Exploring Mobility Behavior Around Ambient Displays Using Clusters of Multi-dimensional Walking Trajectories

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Background

- Ambient displays are typically evaluated through an understanding of how people **behave** in their vicinity.
- In-the-wild research nowadays regularly utilizes modern **camera sensors** to unveil people's mobility behavior [e.g., 4, 6].
- Multi-dimensional **walking trajectories** have been used as valuable tools to visualize the data from these sensors [e.g., 6].
- At the methodological level, **shape-based clustering** is increasing in popularity lately to distill the mobility behavior underlying walking trajectories [3].

Challenges

- There are notable challenges when working with depth-based **skeletal data** (e.g., easily grouping together similar data, readily interpreting the mobility behavior, or specifically isolating certain patterns).
- In essence, the **analysis of skeletal data** still requires a great deal of manual effort.
- Techniques are necessary that allow the **automatic analysis** of skeletal data and that, ultimately, in doing so aid the exploration of mobility behavior in ambient display field deployment research.

Method

- Informed by recent research [e.g., 2], we chose to apply in tandem **agglomerative hierarchical clustering** [1] and **dynamic time warping** [5] in our research.
- The **combination** of both algorithms was found to outperform other algorithms such as *k*-means [1] and has been applied successfully to investigate similar problems such as the flyways of birds [2].
- We **evaluated** our implementation using an existing data set [6] from a real-world deployment.

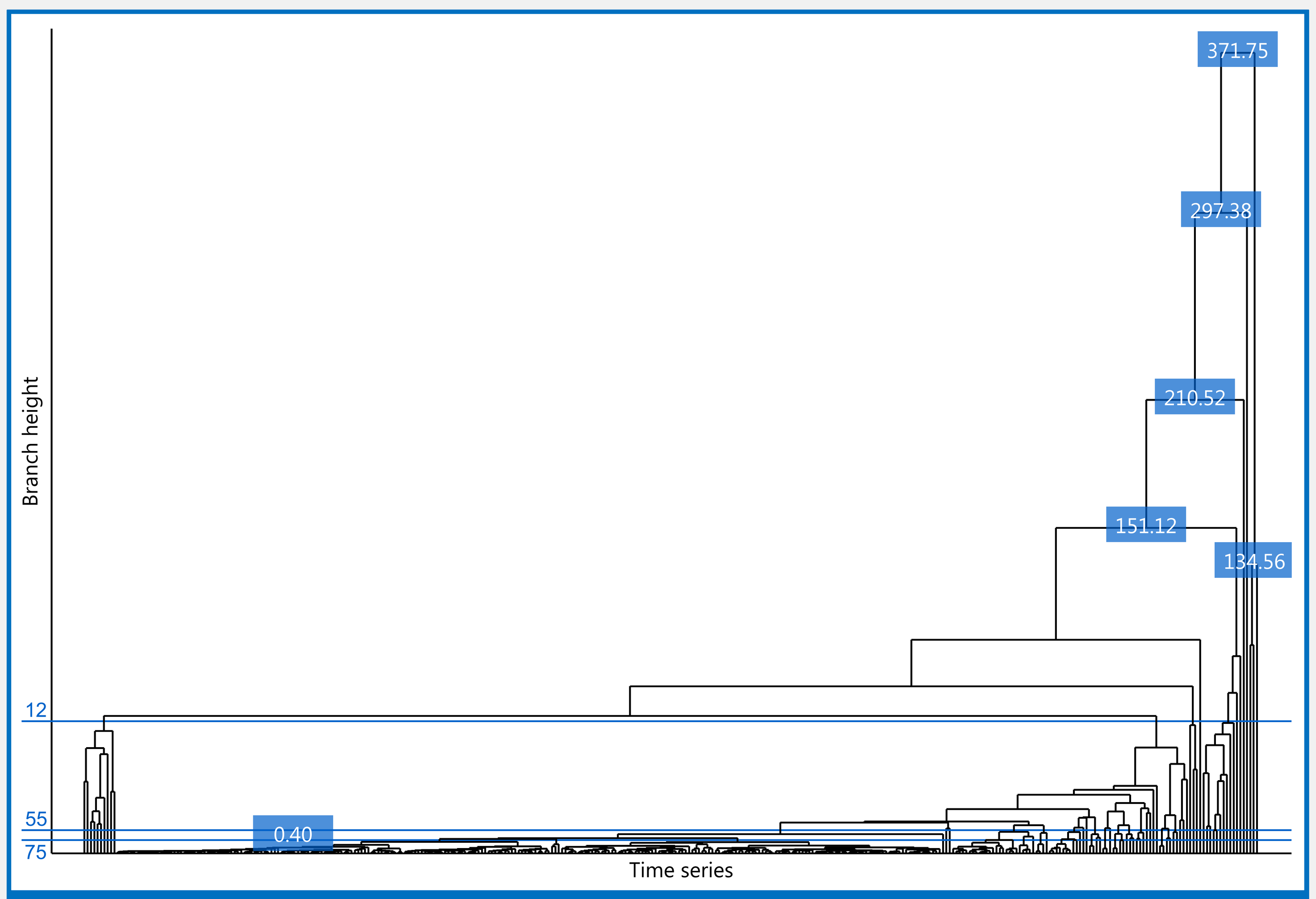

Figure 1. The dendrogram computed by our algorithm, using 352 randomly selected walking trajectories from the chosen data set. Labels are provided for clusters with the five highest values in distance as well as for the cluster with the smallest value in distance. The blue horizontal lines indicate the cutoff levels at 12, 55, and 75 clusters, respectively.

