Happy Hour - Improving Mood With An Emotionally Aware Application

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***Abstract*—Mobile sensing in Cyber-Physical Systems has been evolving proportionally with smartphones. In fact, we are witnessing a tremendous increase in systems that sense various facets of human beings and their surrounding environments. In particular, the detection of human emotions can lead to emotionally-aware applications that use this information to benefit people's daily lives. This work presents the implementation of a Human-in-the-loop emotionally-aware Cyber-Physical System that attempts to positively impact its user's mood through moderate walking exercise. Data from smartphone sensors, a smartshirt's electrocardiogram and weather information from a web API are processed through a machine learning algorithm to infer emotional states. When negative emotions are detected, the application timely suggests walking exercises, while providing real-time information regarding nearby points of interest. This information includes events, background music, attendance, agitation and general mood. In addition, the system also dynamically adapts privacy and networking configurations based on emotions. The sharing of the user's location on social networks and the device's networking interfaces are configured according to user-defined rules in order to reduce frustration and provide a better Quality of Experience.**

I. Introduction

Cyber-Physical Systems (CPS) are typically characterized by complex systems that involve the interaction of many technologies, such as wireless sensor networks or robotics, to achieve the sensing, control and environmental adaptation. Covering many scenarios (industrial monitoring, disaster management, healthcare), these are highly integrated and advanced systems with many challenges, such as interoperability [1] and security [2].

Due to their mobility, flexibility and processing power, smartphones are often made part of larger CPSs, providing cutting edge technology at reasonable cost. On a single device, it is possible to enumerate not only several wireless connectivity interfaces (4G/LTE, Wi-Fi, NFC, Bluetooth) but also various sensors (GPS, accelerometer, gyroscope, proximity/ambient light). In fact, these devices have already been applied in many different fields, for instance, to solve the problem of congestion in traffic and to monitor physical activity and improve health [3].

One of the most recent and important areas of CPS research is human-awareness. In fact, systems where aspects of human nature (e.g. position or actions) are taken into consideration, show tremendous gains in terms of usability, applicability and even efficacy. These CPSs are known as Human-in-the-loop Cyber-Physical Systems (HiTLCPSs), where the human becomes an integral part of the control-loop and his nature directly affect the system's actions. One particular case of HiTLCPSs are emotionally-aware applications. For instance, when a person is stressed, the system responds in order to improve their emotional state; thus, a person's feelings are responsible for direct system actuation. The emotional states of humans affect their performance in learning [4], commitment to work, their relationships with friends, family, and co-workers, as well as their mental health and well-being. Emotional-awareness applied to these areas of e-learning or therapy is directly related with Affective Computing research. The term "affective "computing" refers to systems and devices that can recognize, process and, additionally, "have" human affects.

Previous proposals in the affective computing field have used sensors for emotion recognition. In this regard, facial expressions, posture, speech, body temperature, even the strength and pace of keystrokes, have been employed in conjunction with machine learning algorithms [5]. Different types of approaches have met different levels of success. For example, real-time emotion detection based on facial recognition has been shown to be technically difficult, due to the complexity of image processing algorithms and the inherent physiological distinctions between different humans expressing the same feeling [6]. In speech, Paeschke [7] reported a 77% classification accuracy in recognizing agitation and calmness using neural networks, applied to a call-center scenario. Physiological signals were used in [8] to identify negative and positive emotions with 87% accuracy, as well as in [5] to identify states of high and low arousal with 95% accuracy. A recent the pilot study by Samsung [9] suggests the motivation of the smartphone manufacturer in detecting a user's emotion through simple touching behavior. Some research has combined several of these techniques with some success. For example, a research work presented in [10] fused facial recognition and speech analysis, with results showing significant improvements in the performance and the robustness of the emotion recognition system. This suggests that fusing several different types of information can lead to more a accurate detection of emotions.

In this paper, we propose an emotion inference application,

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HappyHour, in a therapy context. More precisely, we use smartphones to improve physical and mental well-being. This application will be presented in the next section, with its three subsections detailing a specific functionality (emotion detection, rule system and real-time information). We conclude our article on section III, with some considerations and possible future work.

