# Activity and stress monitoring using smartphone and wrist device

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**Abstract.** It is well known that physical and mental health are closely related and impact the overall quality of life simultaneously. Therefore, both these areas should be tackled together. In this paper we propose a smartphone application capable of monitoring physical activity and mental stress. The application consists of two machine learning modules, an activity recognition (AR) module and a stress detection module. The AR module continuously recognizes user's activity using accelerometer data and additional information such as phone orientation and location, with accuracy of 91%. The recognized activities are summarized and presented to the user including health advices, and are also fed to the second module of the application, the stress detection module. The stress detection module, in addition to the information provided by the AR module, uses data provided by a commercial wrist device equipped with standard bio-sensors and an accelerometer. The stress detection module was trained on 21 subjects in a laboratory setting and tested on 5 subjects in a real-life setting achieving accuracy of 92% for detection of stressful events.

**Keywords**: Activity recognition, stress detection, machine learning, sensors, wrist device.

## 1 Introduction

Regular physical activity can have a positive impact on one's life, yet only a small fraction of the modern population exercises sufficiently. To appropriately motivate people for increasing their physical activity, it is important to quantify it first. Modern phones are equipped with a variety of sensors that can constantly track the user, allowing us to deduce much about his/hers behavior. An average smart phone, which most people already have, contains a tri-axial accelerometer, making it arguably the most convenient device to use for this task.

The first goal of our work was to detect person's basic activities, such as standing, sitting, walking, running, etc. with the information available on his/hers mobile phone. To do so, we first determine phone's orientation, relative to the user, and location of wear. Using that information in addition to the accelerometer data we show that user's current activity can be accurately determined. We enhance the application by allowing the user to wear an optional wristband, which provides additional data to the module. AR is a mature area of research that many have attempted with different wearable sensors [12]. AR using a smart phone device has also already been attempted [13]. Our improvement to the other smart phone solutions is that we explicitly calculate phone's location and use specialized classifiers for that location.

The second goal of our work was to implement a stress-detection module which complemented with the AR module (providing physical health care) would provide a mental health care to the users. The need for health monitoring was confirmed by the European Commission by estimating the costs of work-related stress at €20 billion a year due to absence from work and decreased productivity [1]. Therefore, a stress-detection module in combination with an AR module would be useful for self-management of mental and physical health of workers [3], students and others in the stressful environment of today's world.

Thanks to the recent technological advances, some of the "fight-or-flight" components (stress-response components) [11] can be captured using an unobtrusive wrist device equipped with sensors, e.g., Empatica [14] or Microsoft Band [17]. Our method for stress direction is also based on the data captured by such a device, on which we use advanced machine learning (ML) in combination with context information provided by the AR module.

Since 2005, when Healey and Picard who showed that stress can be detected using physiological sensors [5], various studies were conducted to implement stress detection using a combination of signal processing and ML. The problem of stress detection was first analyzed in constrained environments such as a laboratory/office [10], car [5], and call center [6]. Some approaches in which the subjects were allowed to be active based on a predefined scenario came one step closer to the real world [9]. Most recently Hovsepian et al. [7] proposed cStress, a method for continuous stress assessment in real-life using a chest belt. Similarly, our stress detection method is tested in real life, but instead of a chest belt we use a commercial wrist device. As future work Hovsepian et al. [7] suggested better handling of physical activity (which can confuse stress detection) and including context information in the process of stress detection – which is what we have done by combining the stress detection module with an AR.. By combining the two modules we were able to implement a smartphone application for monitoring physical and mental health which is used in several projects [3][15][16].

In the next section we describe the two modules for activity recognition and stress detection, next we present experimental results and finally we present a discussion and conclusion.

## 2 Methods

In this section we are describing the AR and stress-detection modules which were developed and evaluated separately, and then combined in a fully functional Android application.

### 2.1 Activity recognition module

In this module we use ML classifiers to detect activities from accelerometer data. Our approach differs from the related work by explicitly determining phone's orientation and location of wear. Knowing phone's orientation allows to normalize the accelerometer data, so no requirement is placed on the user on how is he to wear his phone. Secondly, since every location of wear (trouser pocket, breast and bag) has different pattern of movement, a specialized classifier is used in each case. Our activity recognition module works in the following way:

1.) If the wrist device is detected, its accelerometer is used instead of phone's accelerometer. In this case, a wrist-device specific classifier is used.

2.) If the phone orientation and location of wear are unknown (at the beginning of application usage), a general orientation and location independent classifier is used.
3.) If a general classifier detects walking segment, orientation and location are calculated. Every location of wear (trouser pocket, breast, bag) has different pattern of walking that a dedicated classifier can learn to detect. Phone's orientation can be determined by its perceived direction of gravity (average of all accelerometer measurements approximates gravity vector). Knowing orientation, data is normalized by translation into an appropriately rotated coordinate system.
4.) If location is known, a location specific AR classifier is used.
5.) If the phone is detected as not worn (simple heuristics: screen is lit, phone is still for too long, phone detects light, etc.), orientation and location reset.

