Stress Dichotomy using Heart Rate and Tweet Sentiment

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Keywords: Sentiment Extraction, Heart Rate, Time Series, Data Analysis, Stress Dichotomy.

Abstract: Automated detection of human stress from markers is very beneficial for the development of assistive technologies. Blood pressure, skin temperature, galvanic skin response or heart rate are typical physiological markers that help identify human stress. However, not only the human body itself but also the human mood expressed in short text messages can be a useful source of such information about stress. This paper focuses on detection of human stress using two different but synchronized sources of information, human heart rate and sentiment extracted from tweets. During the preliminary experiment lasting for two fifty-day periods, we obtained simultaneously 481 708 heart rate data samples from two wearables and sentiment from 2049 tweets. The tweet data contain a subjective sentiment evaluation that was recorded using positive and negative hashtags. A few states of stress were identified as the result of the data processing. The final discussion provides conclusions and recommendations for future research.

1 INTRODUCTION

Detection of stress by using various techniques and methods is a complex problem that many research teams currently focus on. In our work, we build on their results and move it further.

We have designed an experiment and measured two following features: heart rate that gives us information on when stress occurs and human mood extracted as the sentiment from tweets.

These two information sources provide us with another view on stress dichotomy. When we know what kind of stress and when it occurs many applications with a medical base might be designed.

Our motivation and original idea which we want to expand and evaluate is coming from two cases of medical research which have used SMS as the treatment method in both cases and questionnaire (Montes J. M., 2012), or assessment and survey as the output (Agyapong V. I. O., 2015).

We think such methods can be enhanced by measured values or stress dichotomy to determine whether to continue with therapy when the subject is in a relax state or stop it when the subject is stressed out.

2 STATE OF THE ART

Stress is a mental state stemming from tension or demanding circumstances. These circumstances or tension is happening for different reasons (Mitra, 2008).

The paper published already in 1975 (Selye, 1975) provides a model dividing stress into eustress and distress. When the stress has positive effects such as tough training or challenging work it might be considered as eustress. On the other hand, the stress leading to anxiety or depression is considered as negative stress named distress.

The most commonly used physiological markers of stress are as follows (Vassanyi I., 2016):

- Galvanic skin response (GSR): using changes in skin conductivity. During stress, the resistance of skin drops increases due to secretion of sweating glands (Shi Yu D., 2007).
- Electromyogram (EMG): measuring the electrical activity of the muscles. Stress causes differences in the contraction of the muscles which can be used to identify stress (Melin B., 1994), (Wijsman J., 2010).
- Skin temperature: changes in temperature of the skin are related to the stress level (Tanaka S., 2008).

Salamon, J., Černá, K. and Moucček, R.
Stress Dichotomy using Heart Rate and Tweet Sentiment.
DOI: 10.5220/0006650105270532
In *Proceedings of the 11th International Joint Conference on Biomedical Engineering Systems and Technologies (BIOSTEC 2018) - Volume 5: HEALTHINF*, pages 527-532
ISBN: 978-989-758-281-3

- Electrical activity of the heart: the most commonly used stress marker parameters are derived from the electrocardiogram (ECG), heart rate (HR) and heart rate variability (HRV) (Spaepen A., 2009), (Schubert C., 2009).
- Respiration: acute stress causes changes in the breath rate (Choi J., 2009)
- Blood pressure: stressors induce an increase in the blood pressure compared to the baseline (Blangsted A. K., 2004).

Stress can be identified from HR or HRV using a variety of techniques and methods, for instance:

- Wearable monitors measure HR transformed to HRV that is processed by principal dynamic modes (PDM). By using machine learning classification, the stressful events were discriminated with a success rate of 83 % within subjects and 69 % of subjects (Choi J., 2009).
- A camera captures facial landmarks which are turned into physiological parameters (HR and HRV). Then the restful and stressful states, based on training and testing of a dataset used by a machine learning classifier, were predicted (Mcdu D., 2014).

