Toward Robust Interpretable Human Movement Pattern Analysis in a Workplace Setting

TILES

Brandon M. Booth, Tiantian Feng, Abhishek Jangalwa, Shrikanth S. Narayanan

Signal Analysis and Interpretation Lab @ University of Southern California

SAiL

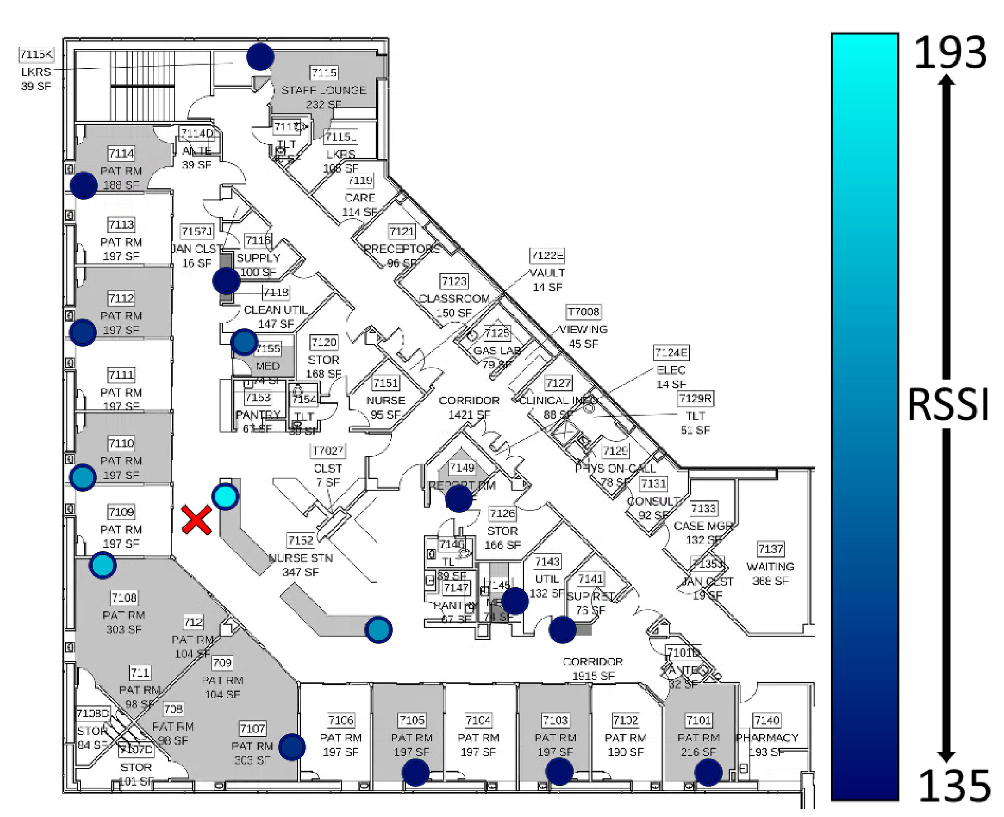
Motivation

- Interested in studying **mental wellness** (stress, anxiety, affect levels) of **nurses** at work from a multi-modal perspective
- Need to better **understand** and **interpret** dynamics of **movement** around the nursing units

Study

- Large-scale study of over **200 nurses** and other hospital workers **over 10 weeks** (TILES data)
- Unobtrusive collection of physiologic, environmental, **proximity**, behavioral and wellness data at home and **at work**

