# Detecting and Locating Stress in Urban Settings with ChillIn

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**Abstract.** In modern society, stress has become one of the main issues affecting both mental and physical health. The ability to detect stress can help people to improve their daily life. This work proposes ChillIn, a mobile application designed to track and localize stress in an urban environment. The application is based on a single wearable device and its sensors to track stress within urban environments, correlating the data acquired with geographic locations, and highlighting areas of a city that tend to induce stress. Preliminary tests show that ChillIn can help in understanding which are the urban areas where citizens are more stressed, for example to understand if traffic or transportation modes play a role from this point of view. ChillIn has a small impact on the battery duration of the wearable device and runs on a commercially available smartwatch.

**Keywords:** urban stress · wearable sensors · well-being · stress detection

## 1 Introduction

Stress is one of the principal causes affecting the quality of life in urban areas [13]. The urban context often exposes individuals to stressors, originating from factors such as traffic, noise pollution, and social or economic pressure [2]. Effective stress detection can significantly improve mental and physical health outcomes. An effective means of detecting stress is represented by wearable devices, which can unobtrusively collect physiological signals and users' behavior. Locating where stress is concentrated in an urban area is particularly important, as it provides information useful to possibly identify the sources of stress and then act

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to mitigate the problem. For example, suppose many pedestrian citizens experience stress when walking along a road characterized by high levels of vehicular traffic. In that case, city authorities can make informed decisions when planning changes to vehicular routes, or an alternative and more pedestrian-friendly route could be suggested by navigation apps. The relationship between stress and urbanicity has been extensively studied in the past, but only recently the availability of biosensing technologies made it possible to capture and quantify geolocated markers of stress in an urban setting. An interdisciplinary research area, neurourbanism, has been called for studying the relationship between mental wellbeing and urbanisation [1]. Collecting biosignals can be useful together with narrative data, collected for instance through interviews, to better understand causal relationships and highlight relevant information, going beyond a purely quantitative estimation [10].

This work proposes ChillIn, an application to visualize stress hotspots on a map. ChillIn exploits commercially available wearable devices to collect physiological data. A remote server is used to offload the estimation of the possible stress level experienced by the user starting from the raw data. As the physiological data is collected using battery-operated wearable devices, the proposed method has been designed to be energy-efficient.

The remaining of this work is organized as follows: Sect. 2 summarizes the most significant related work, Sect. 3 shows the details of the proposed application, Sect. 4 shows the results of preliminary analysis, and finally Sect. 5 concludes the paper and discusses potential future directions.

## 2 Related Works

The relationship between cyclists and stress was studied in [21]. In particular, the impact of cycling infrastructure, such as the presence of segregated cycling paths or intersections, was evaluated by measuring stress biomarkers using an experimental smartband for collecting skin conductivity and temperature. The level of pedestrian stress was also the focus of studies, such as in [10] where stress was evaluated by collecting interviews. The results showed that attributes of physical infrastructure and traffic conditions influenced stress levels. In [11], the level of stress was monitored by collecting Galvanic Skin Response (GSR), also known as ElectroDermal Activity (EDA), and skin temperature values using an Empatica E4 wristband; experimental results showed the relationship between stress and urban walkability, cycling lanes, and commuting. The stress of cyclists in different road environment was also studied using Heart Rate Variability (HRV) [6]. The relationship between noise, transportation mode, and stress was studied in [24], where the involved subjects self-reported the stress levels experienced during transportation.

A review of measurement approaches for physiological stress monitoring is available in [8], while [20] proposes an exhaustive review on stress detection with wearable devices. Obtaining physiologic data is one of the most important tasks for stress detection. Information useful to detect stress, as already mentioned,

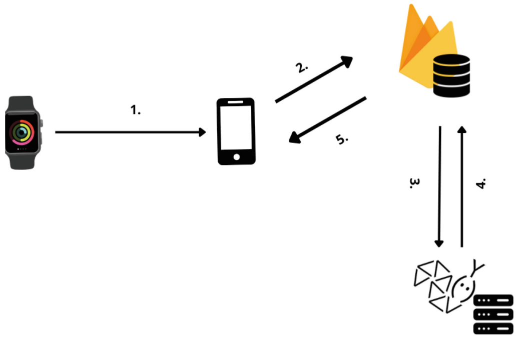


**Fig. 1.** Flow of data between the main components of the ChillIn app.

includes EDA [12,15] and heart rate [17]. Other approaches have been based on using infrared cameras [7] and speech analysis [22]. Even the way users type on their smartphones, measured with an accelerometer, can be used as a stress detector [19].