II. HappyHour Application

In this section, we present a Behavior Change Intervention (BCI) system to improve human physical and mental well-being. BCIs are therapeutic systems that focus on providing advice, support and relevant information to patients, in order to motivate the correction of prejudicial behaviors. Traditionally associated with presential therapeutic consultations, BCIs have recently begun to be delivered through the Internet and smartphones [11]. Using smartphone sensors to monitor humans in BCIs not only helps in providing more effective feedback to help the user in correcting their prejudicial behavior, but also helps behavioral scientists' research.

Previous research has found evidence that moderate walking exercise and the change of environments can contribute to the improvement of mental health. In fact, changing from one place to another while walking provides several cognitive benefits such as improved memory, attention and mood [12]. HappyHour is a BCI application that draws on this premise to positively influence its users' mood. Our objective use a machine learning algorithm to infer the user's current emotion and use this information to trigger suggestive feedback that motivates walking exercises, to positively affect mood. Collaborative data gathering is also employed to determine the near real-time context of nearby points-of-interest (POI) that might be of interest to visit. Additionally, our system dynamically adapts privacy settings and the smartphone's network interfaces based on emotion, to promote positive moods. Figure 1 represents the HiTL (Human-in-the-Loop) mechanism

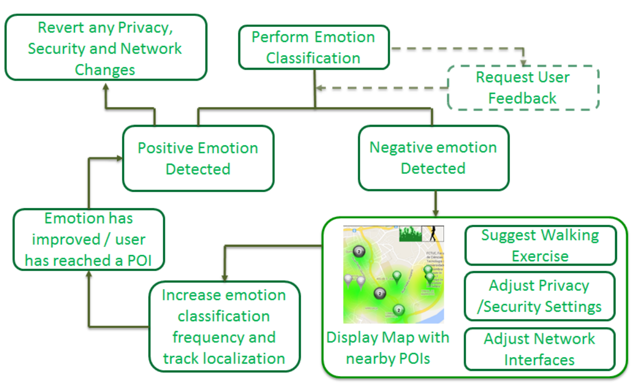

Fig. 1. HappyHour application flow

implemented by HappyHour. Human emotions are periodically inferred and the result is compared with feedback provided by the user himself. This feedback serves as input for the system's self-learning process, which will reduce the number of user feedback requests as future inference tasks become more accurate. Depending on the inference result, the system assumes different behaviors. Negative emotions prompt the system to suggest walking exercises and, at the same time, a map is shown with possible destinations. As previously mentioned, this emotional information also affects the system's privacy settings and the device's network interfaces. If the user's emotion is positive, the system applies the associated rules and attempts to revert the countermeasures applied to the negative emotional state.

From an high-level point-of-view, the HappyHour system is composed by an Android application, a main Server and a Web Server. There are two types of persons that interact with the system, regular users and managers of POI (such as nightclub owners or museum personnel), as seen in Figure 2. POI managers use a web interface, developed in Ruby On

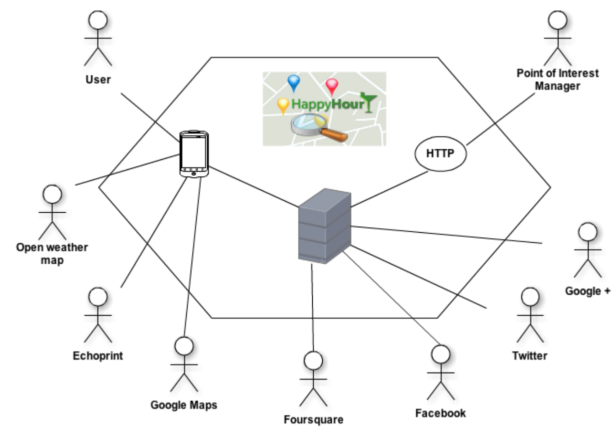

Fig. 2. HappyHour's high-level architecture

Rails, to manage descriptions, events (e.g. "Dinossaur exposition"; "80's night") and other useful information regarding a particular POI. Managers can also schedule notifications, referring to cultural events or public notices, to be delivered to all HappyHour users in the surrounding area (within 700 meters) at a specific time. Managers can also publish the events and notifications to their Facebook, Twitter and Google+ Accounts, in order to reach more audience.

The main server, implemented in Java, handles requests of creation, update or deletion of users, events, notifications and points of interest. It is also responsible for the connection with the Foursquare[1] and Facebook[2] APIs, from where it fetches POI information. The server offers its services in the form of RESTful web services, both to the Android App and to the Management web interface. It also communicates with a database where records of users, POI locations, descriptions and events are kept.