Results

- First, our algorithm was able to **correctly identify and group together** two-dimensional walking trajectories drawn from skeletal data with similarity in shape (see Figure 1). As intra-cluster distances gradually minimized, the better it isolated patterns in the data (see Figure 3).
- Second, at any given cutoff level, the algorithm can **make suggestions** regarding potential outliers and clusters requiring further examination as vividly demonstrated in the example shown in Figure 2.

Contribution

- This study is **the first in its field** to adopt in tandem agglomerative hierarchical clustering and dynamic time warping to perform a data-driven identification of patterns in skeletal data.
- It **adds to existing research** by proposing an approach able to (a) assist in evaluating skeletal data without any pre-existing knowledge and (b) automatically suggest similarities in people's mobility behavior based on walking trajectory characteristics.

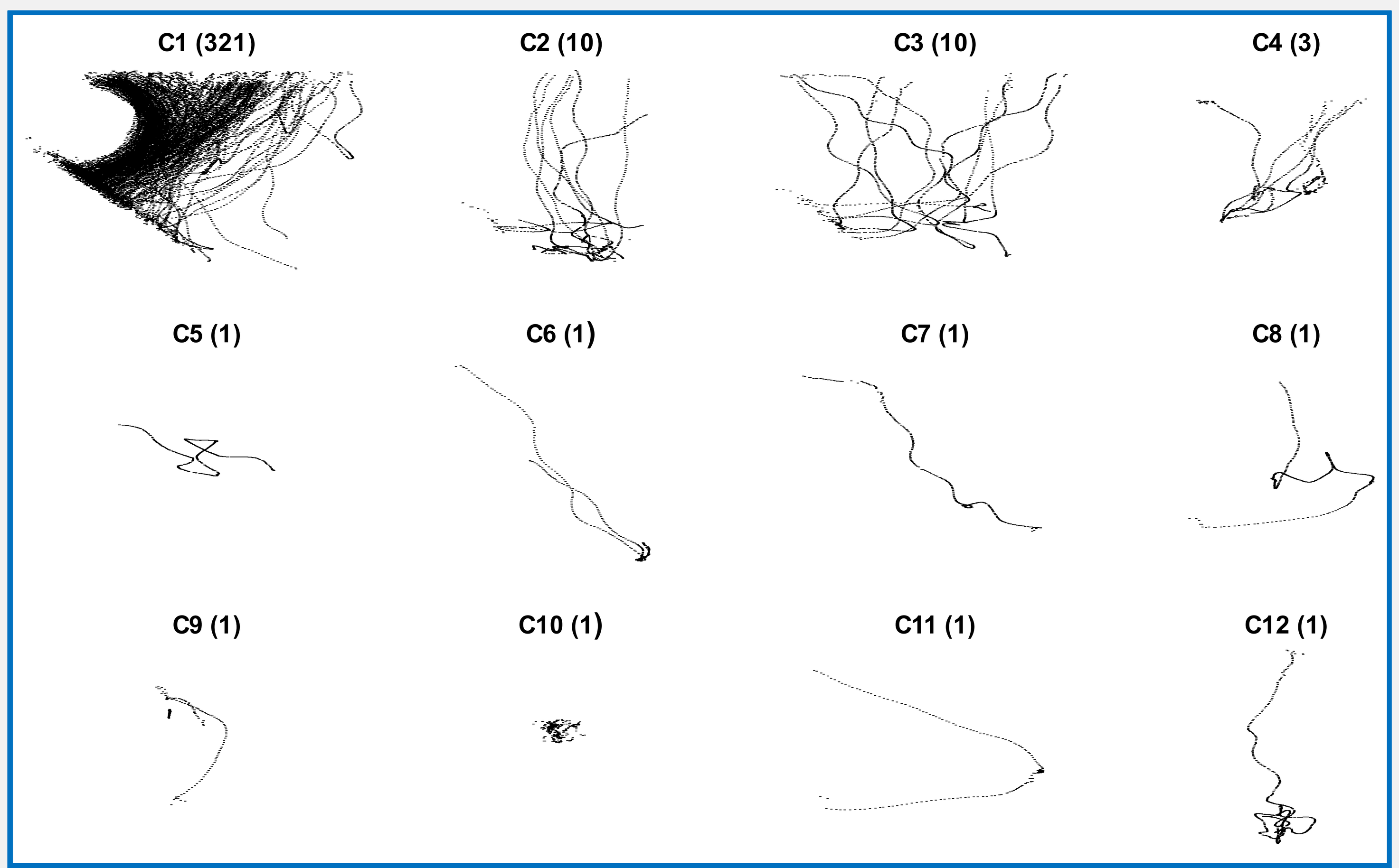

Figure 2. Walking trajectories of the analyzed data set clustered at a cutoff level of 12 clusters (*C1–C12*) and sorted in descending order (number of trajectories in parentheses).