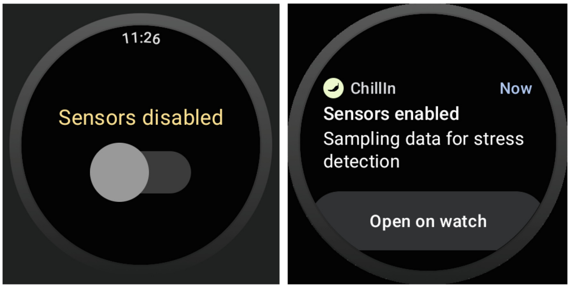
A significant research body tries to address the problem of detecting stress when working, as its reduction is expected to have a relevant economic impact on companies. For example, in [18] an approach is proposed to monitor stress during work hours by combining information from a wearable device and the interaction between the subjects and their computers. In [14], face position, sleep habits, and eating/drinking behavior are used for stress detection. A system for improving work productivity that includes human factors, such as stress, is tested in [5] exploiting a sensor-equipped T-shirt for body signals acquisition.

Our work differs from the previously mentioned ones because it involves an urban setting where the users freely move according to their daily habits. The final goal is the detection of the urban areas that are characterized by higher stress levels, to drive urban planning and transportation strategies according to stress-relieving policies. The system has been implemented using commercial smartwatches, to ease the transition from research to real-world applications of urban stress monitoring. Commercial devices also allow a more naturalistic approach, since users are not forced to wear medical, and more cumbersome, acquisition systems.

## 3 ChillIn Architecture

The system comprises four components: the wearable device, the handled device, the remote service, and the database. The flow of data among the components, shown in Fig. 1, is the following:

1. The wearable device collects the sensed data and sends them to the handheld device through a synchronization channel.
2. The handheld device sends the raw data to a database hosted in the cloud.



Sensors enabled
Sampling data for stress detection

**Fig. 2.** User interface on the smartwatch.

3. A remote service gets the raw data from the database and analyzes the data to estimate the stress level.
4. The remote service stores the information about the stress level and related positions in the urban area in the database.
5. The handheld device retrieves information about the geolocated stress level from the database and shows it to the user.

### 3.1 Wearable Device Application

The wearable device, a smartwatch, collects data from three sensors: skin temperature, heart rate, and EDA. The latter undergoes low-pass filtering and high-pass filtering phases to extract the phasic component of the signal, which is the fundamental part of stress detection. These data are saved with a frequency of 1 Hz to reduce battery consumption and extend the usage of the application. Moreover, the wearable device aggregates 30 samples into a single message sent to the handheld device to further optimize battery consumption, as sending a single message with a larger payload is generally less expensive than sending many small messages (because of the overhead introduced by the layers of the communication stack and the transceiver operational states [3,4,23]). The data for stress detection is paired with the location of the user, acquired with the GPS sensor of the wearable device. The frequency of the location acquisition changes dynamically, adapting to the current speed of the user: if the user is moving at high speed (e.g. the user is driving a car), the location is collected with high frequency, on the contrary, if the user is not moving, the location is collected with a lower frequency. More precisely, the device evaluates the time required to cover 100 m with the current speed of the user and sets this time as the interval between two subsequent location updates. A maximum value of 60 s for the sampling period is used if the user moves too slowly. The wearable device relies on the Google Wearable Data Layer APIs to communicate with the paired smartphone. The app running on the smartwatch provides a simple user interface, shown in Fig. 2, with a single button that enables/disables the sampling of the sensors, in order to allow users to avoid being monitored for instance when involved in privacy-related activities.

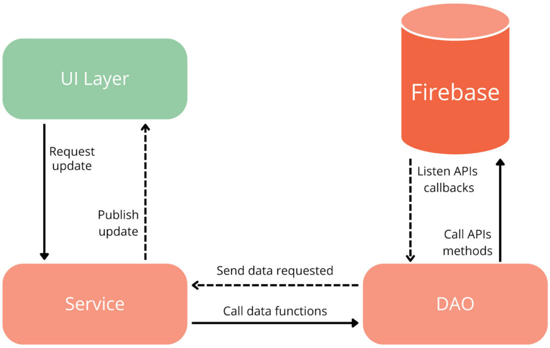


**Fig. 3.** Scheme of the communication between the App and Firebase.

### 3.2 Handheld Device App

The handheld device App is structured following the *Model-View-ViewModel and Service* (MVVMS) pattern. The service module manages the App logic and the communication with the Firebase database while a Data Access Object (DAO) manages data access operations. Figure 3 shows the adopted scheme for communication between the App and the Firebase database.