TILES: Proximity Data

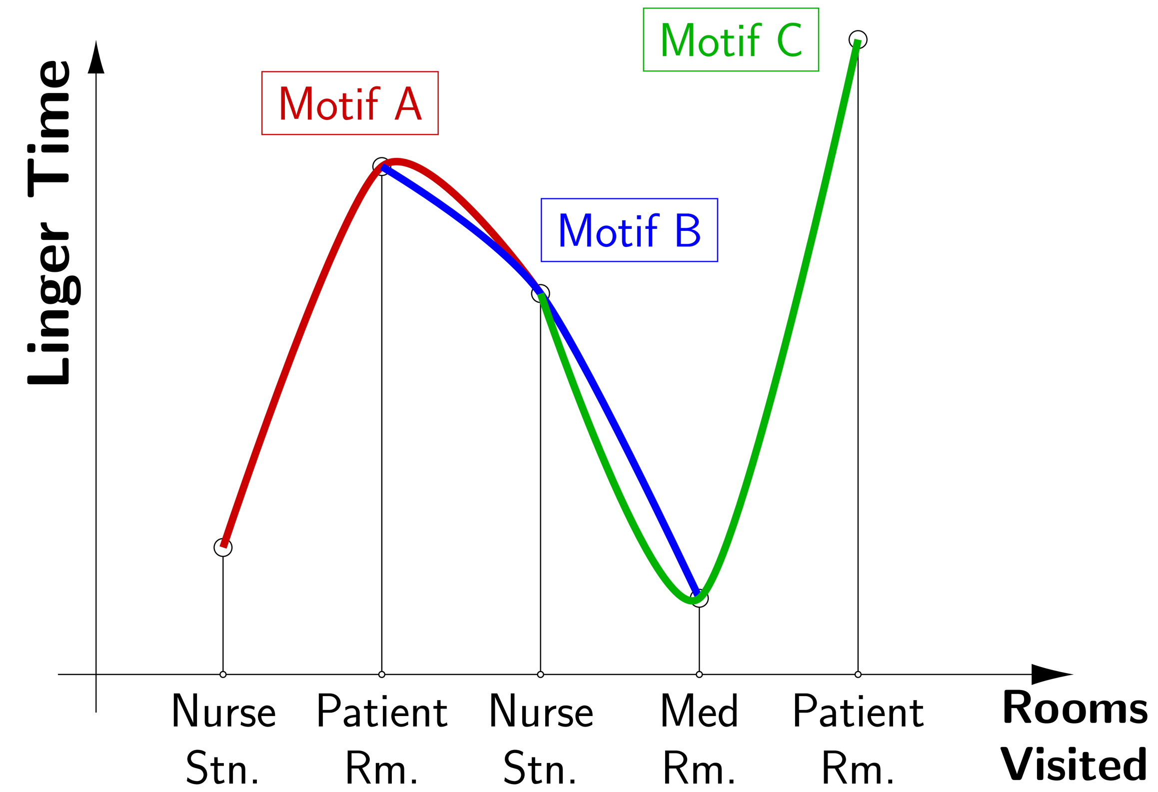


A top-down view of a single nursing unit in the TILES data set. Dots show the locations of Bluetooth hubs and the shade of the dot indicates the RSSI values observed by each hub for an individual emitting Bluetooth packets from a worn smartphone while standing at the "X".

References

[1] Tiantian Feng et al. "Is night time the right time? Psychological well-being in day versus night shift nurses". In: *pre-print* (2018). url: https://sail.usc.edu/beam/papers/Is_night_time_the_right_time_Psychological_well_being_in_day_versus_night_shift_nurses.pdf.

New Concept: Linger-time Motifs



But we **ignore the room labels** and focus only on the linger motifs.

Linger-time Encoding

1. Use the **nearest hub as an estimate of proximal room** location (highest RSSI after data cleanup)
2. Collapse contiguous observations of a participant in a **single location** and record only the **duration of stay** (linger time)
3. Remove linger times shorter than 30 seconds

Linger-time Motif Extraction

$$f : \{2, ..., K-1\} \to \mathbb{Z}$$
$$k \mapsto P(\text{rank}(l_{k-1}, l_k, l_{k+1}))$$

where k is the linger-time series index, K the total number of linger duration samples, l the linger duration time series, and $P(\cdot)$ a function mapping triplet permutations to unique integers.

