Happy Running?

Using an accelerometer to predict the affective state of a runner

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Abstract. This paper explores a method for deducing the affective state of runners using his/her movements. The movements are measured on the arm using a smartphone's built-in accelerometer. Multiple features are derived from the measured data. We studied which features are most predictive for the affective state by looking at the correlations between the features and the reported affect. We found that changes in runners' movement can be used to predict change in affective state.

Keywords: affect • emotion • accelerometer • smartphone • physical activity

1 Introduction

Knowing how an athlete feels can help a sports coach in communication and setting up a more tailored training schedule. Also a continuous measurement of the affective state would be advantageous for a automatic digital coaching system (coaching-app). Affective experiences in activities are usually measured using video recordings [1]. This is unpractical for everyday use. It would be more practical to use a smartphone worn by the athlete, making it possible for a coaching-app to use its affective state. We are developing a system that infers the affective state of a runner from the movement characteristics measured by the accelerometer sensor of a smartphone mounted on the arm. In this paper we present our work on the analysis of the accelerometer data: which movement features from the data correlate best with the perceived affective state?

2 Related work

Recent studies have shown that spatio-temporal body features are indicative for the affective state of a person [1].

In the field of running intensity has an influence on the affective state. Continuous running above the ventilatory threshold (the point during exercise at which respiration starts to increase at a faster rate) changes the affective experience negatively. Running below the ventilatory threshold has little influence on the affective state. [2]

Accelerometers can be used at various places on the body to determine type of activity. The raw signal can be transformed into features and used as an indicator for an activity. [3]

3 Experimental Set-up and Data

We created a dataset consisting of accelerometer data from a smartphone worn by the runners and affective state reported by the runners. Test subjects ran on a treadmill on their ventilatory threshold until they were tired. The threshold was determined for each runner separately in a previous session based on the method of Bood et al. [4]. Running speed, heart rate, movement, ability to talk, perceived exertion and perceived affective state are measured. The data collection was part of a larger experiment. This study uses the accelerometer data and perceived affective state.

Movement was measured using a smartphone's (Google Nexus 5) three degrees of freedom accelerometer (with a sample rate of 100Hz), worn by the runner in a band on the left arm. The phone's X-axis measured forward movement, the Y-axis measured vertical movement and the Z-axis measured sideways movement. Perceived affective state was measured with the 11-point Feeling scale [5] by verbal expression of the subject once every two minutes while running. The questionnaire was displayed on a screen in front of the user.

Eighteen runners participated, four male, fourteen female, with an average age of 23 years (STD 3 years). They ran an average of 16,6 minutes (STD 5 minutes) of which an average of 8 minutes at a constant speed. In total 96 affective responses were given while running at constant speed.

4 Feature extraction

We were interested in features related to the intensity of the movement and to the regularity of the movement. Corresponding to each affective response a data sample of 12000 data points (two minutes of data) was created from the movement signal. The data was transformed with a Hanning-window. For each sample the mean of the signal, the variance of the signal and the entropy of the Fourier transform were determined. We used the individual X-, Y- and Z-axes of the accelerometer as signals. In total we had nine features (three axes times three features) for every time sample.

5 Results

Figure 1a shows the reported affect for the participants as a function of time during the eight minutes of constant speed. All participants show the expected tendency towards negative affect as described by [2]. However, we also observe inter-person differences: some participants report a structural higher affect than others.

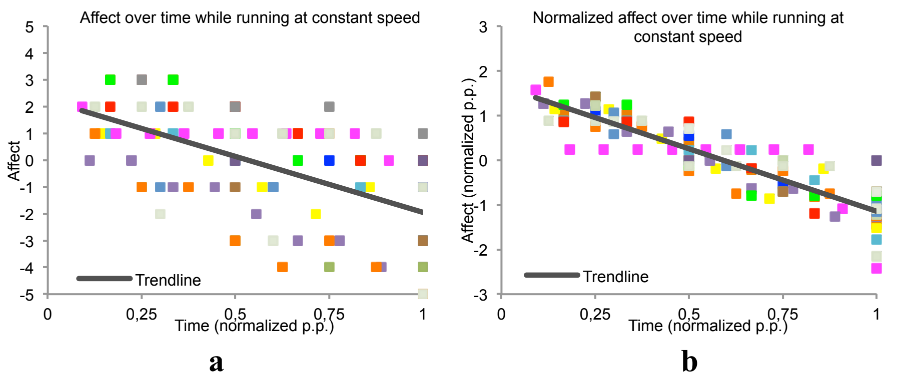

Fig. 1. a. Affective responses as a function of time.

b. Normalized affective responses as a function of time.

In our first approach we determine correlations between the reported affect and the nine accelerometer features. We determined the p values using an independent sample size of 18 (the total number of participants). Overall the correlation values are low. The highest correlation value can be found in the mean of the X-axis (-0,20) with a p value of 0,42. The correlation values are displayed in table 1. One reason for the low correlation can be the inter-person differences, both in affect as in feature values.

Feature	r	p	Feature	r	p	Feature	r	p
Mean X	-0,2	0,42	Mean Y	0,05	0,85	Mean Z	-0,07	0,79
Variance X	-0,17	0,51	Variance Y	-0,005	0,98	Variance Z	0,01	0,97
Entropy X	0,09	0,72	Entropy Y	-0,01	0,98	Entropy Z	-0,19	0,46

Table 1. Correlation of features with affect. r = correlation value. p = significance

Feature	r	p	Feature	r	p	Feature	r	p
Mean X	-0,07	0,78	Mean Y	0,27	0,28	Mean Z	0,25	0,32
Variance X	-0,52	0,03	Variance Y	-0,38	0,12	Variance Z	-0,74	4,03×10-4
Entropy X	-0,11	0,66	Entropy Y	-0,03	0,89	Entropy Z	-0,03	0,91

Table 2. Correlation of normalized features with normalized affect. r = correlation value. p = significance

In order to filter out individual characteristics, the feature values and affect values are standardized using Z-score normalization for each individual participant. Normalized affective responses are depicted in figure 1b. We determine the most likely indicative features by calculating the correlation between each feature and the affective response. The highest correlation value can be found in the variance of the Z-axis (which indicates the sideways movement of the phone) with a p value of $4{,}03 \times 10^{-4}$ and the variance of the X-axis (which indicates the forward movement of the phone) with a p value of 0,03. The correlation values are displayed in table 2.

6 Conclusion

We observe that the inter-person characteristics on affective response are large and that the absolute affect is hard to predict from the accelerometer data. When using normalized response data, a strong inverse correlation between affective state and the runners' forward and sideways movement characteristics is observed. The low correlation values of the Y-axis features show that vertical movement characteristics do not change sufficiently in relation to affective state.

We measured movement on the arm and not on other parts of the body, therefore we cannot determine if the movement is specific for the arm or for the whole body.

Concluding, our model can be used to detect changes in affective state based on changes in movement. Using the accelerometer sensor of a smartphone, our model can be applied in a digital coaching-app.

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