ARGUS: Interactive Visual Analytics Framework for the Discovery of Disruptions in Bio-Behavioral Rhythms

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Abstract

Human Bio-Behavioral Rhythms (HBRs) such as sleep-wake cycles and their regularity have important health ramifications. Smartphones can sense HBRs by gathering and analyzing data from built-in sensors, which provide behavioral clues. The multi-channel nature (multiple sensor streams) of such data makes it challenging to pin-point the causes of disruptions in HBRs. Prior work has utilized machine learning for HBR classification but has not facilitated deeper understanding or reasoning about the potential disruption causes. In this paper, we propose ARGUS, an interactive visual analytics framework to discover and understand HBR disruptions and causes. The foundation of ARGUS is a Rhythm Deviation Score (RDS) that extracts a user's underlying 24-hour rhythm from their smartphone sensor data and quantifies its irregularity. ARGUS then visualizes the RDS using a glyph to easily recognize disruptions in HBRs, along with multiple linked panes that overlay sensor information and user-provided or smartphone-inferred ground truth as supporting context. This framework visually captures a comprehensive picture of HBRs and their disruptions. ARGUS was designed by an expert lead goal-and-task analysis. To demonstrate its generalizability, two different smartphone-sensed datasets were visualized using ARGUS in conjunction with expert feedback.

CCS Concepts

• ***Visualization*** → *Visualization systems and tools;* • ***Visualization application domains*** → *Visual analytics;*

1. Introduction

Disruptions in behavioral patterns can have significant health ramifications such as mental illness, obesity, and heart disease [Vet20]. The regularity of HBRs such as *Circadian Rhythms* [Vet20] (sleep-wake cycles) are important measures of health. Consequently, monitoring HBRs to detect disruptions can inform timely interventions [FPL*14]. However, capturing human behavior data is challenging. Smartphones are uniquely suited for capturing such data because they are ubiquitous and are also equipped with sensors such as accelerometers, gyroscopes and GPS that can record data containing important clues about HBRs. For instance, a lack of phone usage during the night may indicate sleeping [AMM*14]. Such data makes the smartphone a *proxy* for human behaviors. Prior work has used smartphone sensing data to reliably detect certain behavioral changes [WHW*18], as well as to monitor mental health [RACB11] and academic performance [WCC*14].

Prior work leveraged machine learning [AMMC17] to classify smartphone-sensed HBRs but they have limited interpretability and offer few insights into the causes of HBR disruptions. Interactive Visual Analysis (IVA) is a powerful approach to make sense of multivariate data. We leveraged IVA to discover and analyze disruptions in HBRs using smartphone-sensed data. We are interested in not only identifying HBR disruptions but more importantly to *explain* them. We propose ARGUS, an IVA framework to represent smartphone-sensed data using intuitive visual metaphors for analysis. ARGUS leverages an intuitive Rhythm Deviation Score (RDS) that captures the notion of smartphone-sensed *"rhythm"* as well as its disruptions for an individual. We visualize this score using a state-of-the-art metaphor called the z-glyph [CLGD18], alongside linked panes. Overall, our contributions include:

1. A novel Rhythm Deviation Score (RDS) to capture underlying 24-hour patterns in smartphone sensed data.
2. *ARGUS*, an IVA framework, designed using expert-guided task-and-goal analysis, which visualizes the RDS and uses multiple linked panes to contextualize and *explain* rhythm breaks.
3. A comprehensive evaluation of *ARGUS* using an insightful walk-through of use cases along with expert feedback.

2. Related Work

The proliferation of smartphones has created opportunities to gather rich datasets about human behaviors such as mobility and social patterns [CFB14]. Smartphone sensing studies, in which an application runs in the background and collects sensor data that are analyzed using machine or deep learning, have been able to monitor human behaviors [VELW18] and HBRs [AMM*14, SLS*16].

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Data visualization is an effective method of making sense of large, multivariate data including identifying deviations in human behaviors. Examples include the detection of mal-intents such as spreading fake news [RCP*14, SCFM16, SCV*18] or financial fraud [vHBv13, KFS*19]. IVA systems can utilize intuitive visual metaphors [SM08] and techniques [PXQ*11] to highlight anomalous behaviors. Cao *et al* [CSL*16] created TargetVue, a tool to detect bots. They introduced the *z-glyph* [CLGD18], an intuitive visual metaphor to highlight deviations. These works illustrate that IVA can advance the understanding of digital human data problems. Our work expands this field by leveraging IVA and glyph designs for visualizing HBR disruptions with potential health implications.