The core of our HiTLCPS is HappyHour's Android application. Because of the coexistence of many versions of the Android OS, there is a concern to ensure that the application can work with as many versions of Android as possible. We chose the Android SDK 2.3.3 with Google API's for our application because it ensures a compatibility with 99.3% of Android handsets, according to Google's statistics[3]. The Android application is composed by several "Activities", responsible for interacting with the user, and one background

[1]https://developer.foursquare.com/
[2]https://developers.facebook.com/
[3]https://developer.android.com/about/dashboards/index.html?utm_source=ausdroid.net

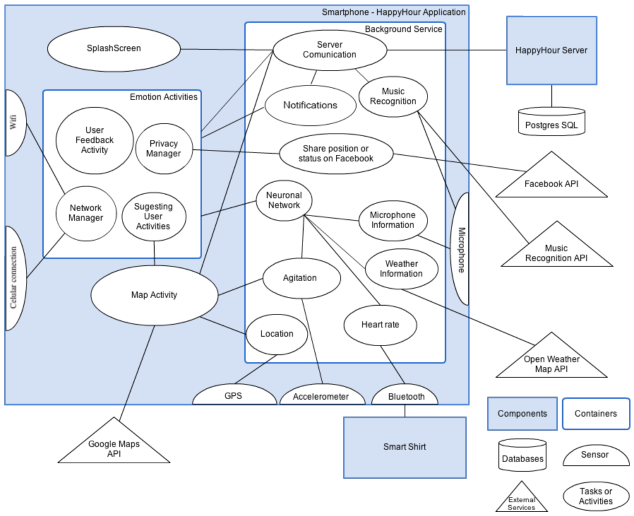

Fig. 3. HappyHour Android application

service, responsible for syncing information with the server, showing notifications, sensing the user and the environment and processing the raw sensor data. Figure 3 shows how each of its components relate to each other.

The **User feedback activity** is responsible for acquiring the user's feedback on the emotion detection result. The **map activity** displays the map, heatmaps, points of interest, and current position. When negative user emotions are detected, the **suggesting user activities** provide suggestions for the user to go for a walk. A **music recognition background service** processes the ambiance sound and attempts to recognize background music through a web music recognition API. The **privacy and network manager classes** are responsible for applying the privacy and network profiles associated with each emotion. A **neural network class** receives sensory input information and performs emotion recognition, training itself based on feedback provided by the user. Finally, there are also classes that **process data** from sensors (agitation, heart-rate, sound) and external services, namely weather information.

The application is, thus, responsible for three main tasks: periodically acquiring sensory information and processing this data through a neural network to infer emotions; dynamically adapting privacy settings and networking interfaces through an emotionally aware rule system; and, finally, interacting with the user through a map and showing relevant information regarding nearby POIs, as well as periodically acquiring and sending GPS position, music identification and accelerometer data to the central server. We will discuss each of these tasks in the next subsections.

A. *Monitoring human emotions*

The core of our emotion-awareness lies in our ability to process different forms of sensing. From the beginning, our objective was not to propose robust methods for emotion detection, but instead, to provide a practical proof-of-concept that shows how emotional information can benefit HiTLCPSs. Thus, in order to determine the best machine learning technique for our application, we studied previous comparisons between the different possibilities. Previous work [13],

Machine learning techniques	**Correct classification rate**	**Ranking of less CPU time needed for classification**
Decision trees	96.5%	5º
Support vector machines	80.2%	1º
Naive Bayes classifiers	81.5%	6º
Bayesian networks	90.9%	4º
Logistic regression	83.4%	3º
Artificial neural networks	87.2%	2º
Instance-based classifiers (KStar, LWL, and IBk).	96.6%, 95.6% and 80.	9º, 8º, 7º

TABLE I. MACHINE LEARNING APPROACH FOR SENSING CONTEXTS IN SMARTPHONES [13].

the results of which are shown in table I, has scored different classification algorithms in terms of correct classification rate and in terms of central processing unit (CPU) time needed for the classification. The latter is of particular importance for smartphone HiTLCPSs, since these are limited terms of available processing power and energy. This has led us to opt for an artificial neural network as our emotion inference tool, since it offers a reasonable correct classification rate while being one of the least time-consuming techniques.

Another important matter is to decide which sources of input are to be used. Our current understanding does not yet provide an exhaustive picture of which factors influence a person's emotions [5]. Thus, we intended to consider at least three general sources of data: environmental clues, vital-signs information and meteorological information.

