My Painting Shows My Stats: Towards a Personal Colorful Activity Display

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Abstract
Regular physical activity reduces the risks of illness, obesity, and falling. Thus, many personal devices support users in monitoring their physical activity to initiate behavior changes. However, activity data is prone to measurement errors; for example a user is seated but typing increases the step count. Such false positives could be easily detected if data from multiple sensors would be connected. We envision a system that combines data from multiple sensors in our surroundings to reduce such measurement errors. Furthermore, the system shows the user’s historical data for the past seven days, the activity level of the current day, and a forecast about physical activity for the next seven days in an artistic and configurable digital wall painting. We argue that this strengthens connectedness and privacy. We are convinced that our system can help to increase user’s trust in activity data and raise awareness for behavior change regarding physical activity.

Author Keywords
Physical activity; ambient information system; informative art; behavior change, self quantification.

ACM Classification Keywords
H.5.m [Information interfaces and presentation]: Miscellaneous

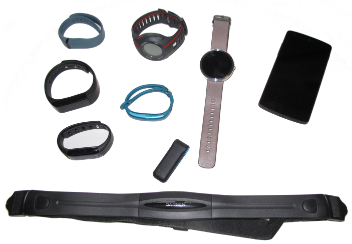


Figure 1: Smartphones, smartwatches, smart bands, fitness clips, training watches as well as heart rate sensors support users to monitor their daily physical activity.

Introduction & Background

Physical activity on a daily basis is important for people of all age-groups to reduce risks of getting illnesses, such as hypertension or coronary heart disease, or falling and vertebral fractures [12]. Additionally, physical activity reduces the risk of obesity, which has more than doubled sind 1980 [11].

Today, humans use many diverse sensors and activity trackers to monitor their physical activity, e.g. smart bands, smartwatches, and smartphones (cf. Figure 1). However, these devices are prone to measurement errors, which might lead to inaccurate metrics. Multiple studies analyzed that the measuring accuracy of activity trackers depends on the brand and device [1, 6], the body part it is worn on [10], and the walking speed [3]. For example, step counters worn on the wrist might calculate steps when working on a desktop computer or might miss steps when the user is carrying something with both hands. The measurement error for step counts can be up to nearly 30% [6].

Furthermore, users might own several devices, which track the same type of activity data. For example, if a user wears a fitness tracker, a smartphone, and a smartwatch, all these devices can monitor steps, heart rate, current sport activities, or sleep patterns. However, these devices track the different physical activities in different measuring units, e.g. steps, heart rate, or calories. Therefore, the tracked activities are not easily comparable for the user. Additionally, the devices might disagree on the actual value of a metrics.

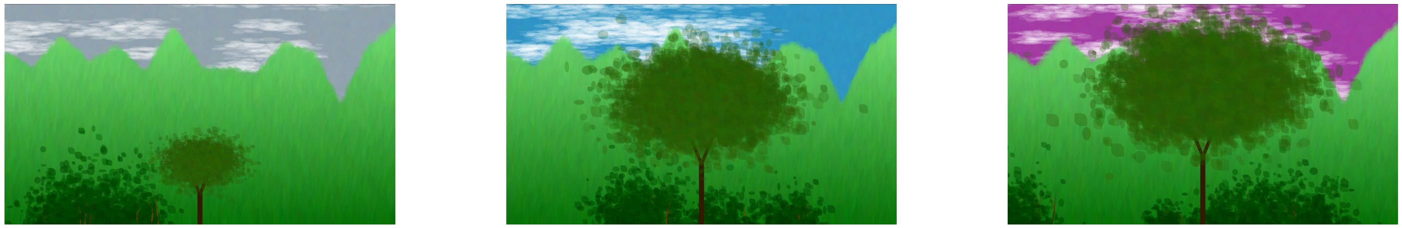
Activity trackers generate big data sets and the users can monitor them for a quantified self-behavior change. However, former studies [8, 9] show that many users stop using their activity trackers after a short time. One reason for this behavior is that all devices calculate different units of activity levels, e.g. steps or calories burned, which are difficult to understand for the user. Additionally, former work showed that ambient displays [2, 4, 5, 7] are a more promising way to support behavior change for physical activity. Consolvo et al. used the background screen of a traditional mobile phone to display a garden. The system rewards the user with a growing garden for physical activities [2]. Jafarinaimi et al. [7] and Fortmann et al. [5] used ambient displays to encourage the people who sit at their workplaces to do breaks filled with physical activities. In contrast, Fan et al. used informative art to display physical activity data in an abstract painting [4]. They represented the achieved steps by the user during the day using spirals, rings, buckets and pollocks.