3. Goal and Task Analysis

We performed a goal and task analysis with a professor of health psychology at our university with expertise in health behaviors. She was particularly interested in rhythms related to sleep. For instance, stress due to external factors may cause lost sleep, which has health ramifications. Existing work shows that smartphone state measurements such as a locked screen [AMM*14] or ambient light [MDW*14, CLC*13] can detect sleeping. The expert suggested conceptualizing smartphone data as *channels* of *contextual* information. Examples of channels are inferred activities, battery charging, GPS location, *etc*. Breaks in patterns within these channels may indicate HBR breaks. The expert said that channel correlation may be meaningful, such as darkness with the screen being locked is useful to detect sleep. She suggested using visual clues for correlations. She summarized her goals of investigating smartphone-sensed HBR disruptions as follows:

- **G1: Discover overall levels of HBRs:** Design a *metric* to quantify the level HBR rhythms and breaks therein.
- **G2: Explain and contextualize causation:** Linked views of data may explain the reasons for HBR breakages to facilitate disambiguation of harmful (e.g. sleep loss due to underlying depression) vs. benign disruptions (e.g. staying up due to travel).

We devised specific tasks to achieve the goals described above:

- **T1, Cohort analysis**: View the rhythmicity of all study participants to find those with the strongest and weakest HBRs.
- **T2, HBR break identification**: Identify specific time periods with significant disruptions in HBRs.
- **T3, Cross-channel HBR exploration**: View participants' rhythmicity across multiple "channels". For instance, contextualize disruption across physical activity vs geo-location channels.
- **T4, HBR contextualization**: Highlight contextual factors that have semantic meaning such as weekday vs weekend.
- **T5, Raw sensor value drill-down**: Visualize sensor readings such as screen interaction at the time of HBR disruptions.

4. The Design of the ARGUS Visual Model

We designed *ARGUS*, an IVA framework that follows the "Visual Analytics Mantra" [KMS*08]: "Analyse First - Show the Important - Zoom, Filter and Analyse Further - Details on Demand". As users may have different body rhythms or body clocks (E.g., *night owls* or people who sleep later at night vs *early birds* or people who wake up early) [AMM*14], ARGUS does not compare the inferred HBRs of different users. Instead, ARGUS adopts a within-participant approach and visualizes each individual's deviation from their own normal rhythms computed using their data.

Rhythmicity Deviation Score (RDS): This score is based on the Lomb-Scargle periodogram [Lom76,Sca82], a method for computing the periodicity of irregularly-sampled data. We apply this method on each *channel* of the data to calculate *Circadian Rhythm* (CR) similar to [WHW*18]. Channels are sequences of (binary) indicator variables such as physical activity (still vs. walking) or sensor readings (smartphone locked vs unlocked). A *channel* C_i corresponds to a time series: $\Big((c_{i,0},t_{i,0}),(c_{i,1},t_{i,1}),\ldots,(c_{i,k},t_{i,k})\Big)$, such that each $c_{i,j}\in\{0,1\}$. The *average occurrence ratio* $\overline{O}_r$ of channel C_i corresponds to the average ratio of positive instances of channel C_i over all days in the set of days $\mathcal{D}$. The *channel rhythm disruption CD* of C_i for day D_j measures the difference in occurrence ratio of C_i for D_j and the average occurrence ratio of C_i, weighted by the CR of C_i. A *channel category* G_k corresponds to a set of channels. Our three categories are: **Sensors**, **Geo-location**, and **Activity**. The channels are mutually exclusive such that no pair of channel categories have any elements in common. *CD* denotes the change in behavior of a particular channel (*i.e.*, changes in duration of positive instances) weighted by the CR of this channel. The change in behavior is weighed by the CR to identify *meaningful* disruptions in behavior. The *Rhythm Deviation Score RDS* of category G_i for day D_j measures the average CD for each channel in G_i on day D_j:

$$RDS(G_i,D_j)=\frac{\sum_{C_k\in G_i}CD(C_k,D_j)}{\|G_i\|}$$

Eyes of ARGUS (EA): Every glyph plots a person's average RDS as a black circle (larger represents more rhythm) against the daily RDS - ordered clockwise (Fig. 1 A). The closer the purple line is to the center, the higher the disruption (T2). The user ID and the number of days in the study are shown at the top left. EA shows the RDS for all days. This visual metaphor is based on the z-glyph by Cao *et al* [CLGD18], shown to be more effective over both traditional line and radial views, for highlighting deviations (or outliers), which is a main goal of ARGUS. The z-glyph family includes both line and star (radial) glyphs. We chose the radial glyph because a user study by Cao *et al* established that users preferred the radial glyph over the line glyph in terms of efficiency and user comfort which is important as ARGUS targets health experts who will likely not be experts in data visualizations.