Regarding environmental clues, obvious choices of sensors are those already provided by the smartphone device. In particular, the accelerometer and microphone have been previously identified as effective sensors for identifying human context [14]. Thus, our application acquires raw data from these sensors processes it through a simple classifier that performs a Fast Fourier Transformation (FFT) on the raw data and sums the fourier coefficients. This sum gives the neural network an idea on the amount of background noise and movement detected by the smartphone. Unfortunately, this information is limiting, in the sense that it only refers to conditions regarding the user's immediate surroundings.

Other important measures may lie closer to the user's internal body functions. In fact, heart-rate has been previously associated with emotion recognition [15]. To bring this information to our system, we used a wearable smartshirt[4] that relays the user's ECG signal through Bluetooth, which is then processed to infer the current heart-rate. This value is directly fed to the neural network.

Finally, previous research has shown links between emotional states and weather conditions [16]. To consider these links, our neural network is fed with the current temperature, precipitation and cloudiness directly from a weather API[5].

The user's emotion is inferred once or twice an hour. The time between two sensory acquisitions is randomly determined within these constraints, in order to avoid user habituation. In

[4]VitalJacket: http://www.vitaljacket.com/

[5]Open Weather Map: http://openweathermap.org/

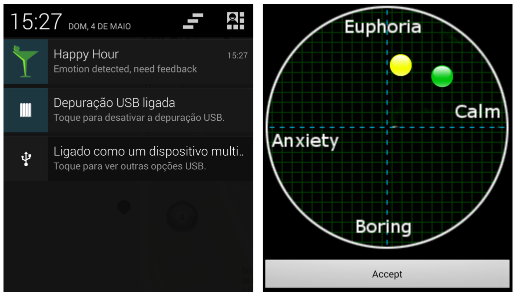

Fig. 4. HappyHour Emotional Feedback

our current implementation, we consider four distinct moods: "euphoria", "calmness", "boredom" and "anxiety". "Boredom" and "Anxiety" are considered "negative" emotions, whereas "Euphoria" and "Calmness" are considered their "positive" counterparts. Users receive a notification when an emotion is detected and, by selecting it, the application opens and displays the feedback screen, as shown in Figure 4. The output representing the inferred emotion is shown as a yellow circle in a two-dimensional circular space containing the four emotions. The user can provide corrective feedback by dragging the yellow circle to a new position, now shown in green. This feedback initiates a neural network re-training process, which will reflect the correction in future inference tasks.

The neural network was implemented using the Encog[6] machine learning framework. When designing its architecture, we found that selecting a number of hidden neurons that provides minimal error and highest accuracy is a challenging task. Previous research has shown that excessive hidden neurons will cause over fitting; that is, the neural networks have overestimate the complexity of the target problem. A thump rule is selecting a number between size of number of input neurons and number of output neurons [17]. Thus, we decided to test two possibilities: using a hidden layer with 4 neurons or using two hidden layers, three neurons in the first and two neurons in the second. Both of these configurations fit onto the thump rule without becoming overly complex and taxing for smartphone hardware. In our decision process, we considered two major requirements: the amount of effort required for training the network (which is important in terms of processing power and battery drain) and accuracy of the network.

In order to test the training effort, we began by generating simulated emotions. For each type of emotion, we empirically defined a probability value for different ranges of its input components (heart rate, cloudiness, movement, etc). This method allowed us to generate 150 simulated emotions, that, while not valid for testing accuracy, are sufficient for testing training performance. Thus, we counted the number of epochs necessary to successfully train the network for each configuration. The results, show in table II, suggest that using

Configuration	Number of epochs
One hidden layer	100
Two hidden layers	3000

TABLE II. TESTING TRAINING PERFORMANCE (150 EMOTIONS).

two hidden layers increases the training effort significantly. Therefore, we also needed to test if using more layers brought any benefits in terms of accuracy. To do so, we requested a test subject to use our application for a period of a week, during which his sensory data and emotional feedback were recorded for a total of 41 records. We then tested both neural network configurations using this data, to evaluate their sensitivity and specificity. These experiments indicate that using a two layer

Configuration	Sensitivity	Specificity
One hidden layer	0,679	0,766
Two hidden layers	0,720	0,830

TABLE III. TESTING NEURAL NETWORK ACCURACY (41 EMOTIONS).

configuration presents considerably better performance, as shown in table III. After pondering over the results, we decided that, despite being more demanding, a two layer configuration presented a better compromise in terms of training time and accuracy. Thus, we opted for a configuration with two hidden layers, the first containing three nodes and the second with two nodes, for our application. The implemented neural network's architecture is presented in Figure 5.

