Visual Analytics System for Monitoring Mobile and Wearable Sensing Data Collection Campaign

Yugyeong Jung*
KAIST, School of Computing

Uichin Lee†
KAIST, School of Computing

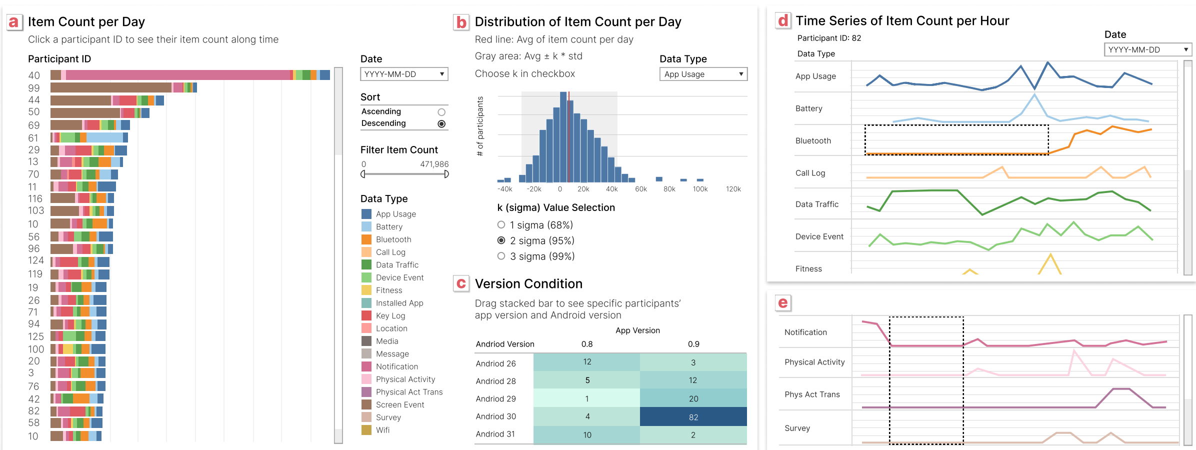

Figure 1: Interface of the mobile and wearable sensing data monitoring system. The system consists of (a) a stacked bar chart representing item count per day for each participant and each sensor; (b) a distribution chart for item count per day providing data-driven guidelines with statistical quality control mechanisms; (c) a distribution of data collection app and OS version conditions for selected participants in (a). If users click a specific participant's ID in (a), the system moves to view (d) and visualize the time series of item counts per hour to understand temporal trends of missing data collection.

Abstract

The proliferation of mobile and wearable sensing research has amplified the need for in-the-wild data collection to capture and analyze human behaviors. However, data quality can be compromised by factors such as participants turning off devices, failing to respond to surveys, or not wearing sensors. To address these issues, we developed a visualization dashboard to monitor missing data in mobile and wearable data collection campaigns. The tool utilizes a simple quality metric, item count, along with statistical quality control mechanisms to help researchers quickly identify and mitigate significant missing data issues. The dashboard's effectiveness was validated through a case study, demonstrating its utility in highlighting missing data and facilitating researcher intervention.

Index Terms: Visualization, human-computer interaction, mobile data

1 Introduction

The current landscape of mobile and wearable sensors and the increased interest in capturing, analyzing, and interpreting human behaviors have placed demands on in-the-wild data collection from many people and sensors. During the data collection, several unexpected factors can compromise data quality; participants (e.g., data providers) can inadvertently turn off smartphones for extended periods, fail to respond to emotional surveys, or not wear wearables, contrary to researchers' instructions [1, 3]. These factors can result in long missing data, leading to insufficient quantity and quality of data. To prevent such situations, researchers have to monitor collected data and reach out to participants to address the issue (e.g., asking to check smartphone status, requesting to wear wearables) and prevent similar issues from reoccurring [6].

However, monitoring missing data from mobile and wearable sensors presents challenges due to their diverse sensing characteristics. Previous studies have used methods such as visualizing quality metrics like completeness (e.g., comparing the number of data items with the ideal number of data items within a time window) to identify missing data [2]. Since the sampling frequency of mobile and wearable sensors is often unspecified for event-based sampling (e.g., data is logged only when a specific event occurs, such as physical activity or app usage), determining the ideal number of rows becomes challenging. To address these challenges, we developed a visualization dashboard to monitor participants with missing data in mobile and wearable data collection. We established a simple quality metric called item count (e.g., the number of rows within a time window), which can be applied across data with various sensing characteristics. The dashboard provides an interactive visualization to identify participants with significantly lower metrics compared to the common data collection patterns. The proposed visualization can support the management of in-the-wild mobile and wearable data collection from many people and sensors.

