Visualizing Self-Tracked Mobile Sensor and Self-Reflection Data to Help Sleep Clinicians Infer Patterns

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Abstract
We present results from a design study of two novel visualization methods for self-tracked sleep data. These methods combine multivariate time series data and ordinal self-reflection data to help sleep clinicians analyze factors related to sleep quality such as noise and movement and make recommendations to improve sleep quality. We conducted an iterative design process, driven by our collaborator's domain specific goals in analyzing self-tracked sleep data. The final visualizations feature a unique spiral clock radial design and interactive controls for ordinal data. We ran a survey with three sleep clinicians to assess the effectiveness of each visualization type. In our user study a sleep clinician also performed a mock in-patient session, which demonstrated their effectiveness in a clinical setting. The new visualizations prove more effective in achieving the domain specific goals of sleep clinicians in comparison to previous efforts from similar work.

Author Keywords
sleep visualization; design; prototyping; personal informatics; multivariate time series; ordinal

ACM Classification Keywords
H.5.m [Information interfaces and presentation (e.g., HCI)]: Miscellaneous

Introduction & Related Works

The main contribution of this work is the validated design of two new visualization methods for self-tracked sleep data. These novel methods combine multivariate time series data and ordinal self-reflection data to help sleep clinicians analyze patterns in patients' sleep cycles and derive recommendations on how to improve sleep quality. The design was created through an iterative prototyping process in collaboration with a domain expert. The first visualization features multivariate time series data from raw sensor data such as movement, noise, start, and end time. The second visualization integrates this multivariate time series data with ordinal data. Ordinal data consists of sleep quality ratings and keywords tracked daily. To the best of our knowledge, there is no pre-existing work that attempts to integrate ordinal self-reflection data into multivariate times series visualizations of sensor data tracked during sleep.

Example Keywords used for Ordinal Self-Reflection Data
work, school, exercise, neck pain, stress, laugh, home, fullmoon, newmoon, nightmare, party, dream, write, class, cpap, cloudy, cold, allergy, sick, flu, sad, happy, talk, diet, coffee, tea, alcohol

This work seeks to build on the previous efforts of sleep clinicians and Personal Informatics researchers who collaborated on the mobile application SleepCoacher [4]. SleepCoacher uses a closed feedback loop to deliver personalized sleep recommendations to users outside of a clinical setting. Sleep clinicians play a vital role in this closed feedback loop between data collection and personalized recommendation stages. They generate recommendations for users by inferring sleep cycle patterns from visualizations and raw ordinal data. SleepCoacher is the first system that involves experts in the feedback loop to build and deliver recommendations from self-tracked data. The inclusion of sleep clinicians in the feedback loop has garnered significant results for positive changes in user behavior.

In the past, sleep clinicians have effectively used actigraphy to gather sleep data. Actigraphy consists of single variable time series data used to visualize and infer sleep patterns in a traditional line chart. [1] This proved ineffective in motivating patients to modify behaviors to improve sleep. In contrast, SleepCoacher enhanced this relationship between clinician, recommendation, and patients. The visualizations sleep clinicians used in SleepCoacher to infer patterns and generate recommendations were not built to scale, omitted all ordinal self-reflection data, and were not designed based on the goals of sleep clinicians. SleepCoacher's visualizations mapped sleep start, sleep end, noise, and movement per day in a traditional line chart. Each of these were then stacked in sequential columns per week. This visualization along with user's self-inputted daily reflection data were sufficient for sleep clinicians to build recommendations. Other Personal Informatics applications such as Lullaby [5] use visualizations to engage users by mapping single variable time series data. Tracer [6] also maps single variable time series data to assist users with self-reflection. Authors of both systems in addition to other researchers [3] state the need to develop visualizations that generate more effective insights. Furthermore, neither system involves domain-specific experts to review or help design the visualizations. Other visualizations have been successfully designed and validated in collaboration with a domain expert through an iterative prototyping process [2]. The work presented here demonstrates how engaging domain experts in the design of visualizations can provide new knowledge in the design of effective visualizations for sleep clinicians and Personal Informatics. SleepCoacher demonstrated that clinical insights could be pattern matched into a collection of recommendations [4]. However, these recommendations might lack key insights due to the omission of daily self-reflection data, such as ordinal sleep ratings and keywords. The visualizations lacked other key data such as naps, oversleeping, and early awakenings that determine the quality of a patient's sleep. Our contributions can help bridge this gap between visualizations of sleep data and clinical insights.