Fig. 1 A provides an overview of all users (G1,T1) to filter interesting users to explore (T2). Clicking on an eye will show it in the Magnified Eye of ARGUS (MEA) (Fig. 1B). The underlying circle has the maximum circumference, indicating perfect rhythmicity. Each slice corresponds to a day and the beige slices denote weekends (G2,T4). Days can be selected by clicking on them for details in (Fig. 1D) and (Fig. 1E) (explained later). This is useful as events on concurrent days may be linked (G2). The channel category to visualize in the EA and MEA is selected by clicking on "Selected Channel Category" (Fig. 1A) (G2,T3).

Duration View (DV): (Fig. 1 D) shows the "duration" for channels for every day by participant, i.e., when the channel was "on", such as how long the phone was charging. Every vertical bar represents a day and the height represents the duration per day. The

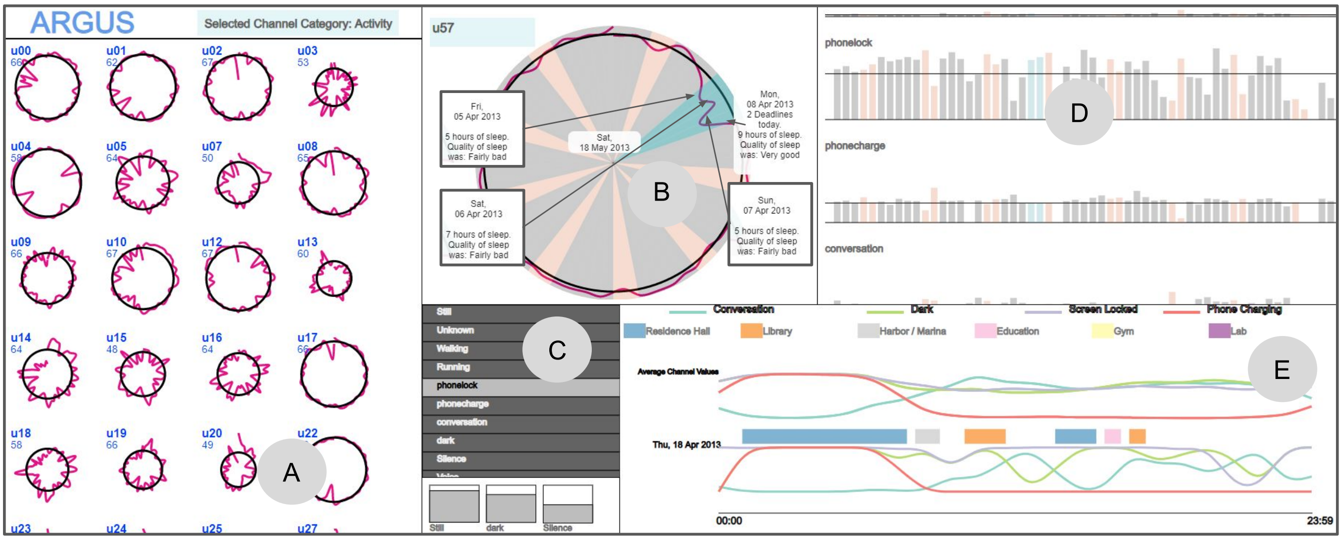

Figure 1: ***ARGUS****: A tool to discover and explain disruptions in HBRs.* ***A: Eyes of ARGUS (EA)****. Overview of breaks in HBRs across all participants.* ***B: Magnified Eye of Argus (MEA)****. User selected from EA. Beige color slices represent weekends. The tool-tip shows day-related information. For example, reduction in sleep leading up to a day with two deadlines.* ***C: Co-occurrence View (CV)****. Overview of the frequency of channel co-occurrence.* ***D: Duration View (DV)****. Total duration of channel positive values per day.* ***E: Explainability View (EV)****. Visualizing multiple channels to contextualize HBR breaks.*

horizontal line represents the mean duration. In Fig. 1 D, the phone appears to be generally more locked than charging (G2, T2, T5).

