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Challenges in Displaying Health Data on Small Smartwatch Screens

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Abstract. Using smartwatches for self-tracking purposes has become increasingly common. This tracking is possible as a result of the many sensors embedded in modern smartwatches including GPS, heart rate monitor, accelerometer, and gyroscope. The ability to obtain personal health-related data is one of the most compelling reason to purchase such devices. However, form factor limitations create numerous challenges for users hoping to access and interpret the data available. Typically, users rely on a secondary device, such as a smartphone to view health data. The aim of our research is to identify methods to improve user consumption of health-related data directly on a smartwatch. To study and apply novel visualization approaches, several key challenges need to be addressed. We present these here along with their corollary methods of circumvention.

Keywords. Smartwatch, health data collection, data visualization, health tracking

1. Introduction

Wearable devices such as smartwatches and fitness bands are becoming increasingly popular across demographic groups, from kids [1–3] to older adults [4,5]. Reasons for this significant uptake include fitness tracking [6,7] and health monitoring [8–13] capabilities, two of the most widely available features on a smartwatch. Other health-related capabilites of smartwatches such as detecting mental/physical disorders and supporting people with difficulties [14–16] can also improve user health significantly. Many of these applications are based on data captured by sensors on smartwatches (e.g., heart rate monitor, GPS, accelerometer, gyroscope) [12,17]. For example, even the very first programmable smartwatch, the *Chronos* [18], made specifically for athletes, contained multiple sensors for the measurement of such variables as acceleration, air pressure, and a temperature. Being lightweight, accessible, and having various sensors and a wide range of novel interaction techniques [19–21] make smartwatches unique and ubiquitous as a data-tracking device.

While tracking data is possible, consuming or viewing their data is significantly challenged by a number of factors. For example, merely displaying raw data or time-stamped series of measurements may be not be sufficiently informative to users. Instead, users of such devices are seeking answers to many questions that cannot be currently accessible. Researchers have identified common questions that arise during users' fitness activities, such as "have I reached my daily goal?", "how am I doing so far?", "how am I doing compared to my friend, Jane?", [22] which require further analysis of the raw data produced. Providing clear answers to these questions should lead users to improved interactions with their devices. Thus, using tools and techniques for data visualization and personal visual analytics, which can provide insights, is key in improving user health [23]. For instance, the raw data gathered by smartwatches can be visualized and analyzed in such a way that users can extract useful information about their daily activities, such as steps taken, average/rest heart rate, intake/burnt calories [24]. This data can also be leveraged to motivate habitual changes for health purposes, such as the cessation of smoking [25]. When the data is presented and interpreted properly, it can also help professional athletes to improve their performances [26].

Meyer et al. [27] have shown how visualizing health data can be a challenging and complex task. In fact, collecting inaccurate health data or misinterpreting such data can lead to undesirable side effects. Due to the various limitations of smartwatches, the process of collecting, visualizing, and analyzing health data can add even more complexity. Thus, we present an overview of the challenges regarding collecting, presenting, and analyzing health data to improve our reliance on smartwatches.

2. Data Collection, Representation, and Analysis Challenges on Smartwatches

2.1. Data Visualization and Interaction

One of the main limitations of smartwatches is their small screen size[27–30]. Visualizing health data, which are mostly highly dense, continuous time-series data is often challenged by these small screen sizes. Researchers [31] have recently shown how different visualization factors such as size, frequency, and colour of the visual displays on a smartwatch can impact the reaction time of users. Depending on the data type, there are various data visualization methods which can represent the underlying data. For example, Amini et al. [32] have shown that bar graphs, line charts, and pie charts, in addition to maps and pictographs are the most frequent data visualization techniques in data storytelling and data videos. However, there is no guideline to solve the issues faced in the representation of complex health data on the small screens of smartwatches.

Various specific interaction techniques have been designed for different visualization methods [33–37]. Interactive data visualizations are necessary to provide users with tools to explore the data to gain additional insights. Due to the small smartwatch screen size, when using touch as input, there is a higher chance of content occlusion and errors as a result of the "*Fat Finger Effect*" [38]. New interaction techniques are needed to improve user performance when data visualization techniques are utilized.

2.2. Storage

Continuously collected data creates various tasks. Millions of data points, sampled at very fine time intervals, without visualization and analysis can be difficult for users to interpret. Researchers in areas such as big data, data mining, machine learning, and deep learning are developing techniques related to analyzing massive data sets in a reasonable time. However, due to their lack of memory [39], smartwatches have data-storage limitations.