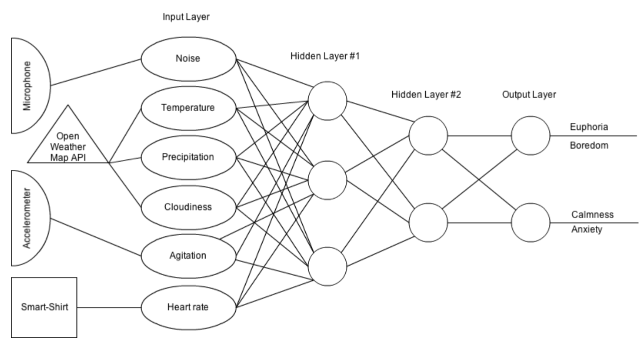

Fig. 5. Happy Hour emotional neural network.

B. *Emotionally aware rule system*

Depending on the emotion classification result and the user's feedback, the HiTL control assumes different decisions. These measures are the responsibility of the "emotionally aware rule system", which is implemented based on sets of actions. Users specify profiles for each emotional state, and actions associated with each profile. These profiles allow the application to automate and specify privacy and networking configurations in accordance to a HiTL paradigm. In particular, if a negative emotional state is detected (e.g. high anxiety or boredom), the default behavior takes direct measures to improve the user's mood.

Privacy configurations allow users to create rules that govern the automatic sharing of location in social networks. Some people feel that negative emotion states may be eased by social-interaction. In these cases, the automatic sharing of location among the user's friends may contribute towards positive socialization. Other people prefer solitude to ease their minds and thus, might want to refrain from publishing their location in a social network. This way, privacy profiles implement a HiTL approach for managing privacy settings.

Network interface configurations are also governed by a emotional profiles. When the user's emotions are positive,

[6]Encog Framework: http://www.heatonresearch.com/encogin

the standard network profile defines that WiFi is used as the primary interface while cellular communications are used as a backup, since they usually involve additional monetary costs. However, if the system enters a negative emotion state, the standard network profile defines that cellular connections and WiFi will be used at the same time. For example, the user can set the configuration to use two interfaces (3G/4G and Wifi) if he feels more anxious. This is done for two main reasons. Firstly, to reduce possible sources of frustration that the user might experience, resultant from intermittent connectivity issues [18]. These issues often occur when the user is walking and loses connection to a WiFi hotspot, or enters an area that does not have cellular coverage. Since the established TCP connection is lost, the system needs to reestablish a new session on the remaining interface which takes considerable time. Using both interfaces simultaneously on the same transport-layer session means that the TCP sessions can continue effortlessly through the remaining network interface, providing a better Quality of Experience (QoE). Users that are emotionally distressed might be willing to pay the additional price of cellular connectivity to reduce frustration and thus, contribute towards the improvement of mood. The second reason is of a more technical nature and is due to the additional data being sent to the server. When the human is on a negative mood, his position and emotional states are monitored more frequently, in order to provide better feedback and improve the impact of the positive reinforcement resultant from walking suggestions. Using several network interfaces provides better reliability in data collection during these negative states. Nevertheless, the network profile that governs these changes is completely configurable by the user in case he wishes to disable cellular connections due to their monetary costs, for example.

Maintaining a single TCP session while using several networking interfaces and performing seamless network handoff between them is achieved through MPTCP [19]. This protocol extends TCP with multipath capabilities by pooling multiple TCP paths within a transport connection, transparently to the application. Thus, defining rules that use more than one interface at the same time requires the smartphone to have an MPTCP-enabled kernel.

