Appendix of Manuscript "PEARL: Physical Environment based Augmented Reality Lenses for In-Situ Human Movement Analysis"

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ABSTRACT

In this appendix, we provide additional information regarding (1) our literature research on human movement analysis and (2) technical details of the prototype.

For the original manuscript this appendix is associated with, please refer to the published article under https://doi.org/10.1145/3544548.3580715 or to our project page www.imld.de/PEARL.

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A LITERATURE ANALYSIS METHOD AND SUMMARY

To better understand how movement data analysis (i.e., knowledge discovery and extraction process [3]) can be performed, we examined the existing research landscape (see Tab. A1). We were particularly interested in what and how knowledge can be derived from the combination of the situated environment and human movement data, and the corresponding motivations of such knowledge extraction. For that, we examined related research publications of the last five years, between 2017 (exclusive) and 2022. We used the ACM digital library[1] and focused on major conferences such as ACM CHI, ACM CSCW or smaller specialized conferences such as ACM DIS and ACM ISS. For our search, we concentrated on various fields, including human motion and behavior analysis (e.g., user study analysis) and spatial analysis (e.g., human building interaction). We found 15 publications and categorized them based on the relations between components of spatio-temporal data and their visual representations (see Tab. A1). With this summary, we provide a foundational overview of research practice on analyzing human motion data to support high-level knowledge building and decision-making.

Categories	References and Mapping		
Single Actor			
▹ Trajectory	[2, 4–7, 9, 10, 12, 13, 15, 16]		
▹ Avatar	[4, 5, 7, 8, 10, 12]		
▹ Contextual Information	[8, 13]		
Actor-Actor Relation	What: Objects		
▹ Co-Located Comparison	[13]		
▹ Interaction Characteristic	[8, 9]		
▹ Other	[4, 5, 15]		
Aggregated Actors	What: Objects		When: Times
▹ Compare	[1, 13, 14, 16]		
▹ Session (Study)	[6, 7]		
▹ Time Unit (Date)	[11, 14]		
▹ Time Duration	[9, 16]		
Actor-Area Relation	What: Objects	Where: Spaces	
▹ Bird-Eye View Map	[2, 6, 9, 13, 16]		
▹ Observation Video	[4–6, 15]		
▹ 3D Environment Model	[8, 9]		
Actor-Area Interaction	What: Objects	Where: Spaces	
▹ Direct Touch	[4–6, 8, 10, 15]		
▹ Attention	[2, 4, 6, 9, 15]		
▹ Engagement	[4, 8, 10, 15]		
▹ Other	[1, 6, 9]		
Aggregated Actor-Area	What: Objects	Where: Spaces	When: Times
▹ Duration	[4, 5, 9, 12, 13, 15]		
▹ Frequency	[5, 10, 12, 13]		
▹ Sequence (Transition)	[4, 7, 9, 10, 12, 13, 15]		
▹ Trail	[5, 8]		

Table A1: A condensed overview of the papers found through our literature search and presented in Sec. 2.2 of our paper. The publications presented here are grouped based on the relations between the components of spatio-temporal data, their visual representation, or task focus.

B PROTOTYPE TECHNICAL DETAILS

This section provides additional information about the implementation of the prototype described in the paper titled "PEARL: Physical Environment based Augmented Reality *Lens*es for In-Situ Human Movement Analysis". To realize the prototype, we facilitated a graph-based data structure to represent topological relations between region of interest (*ROI*s). Here, *Lenses* are considered nodes, while the relationships between them are encoded in the edges.

[1] See: https://dl.acm.org/

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Stacked Bar Chart (see Fig. 1B in the paper) and 2D Bar Chart (see Fig. 11B in the paper). Each *Lens* has the functionality to calculate how many visitors passed through the volume of the *Lens*. For the stacked 3D bars, the highest value of all *Lenses* is used to define the maximum height of the bars. Each bar is then mapped accordingly, also regarding the currently defined entity groups. The same calculation is used for the situated 2D bar charts.

Sequence View (see Fig. 10C in the paper). Similar to the Flow View (see Sec. 5.3 in the paper), to generate the Sequence View, we first identify all directly connected *Lens* pairs that have trajectories passing through. The number of these trajectories then determines the number of fishbone-like links rendered in the texture that is placed on the floor.

Pace View (see Fig. 10D in the paper). We calculated the exit and entry point to define the movement between two *Lenses*. Following, we calculated the highest speed of all those segments which we used for color mapping of the pace links. Lastly, we map the average speed of the segments on the links themselves and drawn them on the texture wchich is placed on the floor.

Approach View (see Fig. 1A in the paper). The Approach View is based on a radial bar chart with 24 bars defining the direction of the approach. We define the values for each direction and therefore bar, we calculate the entry point of every entity. Following, we determine the angle of each entry point in relation to the center of the *Lens*, which we then split into 24 equal parts. Lastly, we count the entry points within each angle group and map them, also based on the currently used entity groups, to the lengths of the bars. Additionally, we normalize the lengths over all *Lenses* that should show an Approach View.

Segmented Trajectories (see Fig. 10A in the paper). In this work, we allow users to use *Lenses* for defining a motion data range. To extract segments of trajectories, we iterate over every trajectory that is within a *Lens*. This means, we trace its previous point and check if it enters or exits any *Lens*: If the point is in a *Lens* while its previous or following point is not, the point has just entered or is currently exiting the *Lens*. Next, we collect every point between the entry and exit points and combine them to a segment.

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