To implement this module, we needed to train 6 different classifiers. To do so, we created an AR learning dataset by measuring ten different people. Each had to follow a fixed scenario that lasted for roughly an hour. In this scenario the subject performed different activities that we aimed to recognize. Accelerometer data was captured by Microsoft Band and three phones (Samsung S4), each worn on a different body location: trouser pocket, breast pocket, bag. True labels of the activities were marked during the experiment. The accelerometer frequency was 50 Hz. The data was then split into 2-second windows. Each window became one instance, totaling to around 80000 instances. We started with 88 features per instance, including signal average, min, max, standard deviation, kurtosis, skewness, correlation between axis, number of times the signal crosses its mean, integral of the signal and also some features in the frequency domain. Using a feature selection technique (features were ranked with ReliefF algorithm, and then iteratively added to the set, until classification accuracy stopped increasing) the number of attributes was narrowed down to 20-40 (depending on the task). For each required task we then used ML to create an SVM [19] classifier for AR.

## 2.2 Stress detection module

For implementation and evaluation of the stress detection module (Figure 1) two datasets were recorded, a laboratory dataset, which included 21 subjects, and a real-life dataset, which included 5 subjects. In both datasets the Empatica wrist device was used to collect data. The Empatica wrist device provides heart rate (HR), blood volume pulse (BVP), galvanic skin response (GSR), skin temperature (ST), time between heartbeats (RR intervals) and accelerometer data. For the laboratory data we used a standardized stress-inducing experiment as proposed by Dedovic et al. [2]. The main stressor was solving a mental arithmetic task under time and evaluation pressure. For the real-life data, five subjects were wearing the wrist device and were keeping track of their stressful events.

On the laboratory data, a laboratory stress detector is built using ML. The laboratory stress detector distinguishes stressful vs. non-stressful events using 4-minute data windows with a 2-minute overlap. For each data window of 4 minutes, features for stress detection are computed. From each physiological signal (BVP, HR ST and GSR), statistical and regression features are computed: mean, standard deviation, quartiles, quartile deviation, slope and intercept. Additional features to quantify the GSR response are computed with an algorithm for peak detection [8]. For the RR signal, we use features obtained through heart-rate-variability analysis in the frequency and time domain. These features are fed into a classifier trained with the Random Forest [18] ML algorithm, which was chosen experimentally by comparing performance measures (precision, recall, accuracy) of several ML algorithms.


**Figure 1.** Context-based output with LOSO evaluation.

On the real-life data, a context-based stress detector is built. The context-based stress detector was introduced to distinguish between genuine stress in real life and many situations which induce a similar physiological arousal (e.g., exercise, eating, hot weather, etc.). As features, it uses the distribution of the last 10 outputs of the laboratory stress detector, the previous output of the context-based detector, and context features: whether there was any high-level activity in the last 20 minutes, the hour of the day, the type of the day – workday/weekend, etc. It classifies every 20 minutes as stressful or non-stressful. The context-based stress detector was trained with the SVM ML algorithm, which was again chosen experimentally by comparing performance measures (precision, recall, accuracy) of several ML algorithms.

## 3 Experimental results

In this section we present experimental results for the two modules, AR and stress detection. The AR module was evaluated on the AR dataset which consists of ten different people performing fixed activity scenario that lasted for roughly an hour. The stress-detection module was evaluated on the real-life data which summarizes in 55 days of data from five subjects. "Leave-one-person-out" (LOSO) evaluation method was used. That means that one subject is left out for testing, the rest data is used for learning and the results are averaged.

### 3.1 Experimental results for activity recognition

Each task was evaluated separately using LOSO evaluation technique. The results are listed in Table 1. They show accuracy for task. Note that activities that are classified depend on the phone's location, as some activities sometimes cannot be distinguished (for example: “sitting” and “standing” when the phone is in your breast pocket). As an example, the last row shows that when using data provided by the wrist device, the AR module achieves accuracy of 92,7% when distinguishing the activities walking, running, standing, sitting and cycling.

**Table 1.** LOSO evaluation for AR

| Task | # | Class values | Accuracy % |
|---|---|---|---|
| **Location** | **31** | **trouser pocket,<br>breast pocket, bag** | **85.8** |
| **Activity<br>No location** | **14** | **walking, running, cycling, other** | **92.2** |
| **Activity<br>Breast Pocket** | **19** | **walking, running, cycling, upright, lying** | **92** |
| **Activity<br>Bag** | **21** | **walking, running** | **92.5** |
| **Activity<br>Trouser pocket** | **26** | **walking, running<br>cycling, standing,** | **89** |
| **Activity**<br>Band | **40** | **walking, running, standing, sitting, cycling,** | **92.7** |

### 3.2 Experimental results for stress detection

The evaluation of the stress-detection module was performed on the real-life data. Because labeling stress is quite subjective [10] and it is almost impossible to strictly define starts and ends of stressful situations, we split the stream of real-life data into discrete events. Each event had a minimum length of one hour. If there was a stressful situation in the event (labelled by the user), the event's duration was extended to capture the stressful situation plus one hour before and after the situation. By this, we allow for a labeling lag of one hour. The 55 days of the real-life data was split into nearly 900 events, each lasting at least an hour.