We envision a system that connects different sensors and devices, e.g., activity trackers, and supports users to monitor their physical activity. For example, the system is connected to step counters, heart rate sensors as well as sensors in the user’s environment to recognize the user’s current context, e.g. participating in a meeting with access to the user’s digital calendar. To support the monitoring the system should have an ambient information display in the users’ physical environment to inform the users about their current physical activity.

In this paper, our contribution is two-folded. First, we envision a system that connects different sensors and devices, e.g. activity trackers. Second, we implemented an ambient representation for activity data to strengthen connectedness and increase users’ awareness for their personal activity data.

Data Collection & Processing

We envision a system that collects physical activity data from all the devices and sensors of the user. On the one hand these devices include activity trackers and sensors worn by the user such as mobile phones, smart watches,



(a) 50% of predicted activity archived, personal goal not archived and not predicted

(b) 100% of predicted activity archived, personal goal not archived yet, but predicted

(c) more than 100% of predicted activity archived, personal goal archived

Figure 2: This painting shows the physical activity as a landscape with a growing tree. The color of sky displays the current state regarding the user’s personal goal. The skyline represents activity levels of the last week (left side), the prediction for today (center) and the next week (right side). The growing tree in the middle represent the today’s current activity level.

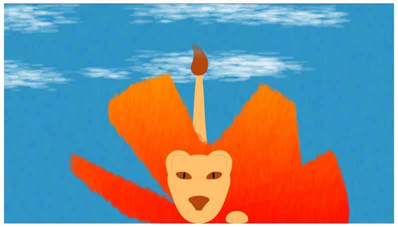
fitness bracelets, GPS trackers, heart rate sensors, in smart clothing integrated pressure sensors, as well as in bike integrated cadence sensors, etc. On the hand, we envision that the system has access to data of integrated sensors in the user’s physical environment. Therefore, the system knows the current context of the user. For example, the system is able to detect if the user is sitting on the couch with integrated pressure sensors in the user’s seat-accommodations or attending in a meeting with access to his digital calendar.

Exploiting Multiple Sources of Sensor Data for Correction
Several devices or sensors of an user may for example count steps, but disagree on the actual amount of steps taken by a user. By combining data from different sensors, faulty data can be detected by performing an aggregation across the different sensors. In addition to the aggregation of data sets from sensors of the same type, data sets from different sensor types can be exploited to check the data for correctness. For example, if the data of a pressure sensor on the chair suggests that the person is seated, no steps can be performed at the same time. Or if the heart rate of a person is not increased, the person might not participate in any physical activity at the moment. This validation helps the system to gain a better understanding of the users’ physical activity, but at the same time might be more trustworthy.

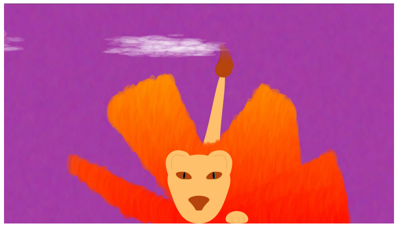
Abstraction of Steps and Calories
Steps and calories are measuring units that are normally shown to people, but it is hard for the users to interpret measurements in different units. We envision a more general activity level that can be tracked by weighting steps, e.g., by the user’s current heart rate or body temperature.