In our ongoing research, we have been working with the HR captured from wearable monitors. This can be later transformed to HRV, but at the moment the HR itself is used. A piece of implicit information about the participant's mood recorded as a text (tweet) is available at the same time together with the HR data. It is enhanced by an explicit evaluation of the participant who marks his/her mood as positive or negative at the moment the text (tweet) is recorded. The use of the machine learning method for text classification is considered for further application.

From two datasets mentioned above and with the assumption that HR increases when healthy subjects are acutely stressed (Schubert C., 2009) the combination of a few states that includes increasing/decreasing HR and positive/negative sentiment can be identified. It could be used together with the eustress and distress definition (see above) for further research and application.

3 EXPERIMENT AND DATA

3.1 Experiment Description

Two parts of the experiment were held in two fifty-day periods using two wearables for the heart rate (HR) measurement:

- Fitbit Charge HR
- Basis Peak

During this time, not only the HR was recorded 24 hours a day, but also the text representing mood and recorded through the Twitter was obtained in two-time windows:

- 7:30 AM CET to 0:00 AM CET during working days,
- 9:00 AM CET to 0:00 AM CET during weekdays.

The text data contain the text itself and own subjective evaluation of the sentiment recorded using the hashtags #p for positive and #n for negative sentiment.

3.2 Data Description

The output of the experiment are two pairs of datasets (the HR data and tweets representing the sentiment for each wearable):

- 9:00 AM CET to 0:00 AM CET during weekdays.
- Experiment #1 using Fitbit Charge HR
  - 1029 tweets with the average of 20.56 tweets per day,
  - 411 799 HR records with the frequency of 6 - 7 records per minute
- Experiment #2 using Basis Peak
  - 1017 tweets with the average of 20.32 tweets per day,
  - 69 909 HR records with the frequency of 1 record per minute

3.3 Sentiment Extraction

In a real application, it is assumed to use an unsupervised sentiment classification method (for instance the classification method described in (Joulin A., 2016)). Since the work is primarily focused on stress dichotomy analysis and not on sentiment extraction, the subjective evaluation of the sentiment is used.

4 ANALYSYS

Since the data obtained from the experiment are two time-series with different granularity, this has to be solved by using the following procedures:

- to aggregate or reduce the HR data to the same granularity as the sentiment data has,
- to interpolate the sentiment data to achieve the same granularity as the HR data has.

Since the heart rate data is supposed to carry original information about stress, the sentiment data needs to be interpolated.

4.1 Sentiment Interpolation

During the sentiment interpolation process, it is necessary to de ne when the sentiment is supposed to be valid. Based on that several interpolation approaches can be used.

4.1.1 Interpolation by Splitting the Interval

The first option is to split the interval between two neighbourhood sentiment values and perform their interpolation (see Figure 1).

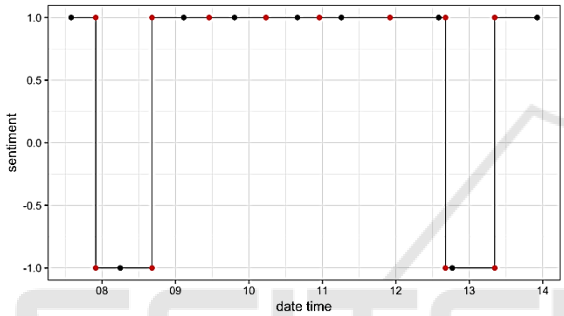

Figure 1: Sentiment interpolation by splitting the interval, the original sentiment is represented by the black points, each splitting of the interval between two black points is represented by the corresponding red points.

The original sentiment is represented by the black points in the graph. The interpolated sentiment is represented by the corresponding red points A and B calculated as

$$A = \{ts_A + \frac{(ts_B - ts_A)}{2}; s_A\} \quad (1)$$

$$B = \{ts_B - \frac{(ts_B - ts_A)}{2}; s_B\} \quad (2)$$

where ts is a timestamp, s represents information about the sentiment and $\forall ts: ts_B > ts_A$.

4.1.2 Interpolation by Moving Window

The second option is to de ne a window around each sentiment occurrence and perform the interpolation process inside this window (see Figure 2).