Figure 1: Final radial spiral design for V2 & V3. Hover for date & hours slept per segment. Color key for sleep states can be found on page 4. On V3 checkboxes for keywords map to ordinal data and a slider maps to sleep rating per segment. Checkboxes and slider control opacity.

Blue: Normal Sleep
Green: Nap
Yellow: Noise
Orange: Movement
Magenta: Noise & Movement
Grey: Early Awakening
Purple: Oversleeping
White: Awake

Figure 2: Color key for sleep state per segment in new visualizations. Please reference spiral design used in V2 & V3 on page 3.

Methods

Our work involves several iterative steps to design and evaluate new visualization methods for self-tracked sleep data. The data used is from SleepCoacher users. Our collaborator and two other survey respondents worked on SleepCoacher. First we conducted an interview with our collaborator to gather design requirements and patterns they look for in sleep data. We built four prototypes, **P1** to **P4**, through an iterative design process to explore and satisfy our collaborator's goals and design specifications.

Iterative Design Process

We built P1 and P2 simultaneously. **P1 is a multivariate time series area chart**. It shares the strengths of traditional actigraphy to appeal to sleep clinicians. Our collaborator felt it was scalable and made a clear depiction of patterns over time. They felt it did not adequately visualize noise, movement, or ordinal data. They also felt this visualization might confuse a patient. **P2 is a radial heat map**. Our collaborator wanted to explore familiar clock based interfaces to help patients. The radial design represents a 24-hour clock. It features five distinct rings that represent an average data value at 15-minute intervals for noise anomalies, movement anomalies, sleep start time, actual wake-time, and scheduled wake-time. The collaborator had a favorable impression of the clock design and the concept of noise and movement anomalies. Sleep clinicians infer patterns from noise and/or movement anomalies, not the baseline measurements. The collaborator felt this visualization lacks the ability to infer daily patterns. This is pertinent, since patients often engage in behavioral and environmental interventions to help improve their sleep patterns per clinician advisement. P1 and P2 did not visualize naps, oversleeping, or ordinal data. P3 is designed to combine the strengths of P1 and P2. P3 also visualizes additional sleep states per our collaborator's requirements.

P3 is a stacked radial bar chart. Rings represent a two day segment. Each 15-minute interval represents the patients current sleep state. The collaborator outlined various sleep states to visualize: normal sleep, oversleep, nap, noise anomaly, movement anomaly, noise & movement anomaly, awake, and early awakening. Each sleep state is mapped to a unique color. Noise and movement anomalies are computed with a median absolute deviation test. The classifier is trained per sleep segment and then each 15-minute interval is tested for anomalies. A slider is used to change opacity by sleep rating per sleep segment. P4 addresses remaining ordinal data requirements by mapping keywords to check boxes. If a sleep segment did not contain one of the keywords its opacity is reduced. **P4's major design revision features a spiral design to represent the data.** This is essential because a spiral allows for linear segments of time to be wrapped around a radial interface. This matches the concept that time is linear. Without the spiral users with abnormal sleep patterns, such as shift workers, can not be accurately depicted across days. The flexibility of this visualization allows for the accurate visualization of naps and other odd sleep patterns over time.

Survey & User Study

We ran a survey to measure the effectiveness of the three visualization types, **V1** to **V3**. The original visualization from SleepCoacher **V1**, the new multivariate times series visualization **V2** (see Figure 1), and the new multivariate times series visualization with ordinal self-reflection data **V3**. V3 is the same as V2, but has interactive controls for keywords and sleep ratings. The survey used 9 visualizations, three for each type. First, respondents performed training tasks and gave recommendations to ensure realistic engagement with the visualizations. Then they answered ten 5 level Likert scale questions:

- How effectively does this visualization depict keywords and interventions?
- How effectively does this visualization depict sleep ratings?
- How effectively does this visualization depict abnormally high noise and movement data points?
- How effectively does this visualization depict naps?
- How effectively does this visualization depict early awakenings?
- What is your confidence level in the recommendations you generated with this visualization?
- How effectively does this visualization infer sleep patterns?
- How likely would you be to use this visualization to explain your recommendations to the patient?
- How effective do you think this visualization would be in allowing patients to infer their own patterns?
- What quality of recommendations do you feel a patient could make for themselves by viewing this visualization?

Likert Scale questions were modeled after each design requirement outlined in the iterative prototyping process. The respondents performed other training tasks in between questions, such as counting naps and early awakenings. Respondents also answered open ended questions and gave feedback on strengths and weaknesses per visualization type. We also ran an in-person user study with our collaborator. First they interacted and reviewed basic functions of the new visualizations with the think-aloud method. After that, they conducted a mock patient session to give recommendations using the new visualizations. Finally, they provided general feedback for each visualization type.