Calculating a forecast for the user’s physical activity
In contrast to current systems that enable reflection about current and former physical activities, our envisioned systems is able to calculate a prediction for the user’s upcoming physical activity on the current day or the next days. This means that the system will distinguish between the user’s personal goal that the user wants to achieve per day and the predicted activity where the system estimates the

(a) 50% of predicted activity archived, personal goal not archived and not predicted



(b) 100% of predicted activity archived, personal goal not archived yet, but predicted



(c) more than 100% of predicted activity archived, personal goal archived

Figure 3: The user’s physical activity is represented as a painting of a lion. The color of the sky displays the state regarding the user’s personal goal. The lion’s forelock represents activity levels of the past week (left side), the prediction for today (center) and the next week (right side). The position of the lion’s tail displays the today’s current activity level.

activity the user will achieve during the day. For example, if the user is on a 10 hours flight the system will estimate that the user will do less activity than he or she intends to do usually. The calculation of the prediction is based on the user’s past tracked physical activities and will distinguish between different weekdays and their digital calendar data. Using calendar data, the system will recognize days with many appointments and less time for physical activities as well as added sport events marked with a tag, e.g. planned running or hiking events.

Personal goal
The system should give the user the opportunity to set a personal goal for the daily physical activity and inform the user if the aspired personal goal was achieved.

Visual Representations

We envision that our system will represent the tracked physical activity of the user additional to traditional statistics with a digital painting in the user’s environment. We conducted two focus groups with 8 participants per group and based on the results we developed two designs which enable the user to monitor and reflect its physical activities.

The first design represents the activity data as a landscape (see Figure 2). In this design, the skyline represents the user’s physical activity on a daily basis. The center of the skyline represents the activity level prediction of the current day, the left side represents the history of the last seven days and the right side represent the prediction for the next seven days. The growing tree in the center of the painting represents the current state of the user’s tracked physical activity for the current day. The color of the sky displays color-coded information about if the prediction says that the user will achieve his personal goal today or not as well as if the user has already achieved his personal goal.

The second design displays the activity data as a painting of a lion (see Figure 3). In this case, the lion’s forelock displays the physical activity on a daily basis. Again, the center represents the prediction of the current day, the left side represents the history of the past seven days and the right side represent the prediction for the next seven days. The position of the lion’s tail displays the current state of the user’s tracked physical activity for the current day. If the tail is placed in the middle, the user archived the predicted physical activity. If the tail is placed on the left side, the user has not yet archived the predicted value. If the tail is shown on the right side, the user did more physical activity than expected. Also, the color of the sky shows if the user has already achieved his personal activity goal or if the prediction indicates that the user will achieve his personal goal or not.

Customization for Connectedness and Privacy
The system should support customization opportunities for the visualization. Furthermore, the system should support different paintings and own color settings for the paintings. On the one hand, personal colors in addition to personal goals for physical activity might prevent privacy issues. On the other hand, users can adapt the painting in a way that it is fitting into their physical environment. Additionally, the users might feel more connected to the painting if they are able to choose their favorite colors.

Conclusion

In this paper, we envisioned a future system to combine different data sets for better understanding for the users about their physical activities and more trustful activity data. Afterwards, we presented two developed and implemented designs for digital paintings in the user’s physical environment which displays the today’s physical activities. The painting enables users to reflect on their physical activity in the past week and shows the trends for future physical activity within the next week. Additionally, the painting displays the user’s current state regarding the personal goal for physical activities. The users can see if they will achieve or has achieved his personal with a glance at the painting. Therefore, the system can increase the trust in the physical activity data as well as the user’s physical activity data awareness, especially for quantified-self behavior changes regarding physical activity.

In the future, we will integrate diverse physical activity data sets from a diverse range of sensor types into our system, e.g., Google Fit, Apple HealthKit or Garmin Health. Afterwards, we will evaluate the system together with our implemented paintings in a long-term study.

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