This is compounded by the fact that embedded sensors are being deployed with higher sampling rates for maintaining the accuracy of the incoming data. Increased storage capacity may compete with other concerns such as connectivity and battery power. This could be particularly problematic in emergency situations when for example, the user needs to send their ECG to the doctor.

2.3. Processor

Processing and analyzing massive data sets is one of the main challenges data scientists face today in medical science [40,41] and can be extremely difficult, even on computers with high-performance CPUs. Processing of such data sets, such as heart rate data for two years with a high sampling rate, with existing weak processors on smartwatches, is almost impossible. To overcome this, users need to transfer the data to the cloud or other platforms such as PCs, and then review the data. However, analyzing the data in-situ and on smartwatches is essential in many cases [24].

2.4. Batteries

Smartwatch batteries are one of the most influential factors that can prevent users from continuous use of their device [42]. There is a direct, positive correlation between the number of sensors and their sample rates with battery consumption. This is one of the downsides of integrating many sensors with the high sampling rate (number of data points can be captured by a sensor, in a specific period of time) into a smartwatch design. This correlation has motivated designers and engineers to explore solutions which decrease the battery consumption of smartwatches. For example, in the Samsung Galaxy gear S3 smartwatch and Fitbit Charge HR 2, there is a way that users can decrease the sample rate of the heart rate sensor, which increases the battery life. However, an increase in sampling rate and data points is known to produce improved accuracy and insight from the raw data. Manufacturers have also developed operational modes, such as power mode (in many smartwatches, such as Samsung Smartwatches and Apple watches), which can decrease the power of the CPU and kill unnecessary applications to make the battery last longer. Many smartwatches stop recording and storing data using sensors in this mode.

3. Health Data Types

Personal data, especially when related to user health, can be linked to more serious outcomes than simply fitness and exercise. For example, heart rate data can play a significant role in preventing cardiovascular diseases. Analyzing and presenting such data is critical to user self-awareness. Considering the smartwatch limitations, such as the small screen size and limited input methods, we need exclusive visualization techniques when compared to other platforms such as smartphones. In this section, we will describe the most common health data that can be captured and visualized with smartwatches.

3.1. Heart Rate Data

Heart-rate data is one of the most important categories of personal data that can be used to anticipate cardiovascular anomalies [43]. To collect heart rate data, many advanced sensors are available on smartwatches and wristbands [44]. Hernandez et al. [45]

introduced new ways of collecting heart rate data from wrist-motion sensing. It has been shown that analyzing data collected by these sensors could help physicians detect cardiovascular disease symptoms [46].

Various data visualization techniques exist to represent such data, including line graphs and bar charts (Figure 1, a). It is also possible to show heart rate data using pictographs and animation. Text or number are some of the simplest ways to show this information, and since they usually occupy a small screen space, they are used commonly. However, in-situ (e.g. while they are jogging/running) visualization techniques should be considered when visualizing heart-rate data [24]. In-situ visualization techniques help users to get the most information in very short periodof time, in the context of their activity. Innovative techniques [47,48] also need to be considered for consuming such data.

3.2. Sleep Data

Sleep quality is another essential category of personal health-related data. Good quality sleep can eliminate stress levels [49,50] and decrease the risk for cardiovascular disease [51]. Using sensors such as an accelerometer and gyroscope in smartwatches, it is possible to detect different sleep stages based on sleeper's movements [52]. Data captured by various smartwatch sensors can be analyzed by algorithms to recognize different activities [53].

Visual displays, such as line graphs and bar charts are the most common visualization methods on smartwatches used to represent such data (Figure 1, b). However, texts and numbers can be used to add more information such as basic statistical reports (e.g. average sleep duration).

3.3. Fitness Activities Data

With embedded sensors, devices can collect and interpret wrist movements for the recognition of different activities [18,54]. Usually, fitness-activity data is visualized using a collection and combination of multiple data sets. For example, for a jogger, the distance travelled, variations in elevation, and calories burnt are all important. Visualizing a combination of multiple data categories, using different visualization methods, makes the visualization a complex process on small screens of smartwatches.

