Predicting self-reported stress from implicit measures recorded during sleep

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Introduction

Stress-related complaints and burn-out are important problems, causing absenteeism and decreased well-being. It is now possible to obtain individuals' data continuously without having to interfere with their daily life, using wearable sensors and information from smartphones. This may enable predicting mental health problems before individuals notice or acknowledge these problems themselves. Real-life studies show that automatically sensed data allow the classification of students into groups with high/low stress scores, and high/low mental health scores (Sano et al., 2018), or predict the next day's self-reported level of well-being (Yu et al., 2019).

One of the challenges in this type of research is the variation of measurement contexts, where often, context can be expected to affect variables more strongly than mental state. This problem may be met by using the collected data to focus on certain context and then recording repeatedly in the same context, such as the office (Brouwer et al., 2018) or lectures in high school (Thamassan et al., 2020). A context that is relatively constant across and within individuals, and can be detected automatically relatively easily, is sleep. Other advantages of this context are that there is relatively little body movement, which is good for interpreting physiological variables, and that features characterizing sleep, such as sleep duration, are informative in themselves (e.g. VollenBroek-Hutten et al., 2019); a downside is that there is no potentially informative data reflecting social interaction or other activities.

We here explore whether we can predict self-reported stress levels in the morning by sleep properties, as automatically detected by heart rate and accelerometry recorded through a smartwatch, and whether measures derived from heart rate during intervals that are identified as sleep, will aid this prediction. In particular, high frequency heart rate variability (HRV) may be informative since it provides an index of the parasympathetic nervous system, which is linked to various cognitive, affective, social, and health phenomena (Laborde et al., 2017). Associations between exposure to acute and chronic stress and HRV measured during the subsequent night have been reported (Hall et al., 2004; Bell et al., 2019).

Methods

We examined data of 16 participants, all military employees, who were followed using ecological momentary assessments (EMA), and a smartwatch (Garmin Tactix Charlie) for an average of 32 nights (minimum of 15 nights; 506 nights in total). The smart watch was used to detect sleep and determine several sleep characteristics using photoplethysmography and accelerometry features. The sleep detection was done using our own developed algorithm (Kamphuis et al., 2020), that uses the open source algorithm GGIR (Van Hees et al., 2015).

<u>Input features</u> for the model were the five automatically detected sleep characteristics (time in bed; time between going to bed and falling asleep; total sleep time; time awake after the first sleep interval and before the last sleep interval; time asleep relative to time in bed), 8 cardiac features (for both the first and the last thirty minutes of sleep: mean, maximum and minimum heart rate; RMSSD heart rate variability) and 1 miscellaneous feature (day of the week).

For the mental well-being outcome variable, we averaged responses to the following morning EMA questions: I feel mentally fit; Whatever happens today, I will be alright; I can concentrate well; I look forward to this day; I consider the things that I plan on doing today worthwhile.

For modelling, the 506 recorded observations were split: for each participant, 70% of the data was used to train the models and 30% was used as a test set. After the data was split, numeric predictor variables were scaled per person; the same scaling was applied to the test set. We examined performance of three models: 1) a random forest model using sleep characteristics, 2) a random forest model using sleep characteristics as well as cardiac predictors, and 3) a null model that always predicted the individual's average well-being score. When running the random forest models, we trained a model for each person individually and then used that to predict the aggregated morning emotional well-being score. We used R^2 as a model performance metric. This procedure was repeated 50 times for each model, using different train and test sets, in order to obtain variability in the models' performance.

Results

An ANOVA showed that there were significant differences between model R^2 means ($F_{2,147}$=28.33, p<.001). Post hoc comparisons were done using a Tukey HSD test. These indicated that both the random forest model using only sleep characteristics (M=.761, SD=.026) and the random forest model using both sleep and cardiac characteristics (M=.749, SD=.025) significantly outperformed the null model (M=.721, SD=.030) (both p-values<.001). However, the two random forest prediction models did not significantly differ from one another (p=.07).

Discussion

Our study showed that self-reported mental well-being can be estimated based on sleep characteristics of the preceding night, as detected automatically using cardiac and accelerometric features from a smartwatch. This worked significantly better compared to using the individual's average well-being score as a prediction. Adding cardiac features did not further improve the results. Perhaps the most important difference between our study and studies that did find an association between stress and HRV as recorded during the night is that these studies recorded extracted measures related to HRV from ECG rather than PPG measured at the wrist, and used data from the whole night (Bell et al., 2019) or non-REM sleeping phases (Hall et al., 2004) rather than the first and last 30 minutes, irrespective of sleep stage. Thus, our determination of cardiac features might have been too coarse (Laborde et al., 2017). Also, in future studies it would be of interest to follow a population with high (variation in) stress levels.

This study represents an concrete example of automatically taking context into account when interpreting automatically collected features as possible sources of information about mental state. We think this is a promising route to improve model predictions. Other contexts may be relatively easy detected as well, such as being at a desk at work using a webcam, or being in the car using GPS information.

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