Co-occurrence View (CV): The co-occurrence between certain channels is interesting as a lack thereof may explain a break in HBRs. Clicking on an EA shows the CV (Fig. 1 C) which has a list of available channels. Clicking on one bar shows the *most commonly co-occurring channels* (ordered left to right, top to bottom), i.e., channels that were "on" at the same time. The gray vertical fill is proportional to the co-occurrence frequency. For instance, "phone-lock" coincided often with "still", "dark" and "silence". To link the co-occurrence, hovering over a commonly co-occurring bar highlights the duration of the channel selected and hovered over in the EV (blue for selected and yellow for hovered over channel).

Explainability View (EV): (Fig. 1 E) provides a day-level view for *causes* of HBR disruptions (G2,T5). The lines show changes in the channel data with their height representing average channel values per hour. The first plot shows the average channel values across the entire period. Every plot after that is a day chosen in MEA. The bars over the lines represent durations for which the user was in the same geo-cluster as determined by DBSCAN [EKSX96]. We show the top 6 clusters (Fig. 1E). The colors are from a 10-color palette from ColorBrewer [BH09]. The cluster categories (*i.e.* "Residence Hall" vs. "Library") were gathered using the Foursquare API [Fou].

5. Illustrative Use Cases

ARGUS targets users with background knowledge and training in interpreting behavioral rhythms including psychologists and counselors. We next introduce Emma, a psychology graduate student who specializes in the study of behavioral rhythms. Emma will interactively explore two real world datasets using *ARGUS*.

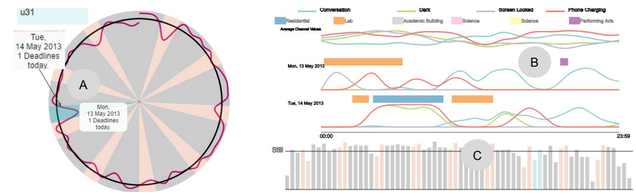

Figure 2: *Channels deviate from mean and the user is in lab early.*

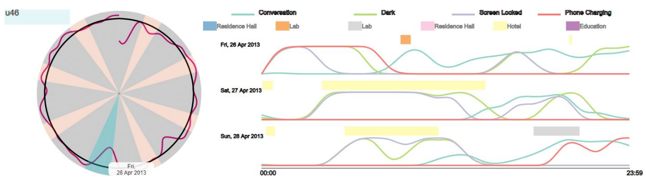

Figure 3: *Geo-location indicates being at a hotel during weekend.*

Dataset 1: The StudentLife study [WCC*14] gathered smartphone sensor data for 49 college students over an academic term of over two months. This data has activity inferences (still vs walking), noise inferences (silent vs. conversation) and geo-location (whenever available). Values are recorded for when the phone was in **Dark**, **Charging**, near a **Conversation** and had the **Screen Locked** (bold indicates being shown as lines in EV), along with answers to daily questionnaires with wellness information such as sleep duration, quality, and stress levels.

Contextualizing HBRs and Deadlines: Emma explores HBRs around stressful times such as student-provided deadlines (G1).

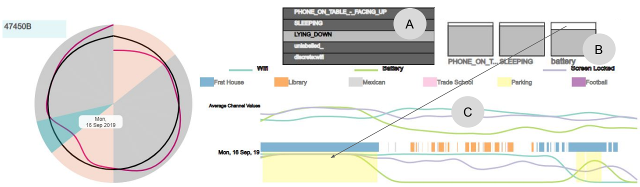

Figure 4: *Hovering over "battery" shows its occurrence of that channel but also no coincidence with "Lying down". The screen is locked throughout indicating a high probability of "Sleeping".*

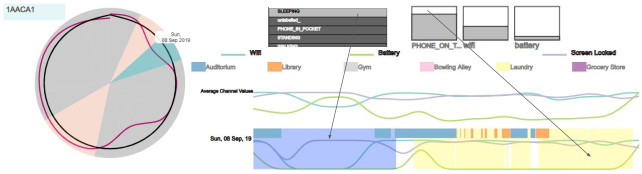

Figure 5: *"Phone on table" and "Sleeping" are usually co-labelled but not for this day.*

Emma looks for users with large breaks in EA (T1) and notices u57 (T2). She views it in the MEA (Fig. 1 B). She sees low sleep duration and quality for three days leading up to April 8*th*, with two deadlines (G2, T4) after which sleep duration and quality improve. Emma believes that deadline induced stress caused this disruption of u57's HBR (G2). Visual overlay of human understandable data along with objective rhythmicity made this insight easy for Emma.