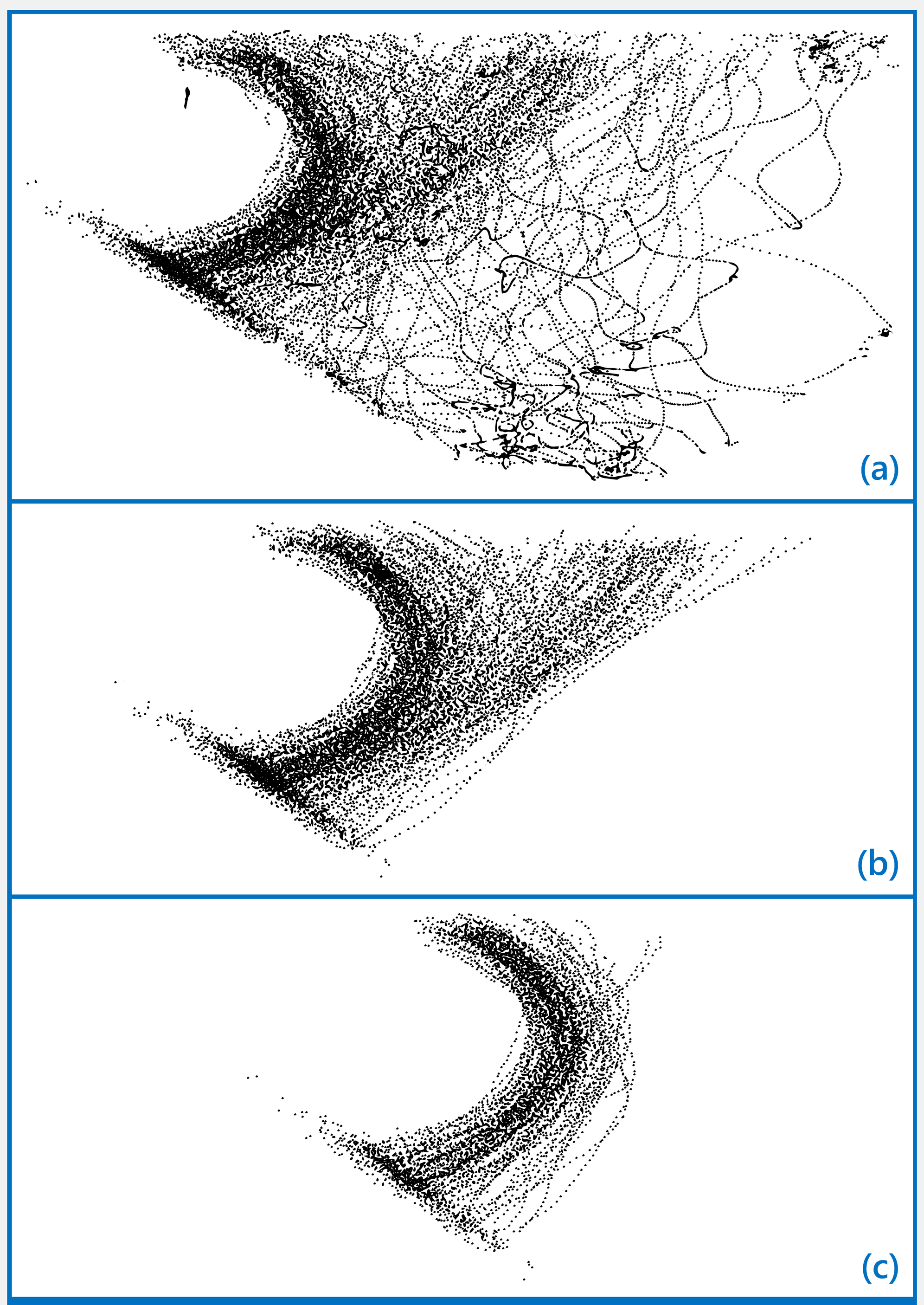

Figure 3. Walking trajectories of the dominant mobility behavior in the data set at different cutoff levels. (a) all data, (b) cutoff level = 55, and (c) cutoff level = 75.

Future Work

- Improving the **algorithm's complexity**.
- Testing **pre-processing steps** such as z-normalization and filtering techniques.
- **Extending** the existing approach to suggest the optimal number of clusters (i.e., readily identify classes of mobility behavior).

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