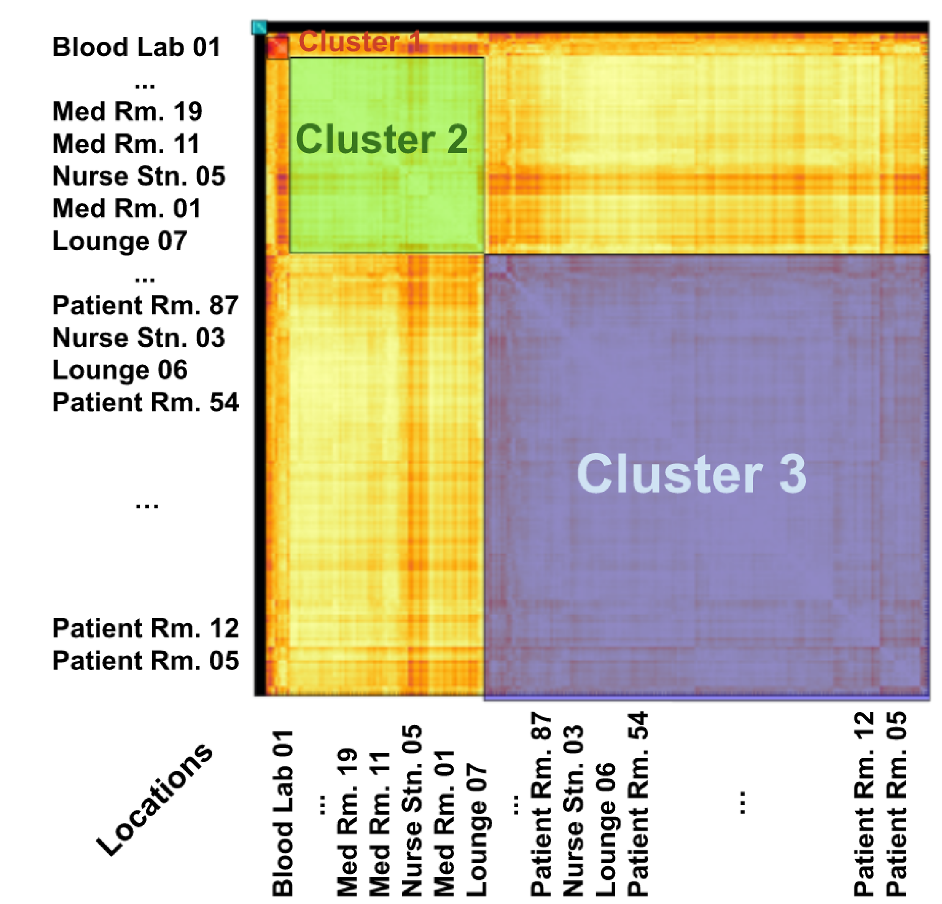
Linger-time Distribution Aggregate the $f(\cdot)$ values per room into a distribution of linger-motifs

Thanks to IARPA and the MOSAIC program for their support.

Clustering: Linger-time Motif Distributions

Idea: Aggregate motifs per room across all participants and compare the distributions.

Figures: Pairwise similarity matrix for 243 Bluetooth hubs computed using $1 - e^{-D_{SKL}(r_i, r_j)}$ applied to normalized motif distributions (r_i). Agglomerative clustering is utilized to **highlight the top three groups** of similar room usage motifs.



	C1	C2	C3
Lab	**17%**	50%	33%
Med Rm.	6%	**88%**	0%
Lounge	0%	**30%**	**65%**
Nurse Stn.	0%	**36%**	**61%**
Patient Rm.	2%	19%	**76%**

(Row-normalized)

Features: Linger-time Motif Deviations

Idea: Extract features from the aggregate motif distributions and use them with learning models to predict self-reported wellness measures per nurse per shift.

Feature	Definition
Normalized motif distribution	$m_s^{(i)} = \mathbb{1}^{1\times L} M_s^{(i)} / (\mathbb{1}^{1\times L} M_s^{(i)} \mathbb{1}^{W!\times 1})$
Difference from overall average	$D_{SKL}\left(m_s^{(i)}, \frac{1}{N}\sum_{j=1}^{N} \frac{1}{S(j)} \sum_{s=1}^{S} \mathbb{I}_s^{(j)} m_s^{(j)}\right)$
Difference from personal average	$D_{SKL}\left(m_s^{(i)}, \frac{1}{S(i)}\sum_{r=1}^{S} \mathbb{I}_r^{(i)} m_r^{(i)}\right)$
Difference from job type average	$D_{SKL}\left(m_s^{(i)}, \frac{1}{N(T(i))}\sum_{j=1}^{N} \mathbb{I}_{T(i)=T(j)}^{(j)} \frac{1}{S(j)} \sum_{s=1}^{S} \mathbb{I}_s^{(j)} m_s^{(j)}\right)$

Let $M_s^{(i)} \in \mathbb{R}^{L\times W!}$ be the aggregated motifs for participant i, work shift s, L total Bluetooth hub locations, and motif window size W ($W = 3$ in our work). D_{SKL} is the symmetric KL-divergence, N is the number of participants, S is the total number of work shifts, $T(i)$ denotes the job type of participant i. Other symbols are defined in our paper.

Inference: Mental Wellness

Using **random forest classifier** with different feature sets to predict each participant's daily SVD-binarized **self-reported mental wellness** label [1].

Features	F1	Accuracy
Fitbit, OMsignal	0.52	0.54
Fitbit, OMsignal, and room types	**0.56**	0.57
Fitbit, OMsignal, and motifs	**0.56**	0.58

Conclusion

- Different **rooms** have **usage patterns** in time that **reveals their types**
- **Linger-time motifs** provide similar information to room type labels and could be **helpful** for in-situ **studies at huge scales** where room types are a burden to collect