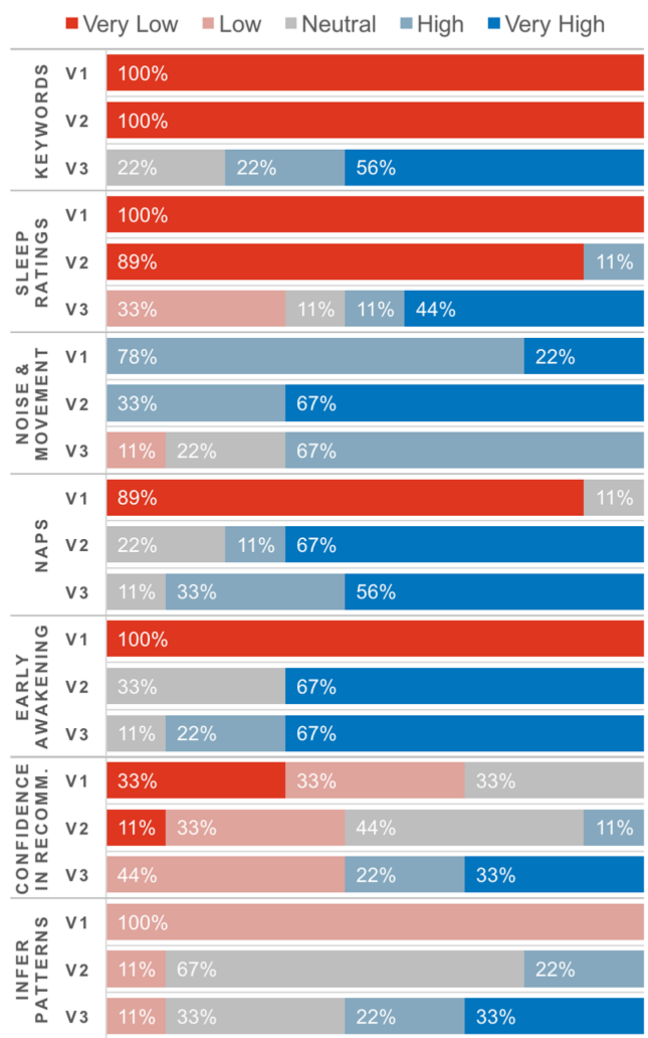

Figure 3: Survey Results for Effectiveness. (V1 old, V2 & V3 new) Answers correspond to the first seven Likert scale questions.

Results

The survey yielded 9 responses per visualization type from 3 respondents. Survey results are summarized in figure 3. All three visualization types rate similar in their effectiveness to depict anomalies in noise and movement data. This can be seen as a positive result for the new visualizations since they visualize 12 to N data points in contrast to V1's 5 data points. V2 and V3 are more effective in all other measurements compared to V1. V3 was also more effective than V2 in all other measurements. V2 and V3 proved to require less effort to generate recommendations. All respondents chose V3 as most likely to use in a patient session. These results support the realization of the goals for this work, to create new validated designs of multivariate time series and ordinal visualizations for self-tracked sleep data.

We also conducted a user study with our collaborator. The collaborator commented *"I love the visual depiction, I think it's incredibly compelling."* The keywords garnered meaningful insights. They were used to inform the clinician of lifestyle choices, such as neck pain, work, or school. The collaborator used keywords and sleep ratings to isolate and display unique correlations for each patient. These directly determine patient recommendations. They felt the radial spiral design used in conjunction with the interactive controls were compelling tools that could help sleep clinicians communicate how behavior changes affect sleep patterns for both patients and sleep clinicians.

Conclusion

In summary, we have designed and evaluated two visualizations for self-tracked sleep data in collaboration with a sleep clinician. The design has been refined based on sleep clinician feedback gathered through an iterative prototyping process. These new visualizations show double the number of sleep states when compared to the original visualization used in SleepCoacher. Evaluation results suggest that the spiral design is intuitive, reveals sleep patterns across long time spans, and requires less effort than a standard line chart. Embedding ordinal self-reflection data as filters through the use of interactive controls helps sleep clinicians gain more insights into the patients life style choices and contextualizes sleep patterns in those choices. This study shows the potential impact of these visualizations for clinicians and patients in and outside of a clinical environment. Going forward, we hope this new design of self-tracked sleep data can help answer and form new open questions in Personal Informatics. For example, can visualizations developed in collaboration with domain experts be more effective in aiding behavior modification of quantified selfers?

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