Table 2 presents the confusion matrices for the event-based evaluation using leave-one-subject-out (LOSO) cross-validation. On the left are the results for classification without context (based only on the predictions of the laboratory stress detector) and on the right are the results for the context-based stress detector. The accuracy achieved by the context-based stress detector (for distinguishing stressful vs. non-stressful events) is 92%, which is for 16 percentage points better than the no-context classifier.

**Table 2.** Confusion matrices for event-based evaluation. Context vs. no-context.

| | No Context | | With context | |
|---|---|---|---|---|
| | **0** | **1** | **0** | **1** |
| **0** | 638 | 175 | 790 | 23 |
| **1** | 44 | 70 | 51 | 63 |
| **Recall** | **78%** | **61%** | **97%** | **55%** |
| **Prec.** | **94%** | **29%** | **94%** | **73%** |
| **F1** | **85%** | **39%** | **96%** | **63%** |
| **Acc.** | **76%** | | **92%** | |

Additionally, Figure 2 depicts the output of the context-based stress detector for the real-life dataset. On the x-axis is the day, on the y-axis is the hour of the day, the black stripes label to which subject belongs the data, and the colored squares correspond to the false positive (FP), false negative (FN), true positive (TP) and true negative events (TN). From the figure it can be seen that subject 1 (S1) has many

FN events, and subject 2 (S3) has many FP events compared to the rest of the subjects.

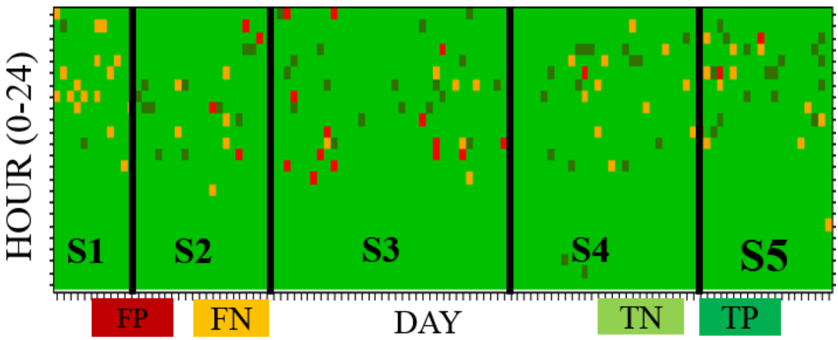


**Figure 2.** Context-based output with LOSO evaluation.

## 4 Discussion and conclusion

In this work we presented our modules for AR and stress detection. Both are implemented as an Android application (Figure 3) currently used in the Fit4Work project [3]. Our AR approach was additionally used in the projects Commodity12 [15] and E-Gibalec [16]. The AR experimental results were quite encouraging and comparable to other similar works [13]. In contrast to most other work, we are able to differentiate between "lying", "sitting" and "standing" with phone alone. It also works robustly in practice independently on where and how the user wears the phone.

The stress detection module continuously tracks stress in real time, which makes it different from other related approaches. By introducing a context-based classifier we provided more information about real-life circumstances and the user, which improved the detection performance compared to no-context approach. The experimental results for stress detection show that there is still room for improvement, but they are encouraging for such a challenging problem. For now, the context-based stress detector receives information from the laboratory stress detector and from the activity recognizer. Additional context information can be provided from other components that recognize events which induce similar physiological arousal to a stress event (e.g., exercise, eating, hot weather etc.).

Because stress is quite subjective and perceived differently by different subjects, we also plan to implement personalization to allow to the general model to adapt to new users. The need for personalization was confirmed by the visualization in Figure 1, where it can be seen that distribution and the type of the classification errors (e.g., FP vs. FN) is subject-specific.


**Figure 3.** Smartphone application for physical (left) and mental (right) health monitoring.

Future work on the topic will also be focused on phone energy efficiency, as draining the battery too quickly is a major limitation in the practical use for such application.

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## For wider interest

Physical and mental health are closely related and impact the overall quality of life simultaneously. The need for health monitoring was confirmed by the European Commission by estimating the costs of work-related stress at €20 billion a year due to absence from work and decreased productivity.

Regular physical activity has a positive impact on one's life, yet only a small fraction of the modern population exercises sufficiently. To appropriately motivate people for increasing their physical activity, it is important to quantify it first. Similarly, the stressful environment of today's world introduces another problem, stress, which should be addressed in order to prevent negative health consequences of chronic stress.

We propose a smartphone application capable of monitoring physical activity and mental stress using data provided from smartphone sensors and a commercial wrist device. The application consists of two modules, an activity recognition (AR) module and a stress detection module. The AR module continuously recognizes user's activity with accuracy of 91%.

The stress detection module uses data provided by the AR module and a commercial wrist device equipped with standard bio-sensors and an accelerometer. The stress detection module was trained on 21 subjects in a laboratory setting and tested on five subjects in a real-life setting achieving accuracy of 92% for detection of stressful events.