Another critical factor when representing fitness-activity data stems from the nature of smartwatches as *glanceable devices* [55]. In-situ data visualization is a technique that provides users with enough information in a way that they can get necessary information based on the different situations and conditions in a short period time (Figure 1, c). This can prevent excessive cognitive load while interpreting the visualization. Previous work has shown that smartwatch users find in-situ data visualization a beneficial technique which can be used to deliver the right amount of information in a short time period [24].

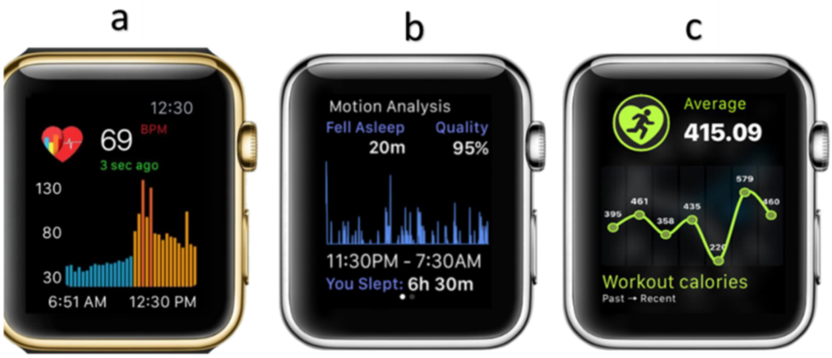

Figure 1. a) Heart rate data, b) sleep data, and c) fitness activities data representation on smartwatches

4. Visualizing Health Data on Smartwatches

Techniques such as the compression of existing visualization methods (e.g., line and bar graphs) can help designers represent more information on the small screens of smartwatches (Figure 2, a, c). For instance, Sparklines [56] are compressed line graphs on the y-axis, which are designed to be embedded in texts, images, and tables (Figure 2, b). Using visualization techniques such as sparklines can provide users with meaningful information in a tiny segment the smartwatch screen and the remaining segments can be used to represent more health data and related information. For example, representing heart rate data, sleep quality, and body temperature simultaneously (Figure 2, c), can help users to understand their stress level to prevent future side effects.

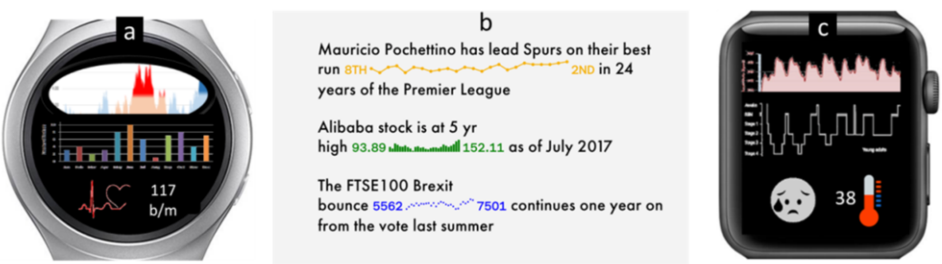

Figure 2. a) Compressed horizon and bar graphs to present fitness activities data, b) Sparklines in texts, c) compressed line graphs to represent heart rate data and sleep quality

5. Future Directions

Many researchers are currently working to eliminate hardware issues with wearable devices and especially smartwatches, which include a lack of memory, limited processing power, and limited battery life, by either software or hardware solutions. Solving these issues stands to make a significant, difference as smartwatches might provides users with more accurate and robust data which. This data can be crucial issue in health science, since the decision-making process of the user is often based on the collected data. In the future, we expect to see more people using smartwatches as the reliability of the data collected collected improves.

Given the limited output and input modalities of smartwatches, new interaction and visualization techniques are required to enhance user interaction and engagement. Novel visualization techniques are necessary to represent thousands of records of health data. New interaction methods to interact with massive datasets on the small screen of smartwatches are also required. Facilitating the use of smartwatches by providing novel interaction and data visualization techniques, as well as improving the reliability of the collected data would be the next step of future research on smartwatches, which stand to make them a truly ubiquitous wearable device.

6. Conclusion

This paper describes some of the most significant challenges regarding data presentation of the most common health data (e.g., data related to heart rate, sleep quality, and fitness activities) on smartwatches. Hardware challenges such as limited storage, processing power, and battery life can affect the processing, representation, and analysis of data. We also show that representation of complex health data on small screen of smartwatches requires further investigation and the development of novel techniques.

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