Explanations of disruptions in EV: Emma wants to analyze days with no sleep responses. She notices a disruption for 2 days (both with deadlines - Fig. 2A) for u31 (T2). Emma views them in EV and DV. She notices lower levels of the "Still" state on May 13th (Fig. 2C). The participant had much lower levels of screen locked and being in a dark environment in EV (Fig. 2B) (T5). For both days, this student was in a "Lab" during very early hours of the day (T4). The intuitive overlay of channels enabled Emma to contextualize a potentially concerning (sleep loss) HBR disruption.

Geo-location based HBR: Small disruptions may not be concerning [Vet20]. Emma selects "Geo-location" (T3) (top of Fig. 1A) and notices u46 had a large deviation, which occurred on the weekend (T4). She clicks on the days (Friday, Saturday and Sunday) and notices in the EV that the participant had a geo-location recording showing that they were at a hotel and more readings for the 2 weekend days (Fig. 3). Emma sees this as no cause for concern as travel tends to be disruptive. The overlay of channels allowed Emma to disambiguate this disruption in HBR as non-concerning.

Dataset 2: Study 1b is a smartphone sensor dataset gathered by our team for 103 people who were more demographically diverse and had a shorter participation (two weeks) than StudentLife. We used a modified version of the ExtraSensory application [VELW18], which gathered sensor data for 20 seconds after every minute. Users provided 18 different labels for activities such as "Walking", "Sitting" and "Phone in Pocket" which were used as ground truth for machine learning. The application collects channels such as geo-location, **Screen Locked**, **Battery Charging** and **Wifi** (bold indicates being shown as lines in EV).

Absence of labels: Emma notices in the DV that the participant 47450B has provided inconsistent labels. She has to rely on objective sensor values and selects "Sensors" as the channel category (T3). She visualizes an off-rhythm day (Fig. 4) in the EV. She notices that the user was in the "Frat House" cluster (on campus residence). The DV showed that the participant provided no labels for "Lying down" or "Sleeping". She clicks on the "Lying down" bar in the CV and notices that the top co-occurring values for "Lying down" are "Sleeping", "Phone on table" and "battery" (Fig. 4B). She hovers over the co-occurring bars for "Sleeping" and "Phone on table" and notices they were not provided. She hovers over "battery" and sees its yellow overlay (Fig. 4 C) but no blue overlay for "Lying down". The screen was also locked and the disruption in this day was probably caused by other factors later in the day, which is uninteresting for Emma (T4, T5, G2). Linking such information allowed her to dismiss this day as non-concerning, which may not have been possible using traditional statistical analyses.

Detecting erroneous labels: Emma chooses the "Sensors" channel category (T3) and analyzes user 1AACA1. She notices in the EV that the screen was unlocked after midnight on Sept 8th. The "Sleeping" bar in the CV shows the most commonly co-occurring channels ("Phone on table", "WiFi" and "battery" (Fig. 5)). Hovering over "Phone on table" shows no co-occurrence. Also, the screen was unlocked after midnight and sleeping and phone usage are unlikely to co-occur. Emma concludes that this is mislabelled data and that there was in fact a disruption (T4, T5, G2).

Expert Feedback: After implementing ARGUS, we asked the expert from the goal and task analysis to go through the same use cases as Emma. The expert came to similar conclusions. She was easily able to discern HBR breaks from EA and MEA. She liked the ability to discern "predictable" i.e., around deadlines vs "unpredictable" breaks. She said how "everyone has their weird behavior at times, especially students which is not necessarily concerning overall" and how this multi-channel view helped her understand those breaks. Overall, she found the ARGUS approach useful.

6. Conclusion and Future Work

ARGUS is a novel IVA framework that facilitates the identification and explainability of HBR disruptions. We presented illustrative use cases and evaluated *ARGUS* in a study with an expert. In future, we will explore its scalability with regards to the number of participants (thousands vs dozens) and the length of time they are monitored (years vs. weeks). As the number of participants visualized using ARGUS increases, it might be useful to categorize them into groups with similar bio-rhythms to facilitate larger scale analysis. The display of users' levels of activity and sleep may also be useful for personalized health informatics.

7. Acknowledgements

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