C. *Points of interest informations*

The information provided by the application allows users to identify the best place in a local area to visit. Since every person has their own music tastes and emotional responses, providing detailed information about the environment of each POI might have impact on decision-making process. For instance, a person could choose a crowded bar with music if they want to dance, or decide to go visit a more quiet nature park for a relaxing walk, instead. Tracking and aggregating users' emotions and their activity allows HappyHour to categorize points of interest. The android application allows users to select a destination for their walk through a map. Each place of interest is represented though an icon, which is aggregated into a cluster of icons when the map's zoom is low. These clusters are represented as circles with the number of aggregated places. The application renders real-time information about each place, namely the average movement (from accelerometer data), the attendance of other users to that place, current music

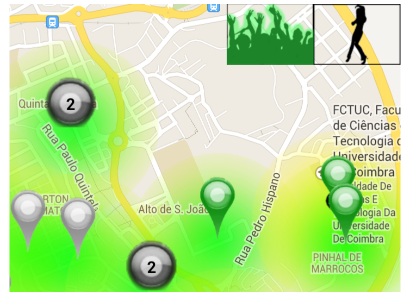

Fig. 6. HappyHour's Heatmaps

being played (music detection is particularly interesting for bars or nightclubs) and the average mood of the place.

The movement and attendance are represented through heatmaps (fig. 6), colored layers surrounding the point of interest. The colors green, yellow and red classify the amount of attendance or movement, with green representing low movement/attendance and red representing high movement/attendance. These heatmaps can be toggled through two buttons located in the upper-right side of the screen: the left-side button represents a crowd and activates the attendance heatmap, while the right-side button represents movement. By clicking on a POI's icon, the users can access a description, and request navigation to the place through an external navigation application. Users can also browse a list of events associated with that place, which are maintained by the place's managers through the management web-interface. Managers can also schedule notifications that are to be delivered to all HappyHour user's in the surroundings of the POI. The primary purpose of these notifications is to advertise current cultural activities or initiatives, events, or promotions that might be of interest to the public. Information about music being played at each point of interest is also presented and acquired using the smartphone's microphone. Sound samples are processed, generating a fingerprint which is identified through a web-based music recognition API[7]. This music recognition feature may be of particular interest to users who wish to visit bars or establishments where certain types of music are played, for venting their emotional stress.

All of this near real-time POI information is made possible by automatic periodic sharing (every 5 minutes), of the user's location, movement, emotion and acoustic fingerprinting. Since some of this information may be sensitive, the sharing is made in an non-identifiable fashion.

III. Discussion and Future Work

HappyHour draws concepts from many areas, such as near-real time POI characterization, people-centric sensing, and affective computing. Previous research had already approached these aspects. EmotionSense [11], for example, was a mood tracking framework used for experimental sociology and psychology, which collected data about how users feel. The system used sensors (movement, proximity of other devices and location) and voice recognition for the detection of emotions and speaker identities. Users were asked to fill a form twice a day, where they marked their mood using a ”emotion grid”.

[7] Echoprint: http://echoprint.me/

The researchers found that the distribution of the emotions detected through EmotionSense generally reflected the self-reports by the participants. On the other hand, VibN [20] also explored the idea real-time POI information by exploiting multiple sensor feeds. The application allowed its users to explore cities by presenting real-time information on hotspots, derived from sensor data. Each hotspot was also characterized by a demographics breakdown of inhabitants and a list of short audio clips.

HappyHour's emotion inference model was inspired in the emotion grid system from EmotionSense and the near real-time information about places draws many parallels with what was proposed in VibN. However, HappyHour takes a proactive approach and encourages the user to take walks and to discover different places. This objective of promoting the improvement of mood through moderate physical exercise, emotional-awareness and near real-time information about places makes it, as far as we know, unlike any other collaborative App. Additionally, HappyHour's HiTL paradigm, where emotion is used to adapt application and smartphone configurations, is a novel aspect. While the inference of emotions is still a developing area, in today's world where users wear smart watches, smartshirts, smartphones and other smart wearables, the process of gathering the user's contextual data is greatly simplified. With the increase of available data there will be a proliferation of promising applications, progressively more aware of the user's emotional state. These can have diverse goals, such as improving the user's mood, promote socialization or even improve learning and working tasks. In fact, this type of awareness allows technology to evolve in powerful new ways, as the inclusion of human contextual information can vastly improve usability, performance and efficacy. On the other hand, this technology is vastly more challenging, requiring the accurate sensing and modeling of behavioral, psychological and physiological aspects of human nature.

In the future, it could be interesting to perform an in-depth experimental study of which machine learning techniques are better for classifying emotion based on smartphone sensors. Our HiTLCPS could also be expanded to consider other types of contextual data in the control-loop, such as human actions and position. Additionally, it could also be relevant to understand how much the addition of new types wearable devices to the machine learning algorithm's input can improve the accuracy of the detected context.

Acknowledgments

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