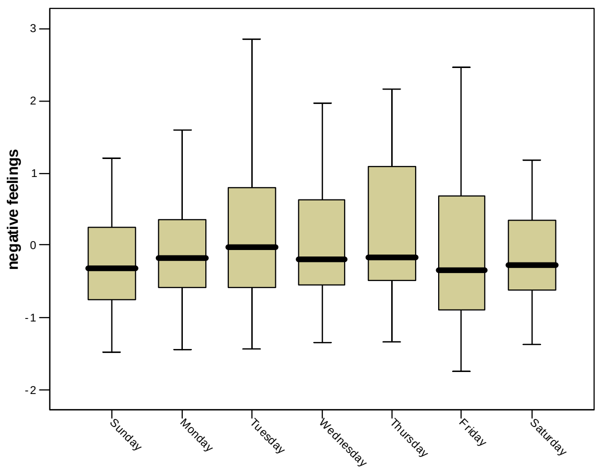

Figure 2: Box-and-whiskers plots depicting different distributions for *negative feelings* for weekdays. Thick lines indicate the median, box edges represent the 25-75% quartile range and the whiskers indicate the overall range.

According to Figure 2 *negative feelings* increase at the beginning of the week having a maximum on Tuesday and slowly decreasing towards the end of the week. Somewhat clear rhythm was also found in alcohol use which is on a higher level during the weekend.

The TwoStep clustering analysis performed on PFA variables resulted in division into two groups, C1 and C2. This division contained 62% of all variable entries with relative portions 40% (C1) and 60% (C2). These groups were described by their PFA values, respectively (Table 8).

Table 8: Named PFA variables and their typical values in C1 and C2. Only values with a significant ($p<0.05$) deviation from zero mean are filled.

#	PFA variable	C1	C2
1	negative feelings	high	low
2	cope with life	bad	good
3	activity (d)	-	-
4	activity (e)	-	-
5	coffee use (e)	high	-
6	alcohol use	low	-
7	mental strive (e)	low	high

A group C1 or C2 was given a characterizing term if the 95% simultaneous confidence interval of mean of PFA values in the group did not cross the overall mean of the current variable. Based on the characteristics, C1 and C2 were named as *bad* and *good* days/evenings (entries).

This division was applied to FBT values originating from corresponding days. Mann-Whitney test was used to study whether FBT values have significant difference when assigned to the groups (Table 9).

Table 9: Results of the Mann-Whitney test apllied on FBT variables assigned to groups C1 and C2.

FBT variable	p	grp.	mean	std
stress time (min)	0.001	C1	470	178
		C2	410	150
stress percentage	0.002	C1	60	19
		C2	52	17

Based on the results FBT variables of data collected during bad days (group C1) have higher values of absolute and relative time spent in *stress*. The same applies to estimated energy consumption.

Discussion

At best, excluding the number of smoked *cigarettes*, 13% of variability between pooled FBT and DRY and variables were explained (Table 4, Table 5). This is a quite usual result due to the subjective nature and high inter and intra subject variability of self-assessments. Even small correlations involving subjective variables can still give valuable implications of possible connections between variables in question. Results on subject wise computed correlations (Table 6) show somewhat similar results to pooled ones. The negative correlation between daytime *physical strive* and *stress percentage* is probably due to increased amount of time classified off *stress* or *relaxation* to other groups such as physical exercise. The strongest correlation was found between *stress/relaxation* and the number of smoked *cigarettes*. However, this is based on only two smokers in the group.

Usually only interval variables can be subjected to the PFA. Although DRY variables seem like interval variables, they should be considered more like ordinal. However the use of PFA on ordinal variables could be justified in exploratory data analysis such as this one. Even though the PFA was done on ordinal variables it resulted in a sensible outcome (Table 7).

The cluster analysis of PFA variables gave a result of a division into two groups, which had distinct values of the most powerful PFA variables #1 and #2 named as *negative feelings* and *cope with life* (Table 8). According to the characteristics the groups were named as *bad* and *good* days (entries). *Stress time* and *stress percentage* showed clearly higher values on *bad* days (Table 9). However, the differences in *relaxation time* and *relaxation percentage* were not significant.

Due to the natural variability in data obtained with both methods and the subjective nature of self-assessments, the long time frame of measurements is necessary in order to reduce their effect on statistical analysis. In addition, the use of self-assessments as a reference of high resolution measurements, such as HRV, is challenging because of its poor relative reproducibility.

Conclusions

The study showed small but significant correlations between the HRV derived variables (FBT) and psychological self-assessments (DRY) indicating stress. However, advanced signal analysis methods are needed to reveal complex underlying connections in data measured in real life conditions. These results can be used in detecting and monitoring of prolonged mental stress.

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