The user interface on the smartphone is divided into 3 submodules:

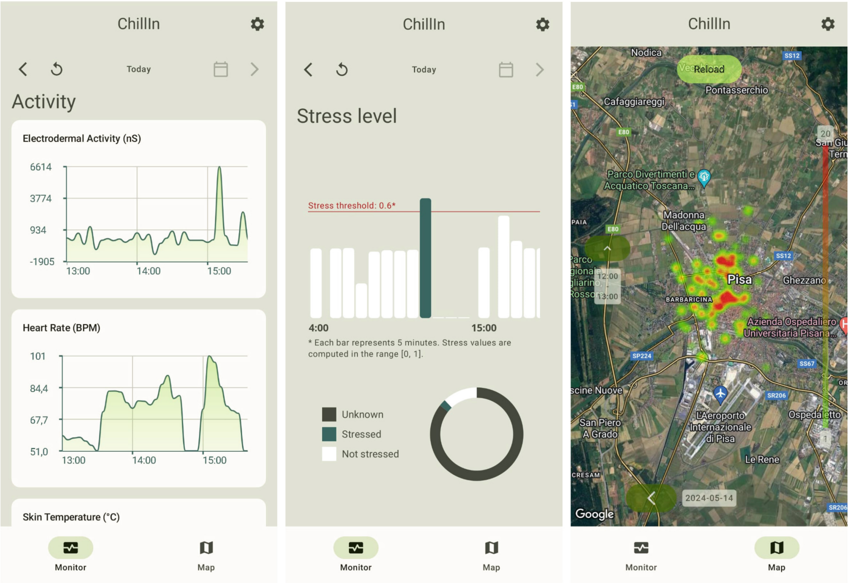
- *Splash module*: it implements the initial splash screen.
- *Access module*: it implements the login, registration, and password recovery functionalities.
- *Home module*: it implements the main functionalities of the App when the user is logged in.

In particular, the *Home* module is composed of two screens: the *Stress Monitor*, and the *Map*. The *Stress Monitor* screen displays the graphs associated with the physiological data of the user, visualizing a report of the data sensed and the stress level computed on a day-by-day basis, allowing the user to check their current state and history. Data is aggregated in 5-minute intervals to avoid excessive load on the UI and to achieve low response times. The *Map* screen shows a heatmap of the stress level at different hours and days in the urban area under analysis. The map is based on the *Google Maps SDK* for Android.

An example related to preliminary data acquired in Pisa (Italy) during the testing phase is shown in Fig. 4.

### 3.3 Cloud-Based Data Storage

The system relies on Google Firebase for data management. *Firestore DocumentDB* serves as the database for storing both raw data collected from the wearable device and stress levels evaluated by the remote service. The database contains one data collection for each user account and a public collection for real-time updates and visualization of the heatmaps. *Real-Time Key-Value Firebase*



* Each bar represents 5 minutes. Stress values are computed in the range [0, 1].

**Fig. 4.** Smartphone user interface.

*DB* integrates Firestore to handle the exchange of information with the handheld device. Data is organized into two buckets, one to temporarily store the 30 samples periodically acquired from the wearable device and one to store the stress levels associated with different geographical positions. Moreover, the Firebase database is used to store the information related to the user accounts, namely username and password, and to ensure secure access control.

## 3.4 Remote Service

The remote service implements two stress detection algorithms in Python. The remote service extracts the raw data stored on Firebase, estimates the presence of stress, and stores back the results onto the cloud. The first algorithm is a Range-Based Algorithm that takes as input the heart rate and checks if it falls within the range that represents the *no-stress* condition. Our algorithm is an adaptation of the algorithm proposed in [9] to continuously monitor the heart rate of the user, using a sliding window to dynamically estimate the *no-stress* range every time new data is received. In particular, the no-stress range is based on a Gibbs sampling approach, and it iteratively estimates the mean and variance of the data.

The second algorithm is a Rule-Based Algorithm that takes as input the EDA and the skin temperature and applies the five rules derived from [11] to detect and quantify moments of stress (MOS). The five rules concern i) the EDA amplitude increase, ii) the skin temperature decrease, iii) the rising time of EDA, iv) the slope of EDA response, and v) the minimum distance between two MOSes.