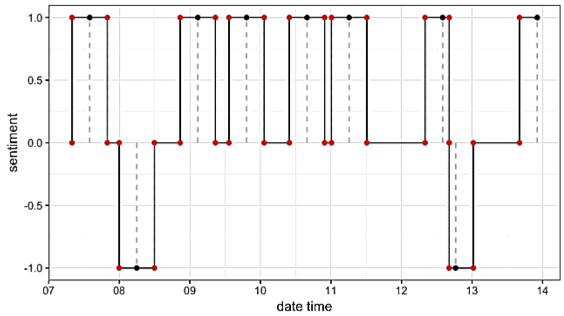

Figure 2: Sentiment interpolation using the moving window around the sentiment occurrence, the original sentiment is represented by the black points, the start and end points obtained by the interpolation are represented by corresponding red points.

The original sentiment is represented by the black points in the graph. The interpolated sentiment is represented by the corresponding red points A and B calculated as

$$A = \{ts_A - \frac{\Delta}{2}; s_A\} \quad (3)$$

$$B = \{ts_B + \frac{\Delta}{2}; s_B\} \quad (4)$$

where ts is a timestamp, s represents information about the sentiment and Δ is the length of the interpolation window (that is set to 30 minutes in our experiment).

4.1.3 Interpolation Notes

The first interpolation method results in an extended time window whenever the sentiment does not change. The second interpolation method is dependent on the width of the time window set around the sentiment occurrence. It is necessary to use the split interval approach (1) and (2) to overlap interpolation windows (3) and (4).

4.2 HR Linear Regression

When both data sources are properly combined the heart rate data can be simplified to express a decreasing or increasing trend. Simple linear regression (5) can be used to extract the trend from the HR data. The application of such statistical method assumes that

$$y_i = \alpha + \beta x_i + \varepsilon_i \quad (5)$$

which describes a line with the slope β and y-intercept α. From this equation, we can take slope, respective its signature as the HR trend (decreasing for the negative slope and increasing for the positive slope).

The results depicting the application of the simple linear regression to the HR data together with the interpolation of the sentiment by splitting the interval and interpolation of the sentiment by using the moving window are available in Figure 3 and Figure 4 respectively.

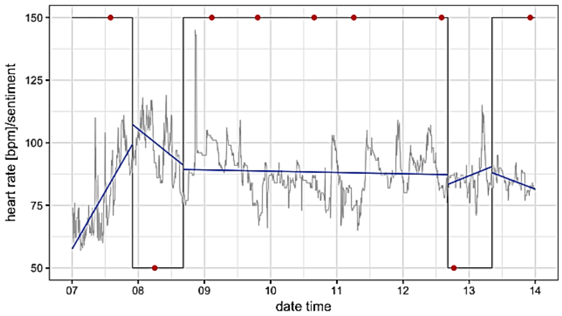

Figure 3: Splitting the interval sentiment interpolation combined with the HR data linear regression.

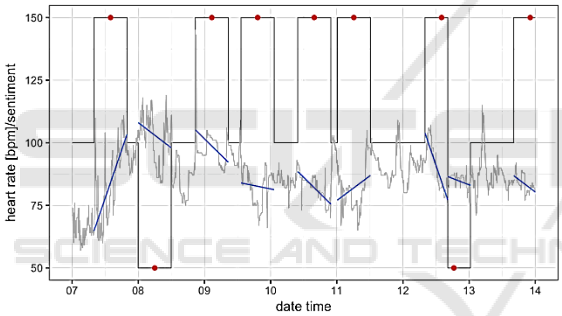

Figure 4: Moving window sentiment interpolation combined with the HR data linear regression.

4.3 Stress Dichotomy

Some approaches to stress identification have been already described in Section 2. Whenever HR increases, the subject could be in acute stress.

The primary goal of this work is to determine whether this stress is positive or negative. The combination of the interpolated sentiment with the trend of the HR data could help us to determine stress dichotomy. Using this approach stress and relax states can be identified from the heart rate trend and on top of that stress dichotomy can be identified from the sentiment (see Table 1).