2 Interface Design

Based on discussions with domain experts, we designed a web-based dashboard using Tableau [5] to identify missing data problems caused by smartphone power outages, non-response to self-reports, or not wearing wearable devices. To identify missing data, we used item count as a data quality metric; low item count represents data including long missing data. To establish the criteria

*e-mail: yugyeong.jung@kaist.ac.kr
†Corresponding author, e-mail: uclee@kaist.edu

for identifying problematic values of the metric, we leveraged the concept of control charts [4], commonly used in statistical quality control in manufacturing domains. A normal range for the metric was set as $[\mu - 1\sigma,\ \mu + 1\sigma]$, where k is a constant, and μ and σ are the average and standard deviation of the quality metric. The choice of k determines the proportion of quality metrics falling within the normal range (e.g., 68%, 95%, and 99.5% for k = 1, 2, and 3). Researchers can consider participants who fall below this range as having significant missing data.

2.1 Overview of data collection status

To visualize the overall status of data collection at a glance, we selected a horizontal stacked bar chart, in which each row indicated a participant ID, the lengths of the bar are the number of rows per day, and colors are data types (Fig. 1a). Users can select a specific date in the "Date" dropdown. The stacked bars represent the total amount of data collected per participant and emphasize participants with considerably smaller or larger amounts of data than others. The item count for individual data types can be seen by clicking on a data type in the legend.

2.2 Data-driven guidelines with statistical quality control mechanisms

The concept of a control chart supports quality criteria setting based on the distribution of the item count per day (Fig. 1b). When a user selects a specific data type on the "Data Type" dropdown, the chart shows the distribution of our quality metric with a mean as a red line, upper and lower limits as gray areas, and detailed statistics by hovering on the mouse. Users can choose the parameter k in the checkbox, which helps set quality thresholds and filter participants out of the threshold. The bar plot can be filtered using a "Filtering Item Count" range slider to find participants out of the thresholds.

2.3 Visual exploration of missing data collection

For participants below the lower limit, the dashboard helps observe, on a more detailed level, how each participant's multiple data items were collected over time. By clicking a participant ID in the stacked bar (Fig. 1a), users can access a more detailed view of data collection status (Fig. 1d). We resampled data at an hourly level and visualized the temporal trends with small multiple representations (Fig. 1d). Users can check missing areas of a single data item (Fig. 1d), and multiple data items (Fig. 1e). Additionally, we visualized a heatmap to represent the number of participants (indicated by color brightness) using a specific version of the OS (each row) and data collection software (each column) (Fig. 1c). By dragging multiple participants' bar graphs in Fig. 1a, the heatmap shows the distribution of participants according to OS and data collection software versions. Dragging participants with low item counts helps identify the popular versions they use, and provides hints to researchers about possible version problems in data collection.

3 Case Study

We conducted a case study on an in-the-wild data collection campaign. The campaign collected 17 kinds of mobile and wearable sensor data from 116 participants during one month. The quality metrics were calculated daily on a designated server computer and transmitted to the visualization dashboard. We recruited two researchers (R1 and R2) with background knowledge in this domain. They used our tool to monitor data and contacted participants if they had a missing data issue. After one month, we interviewed the researchers about their experiences.

Overall, researchers welcomed the idea of item count metrics and visualizations as capturing missing data issues. By interacting with the distribution chart and the stacked bars, they identified participants whose quality metrics were below the normal range. R1 mentioned, " *The advantage of this bar chart is that I could intuitively find people whose whole number was not collected, particularly when the length of the bar is zero or very small. Especially for event-based sensing data, the histogram was helpful in determining the criteria for filtering participants with small item counts, who can have potential missing data.*"

After finding participants with a small item count, they clicked the participant ID and moved to the time series view to understand the detailed data collection status. One of the interesting findings was that this view was helpful to *diagnose* the causes of missing data problems. R2 said, "*After finding a participant with a small count, I was surprised that the entire data was not collected during the whole night! Maybe his smartphone was turned off while sleeping.*" Based on their diagnosis, researchers could contact participants and send messages to figure out the issues and provide instructions (e.g., checking their smartphone status, etc.) Though they pointed out that basic knowledge of mobile and wearable sensor data (e.g., sensing frequency or the meaning of each data type) is necessary for using the tool, they acknowledged that the tool can facilitate the monitoring of mobile and wearable data collection.

4 Conclusion and Future Work

We developed a visualization dashboard to monitor missing data in mobile and wearable data collection campaigns. Using a simple quality metric and statistical quality control mechanisms, our tool helps researchers quickly identify and address significant missing data issues. The dashboard's intuitive visualization, validated through a case study, proved effective in highlighting missing data issues and facilitating intervention by researchers.

For future work, we plan to incorporate diverse visualizations that can represent multivariate mobile and wearable sensor data, allowing researchers to identify a broader range of data quality issues such as outliers and abnormal values. Additionally, by patterning common missing data and visualizing them, we aim to provide visual analytics methods that enable researchers to diagnose the causes of missing data more deeply.

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