**Table 1.** Components of every sample.

| Name | Description | Size |
|---|---|---|
| Timestamp | Time of the recorded data in milliseconds | 8 Bytes |
| Eda | Electrodermal activity value in nanoSiemens | 4 Bytes |
| Temperature | Temperature value in Celsius degree | 4 Bytes |
| Heart Rate | Heart rate value in beats per minute | 4 Bytes |
| Latitude | Latitude value of the location | 8 Bytes |
| Longitude | Longitude value of the location | 8 Bytes |

Except for the fifth rule, which states that it is possible to experience only one MOS every 10-s window, all the rules assign a stress score to the input data with 0, 0.5, and 1 as possible output values, depending on specific conditions and thresholds. The overall stress score value is the weighted mean of the scores produced by the four rules, with 0.6 as the threshold to identify an MOS.

## 4 Preliminary Tests

The preliminary tests consisted of using the application while traveling the urban contexts of Pisa both by car and afoot. The application was tested using a *Redmi Note 8 Pro* (Android 11) smartphone and a *Google Pixel Watch 2* (WearOS 4.0) smartwatch. Each data sample collected by the smartwatch consists of 36 bytes as detailed in Table 1, resulting in the sending of 1 message every 30 s to the smartphone. The message contains the 30 samples collected with a frequency of 1 Hz and its payload is 1080 bytes (30 samples × 36 bytes).

The metric used for assessing the capability of the stress detection algorithms is the comparison between the stress level displayed by ChillIn and the perceived stress of the user that has been annotated during the preliminary trial. This metric provides a qualitative evaluation of the capabilities of the adopted algorithms.

The metric used for evaluating the impact of ChillIn on power consumption is the difference between the battery percentage before and after the trial. This metric provides a quantitative evaluation of the power consumption of the devices while running ChillIn.

Figure 5 shows the *Map* screen after a car trip from Pisa to the countryside (San Piero a Grado onto the map). The MOSes displayed on the map match the stress perceived by the user during the trip. The battery level displayed on the device dropped by 16% during a task of roughly 3 h. This drop is consistent with the daily usage of the smartwatch.

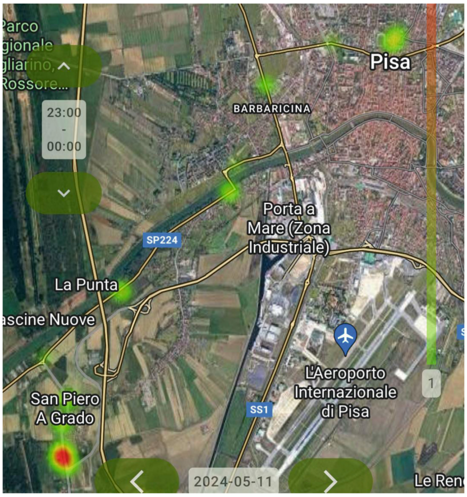


**Fig. 5.** Example of heatmap resulting after a trial.

## 5 Conclusions and Future Work

This ongoing work represents a step forward in addressing the pressing issue of stress management in modern society, in particular in urban areas. Thanks to a wearable device, the proposed application, ChillIn, allows users to monitor their stress levels in real time, providing useful insights into the impact of the urban environment and transportation modes on mental well-being. Indeed, the real improvement offered by the application is the ability to correlate stress data with geographical location providing a better understanding of stress triggers for the user and discovering stress hotspots within cities. Overall, ChillIn has the potential to be useful in several fields, from public health and personal wellness to urban planning and community development, as it could also be included in employer wellness programs. Preliminary tests showed promising results for stress detection and power consumption. The code of the application is available according to an open-source license at the following repository: https://github.com/Gianma23/ChillinApp.

We planned to perform a larger and more structured test campaign, to soundly assess the performances of ChillIn. The evaluation campaign will include different types of users (e.g. in terms of age), transportation systems, and devices (in particular smartwatches, as they are responsible for the collection of physiological data). From a usability perspective, the application could be extended to support a larger range of operating systems. Currently, the data layer limits the platform to Wear OS. A Swift version of the mobile application could support also iOS devices. From a more research-oriented point of view, the study of techniques useful to limit the impact of malicious users and/or improper data is a relevant challenge.

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