# Poster: Interest Detection While Reading Newspaper Articles by Utilizing a Physiological Sensing Wristband

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## Abstract

In this paper, we present how physiological measures including heart rate (HR), electrodermal activity (EDA) and blood volume pulse (BVP) can be retrieved from a wristband device like an E4 wristband and further used to detect the interest of a user during a reading task. From the data of 13 university students on 18 newspaper articles, we have classified their interest level into four classes with an accuracy of 50%, and 68% with binary classification (interesting or boring). This research can be incorporated in the real-time prediction of a user's interest while reading, for the betterment of future designs of human-document interaction.

## Author Keywords

Reading; interest; heart rate; blood volume pulse; skin temperature; inter-beat interval; electrodermal activity

## ACM Classification Keywords

H.5.0 [Information interfaces and presentation (e.g., HCI)]: General

## Introduction

Interest in reading is built with concentration, curiosity, and demand. It may not rise out of habit but it will help motivate the habit and subsequently the learning process [8]. The urge in reading, if recognized, can be used to improve the data made available to the reader and also help in better

**Figure 1:** E4 wristband and signals

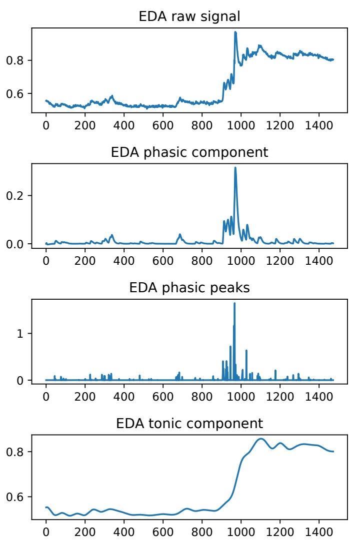


**Figure 2:** The decomposition of an EDA signal by cvxEDA algorithm

human-document interaction and the design. Predicting a reader's interest can help to make document more interactive or dynamic [1, 4]. Wearable devices like the E4 wristband [1] are unobtrusive and will assist in the real-time monitoring/gathering of physiological data. The E4 wristband can also be used for monitoring signals during reading from paper as well as a computer screen.

In this paper, we pursue to study a reader's interest and its association to a physiological wristband measured features like heart rate, blood volume pulse, electrodermal activity and arm temperature. Research questions addressed in this study are two-fold. RQ1: What useful features can be extracted from the physiological data obtained from a wearable, RQ2: How accurately can HR, BVP, EDA, and TEMP estimate a reader's interest?

## Background of Physiological Sensing

Electrodermal activity (EDA) refers to the autonomic changes in the electrical properties of the skin. It is a physiological signal which reliably represents the sympathetic nervous system (SNS) and hence can be used to assess the human emotional state. EDA is composed of a low frequency tonic component which includes slow drifts of the baseline skin conductance level and spontaneous fluctuations in the component; and a high frequency phasic component i.e., the skin conductance response (SCR), reflects the short-time response to the stimulus.

EDA has been closely associated with emotional and cognitive processing, and also used as a sensitivity index for emotional processing and sympathetic activity [2]. Implicit emotional responses that may occur unconsciously like threat, anticipation, salience, novelty; can be examined using EDA. Analysis of the data by Setz et al. showed that the EDA peak height and the instantaneous peak rate depict the stress level of a person [7].

Blood volume pulse (BVP) is the change in volume of blood over a given period of time. Certain emotions can trigger the release of hormones, such as epinephrine and norepinephrine, which will increase blood flow to bring more oxygen to the muscles. BVP can be monitored using photoplethysmography (PPG) which is a non-invasive technique that relies on light absorption and reflection. The signals detected will form a wave, which represent the change in blood volume proportional to the heart rate. Adjacent local peaks from this wave indicates heart beats and the time interval between these peaks is the inter-beat interval (IBI). Heart rate, IBI and BVP has been associated with frustration and anxiety [5].

## Approach

We utilize E4 for to measure a user's behavior. It is used for the acquisition of real-time physiological data with the help of sensors designed to gather high-quality data. It has a *PPG sensor* which measures BVP, an *EDA sensor* to measure electrical properties of the skin, an *infrared thermopile* to measure skin temperature.

We decompose a raw EDA signal to the phasic and tonic component as shown in Figure 2 by utilizing *cvxEDA* algorithm [3]. Then the following 6 features are calculated from the components. (1) the slope of the tonic part of the signal for which the slope of the line of best fit was used (Linear Regression), (2) EPC - sum of all positive EDA changes, (3) Minimum peak amplitude of the phasic signal, (4) Maximum peak amplitude of the phasic signal, (5) Mean amplitude of the phasic signal and (6)Number of phasic responses [6].