Table 1: Stress and relax states identified by the heart rate trend and stress dichotomy identified from the sentiment.

	HR Trend	
	Decreasing	**Increasing**
Negative Sentiment	Relax	Distress
Positive Sentiment	Relax	Eustress

4.4 Results

The interpolation methods and simple linear regression were performed on the data from both experiments. Table 2 presents the detailed results, the numbers of distress, eustress and relax states are provided for each experiment and interpolation method.

Table 2: Stress and relax states for each experiment and interpolation method.

Experiment	Distress	Eustress	Relax	Total
#1 split	126 (12.2 %)	297 (28.9%)	606 (58.9%)	1029
#1 window	129 (12.6 %)	355 (34.6%)	541 (52.8%)	1025
#2 split	144 (14.2 %)	297 (29.2%)	576 (56.6%)	1017
#2 window	137 (13.5 %)	332 (32.6%)	548 (53.9%)	1017

From which we can calculate mean and standard deviation for distress, eustress and relax over all experiments and interpolation methods or per each of them as presents Table 3.

Table 3: Mean and standard deviation overall and per interpolation method and experiment for stress and relax states.

Mean ± SD	Distress	Eustress	Relax
Split interpolation	135 ± 12.7	297 ± 0	591 ± 21.2
Window interpolation	133 ± 5.7	343.5 ± 16.2	544.5 ± 5
Overall	134 ± 8.1 13 ± 0.9 %	320 ± 28.4 31 ± 2.8 %	568 ± 29.6 55.5 ± 2.8 %

5 CONCLUSIONS

5.1 Discussion

The relax state was identified on average in 55.5 % cases, distress in 13 % and eustress in 31 % cases. When we compare the average results with the results of individual experiments in which both interpolation methods were used we can see that the resulting values are similar. This could imply that the choice of the interpolation method does not significantly influence the determination of stress and relax states in this case.

On the other hand, the use of the interpolation by moving window gives us more flexibility. Compared to the interpolation by splitting the interval, we can experiment with the delta parameter and achieve a better fit of the linear regression method to improve the identification of stress dichotomy. We are fully aware of this matter, but the confirmation of such hypothesis can be achieved only with a bigger data sample in the following research.

5.2 Further Research

The presented approach and the preliminary results themselves are good starting points for further research.

It is evident that the method itself has several problems. For example, it describes the situation related to acute stress within the time window that is given by the sentiment interpolation window in which the linear regression applied to the HR data was performed. Since the stress state is supposed to be present in a time window around its occurrence, we can experiment with the length of the interpolation window.

Moreover, when using the simple linear regression, the regression fit was not calculated. This needs to be considered in the next work. Besides using the simple linear regression, we can also process the HR data by using the method of simple moving average (SMA).

Furthermore, the current study focuses on fairly simple signal pre-processing steps rather than using arguably more appropriate methods such as dynamic Bayesian networks (DBN) (Dagum P., 1992; Dagum P., 1995) and Hidden Markov Models (HMM) (Wahlström J., 2017).

About the related work on the topic of fusing social media and sensor data, we would also take into account existing research in similar fields such as (Farseev A., 2017) and (Choudhury M. De, 2017).

5.3 Further Data Collection

With a bigger and more rigorous experimental setup (multiple subjects of both genders and various age categories) would be possible to validate the presented results and make more generalizable conclusions.

The current approach of data collection and pre-processing is described in (Salamon J., 2017) including the description of heart rate devices accuracy. The accuracy of the used measurement devices and uncertainty is sufficient to determine the slope of the heart rate used in this paper.

Nevertheless, other experiments validated one of the devices (Fitbit Charge HR) with various results (Montoye A. H. K., 2017), (Dooley E. E., 2017) and (Boudreaux B. D., 2017). It leads to the conclusion the uncertainty modeling for more complex methods (such as DBN or HMM) needs to be considered for further research.

ACKNOWLEDGEMENTS

The work is supported by the UWB grant SGS-2016-018 Data and Software Engineering for Advanced Applications.

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