The Empatica developer SDK includes a sample application which calculates IBI values from the wristband. However,

[1] https://www.empatica.com/research/e4/

| No. | feature |
|---|---|
| 1 | Slope of the tonic component |
| 2 | EPC - number of positive EDA changes |
| 3, 4 | {Min, max} peak amplitude in the phasic component |
| 5 | Mean amplitude of the phasic component |
| 6 | Number of phasic responses |
| 7, 8 | {Mean,SD} of BVP |
| 9, 10 | {Mean, SD} of HR |
| 11, 12 | Difference in {mean, SD} of HR amplitude during task and baseline |
| 13 | SD of IBI normalized by baseline |
| 14 | RMSSD between IBI normalized by baseline |
| 15, 16 | {Mean, SD} of temperature |
| 17 | Mean difference of temperture with baseline |
| 18 | Slope of temperature |

**Table 1:** List of features

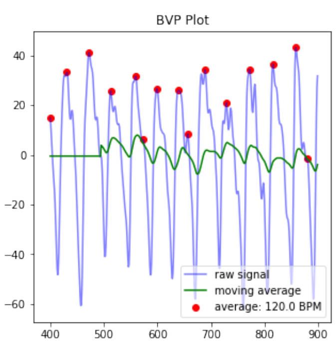


**Figure 3:** Peak detection on BVP signal over the moving average.

this was not very reliable since even the smallest of movement artifacts resulted in getting no IBI data at all. Hence, the blood volume pulse data was used to retrieve HR and IBI. BVP data comprises of peaks called $R$-peaks which can be detected by determining the region of interest for each $R$-peak. A moving average is calculated so that the region of interest will lie above this. The highest point of the retrieved region of interest is the position of the peak in the BVP signal (see Figure 3). The time interval in milliseconds between the $R$-peaks is the inter beat interval and 60/IBI is the heart rate. To further smoothen the signal, the Butterworth low-pass filter was used before the peak detection.

Features relevant to HR, IBI and BVP are extracted from the data. The features used are - (7, 8) mean and standard deviation of BVP, (9, 10) mean and standard deviation of HR, (11, 12) difference in mean and standard deviation of HR amplitude during task and baseline, (13) standard deviation of IBI normalized by baseline (data recorded 5 seconds before start), (14) RMSSD - square root of the mean of the square of the successive differences between IBI. Features from skin temperature recorded by the wearable are also included namely, (15, 16) mean and standard deviation of skin temperature, (17) difference in mean of temperature during task and baseline, and (18) slope of temperature.

## Experiment

In order to evaluate our proposed interest detection method, we conducted an experiment. The following section describes the experimental design and the analysis results.

*Experimental design*

Thirteen university students (mean age: 25, std: 3, male: 6, female: 7, 2 of them are familiar with sensors) participated in the experiment where each of them was asked to read eighteen newspaper articles comprising of 403 - 649 words each (mean: 555, std: 70) with wearing E4. After reading each document, participants answered questions regarding their interest and objective comprehension; (1) the level of interest they had in the article, which was used as ground truth (from 1 to 4, where 1 indicated ’No interest’ and 4 indicated ’High interest’), (2) one question on the article (i.e., objective comprehension).

We followed three different approaches to separate the train-test data before classification. *Leave-one-recording-out* (LORO) uses each recording (data of each participant on each document) as test data, the rest as training and the average of the accuracy in all cases together is taken as the classification accuracy. Similar to this approach, *leave-one-document-out* (LODO) approach exempts the data of a document completely from the training set and uses it for testing. *Leave-one-participant-out* (LOPO) approach uses the data from all participants except one as training.

*Results and Discussion*

Table 2 represents the classification accuracies using the SVM classifier with hyper parameters C: 4, gamma: 0.18 and kernel: Radial Basis Function. We also incorporated feature reduction techniques like PCA (Principle component analysis) and LDA (Linear discriminant analysis), but found no commendable improvement in the classification.

We eliminated features like - maximum phasic peak, mean BVP and standard deviation of temperature; as SVC performs better with a reduced feature set. A backward stepwise approach was used for this purpose, where each feature was iteratively removed to achieve better classification results. We also removed records pertaining to document number 16 as only one of the participants had correctly answered the objective question, which suggests that participants did not comprehend the document as expected.

|  | 2-class | 4-class |
|---|---|---|
| LOPO | 52 | 37 |
| LODO | 63 | 46 |
| LORO | 68 | 50 |

**Table 2:** Classification accuracies using SVM and features from E4

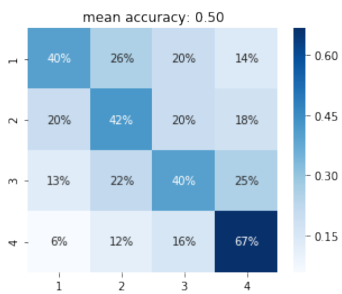


**Figure 4:** Confusion matrix with 50% accuracy for four-class SVC. 68% accuracy for binary classification (1 and 2 vs. 3 and 4)

An accuracy of 50% was achieved by using a 4 class SVM classifier (Figure 4) and 68% was achieved for binary classification using cross validation and the leave one recording out approach (LORO).

## Conclusion

Although the accuracies were not as high as expected, this research threw light on the features that could be extracted from the physiological data from a wearable device and its role in predicting the cognitive state of the reader. The collection of ground truth related to interest and understanding are widely prone to human error and individual behavior, which is also a reason for the low accuracies.

This study brought to light that physiological signal can be used to analyze cognitive states of a person with a minimum accuracy of 68%. With prolonged analysis, filtering, extraction and better data acquisition, physiological data collected by a wristband can provide better classification results while not only reading but aid in affective computing during social activities, driving, and in work environments.

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