Analysis on Sensorimotor Adaptation and Learning Performance

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Introduction

- The data for this project were provided by Jonathan Tsay, motor learning researcher at CMU. The research focus is about sensorimotor adaptation and learning performance, which measures how human movements remain well calibrated in response to changes in body and environment. Findings of our study can be crucial in the design and application of physical therapy to better assist patients to regain control and coordination of their body.
- The goal of the study is to identify **if there are different phenotypes of the learners among the participants**. We have developed a web-based visuomotor rotation task wherein participants must acquire the skill of adjusting their behavior, specifically altering their hand angle, to correspond with the rotation of the cursor. This adaptation is essential for accurately reaching the designated target position on the screen, and our focus is to identify different learning patterns among the participants through clustering.

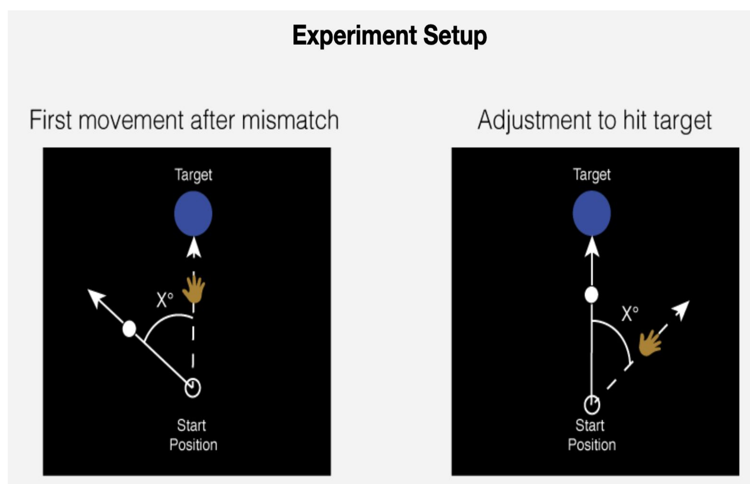

Fig 1. Setup of the Web-based Experiment

Data Overview

- The data is collected through 2121 sessions of data on the web-based visuomotor rotation task. This complete kinematic dataset consists of 13 variables including information on the cursor movement, target position, and hand position of participants.
- The primary variable we employ for our clustering problem is **hand angle accuracy** across multiple trials for each participant, which measures the extent to which the participant's hand angle deviates from the target position with the cursor movement applied. Each participant's learning pattern is therefore treated as a time-series function to be clustered.

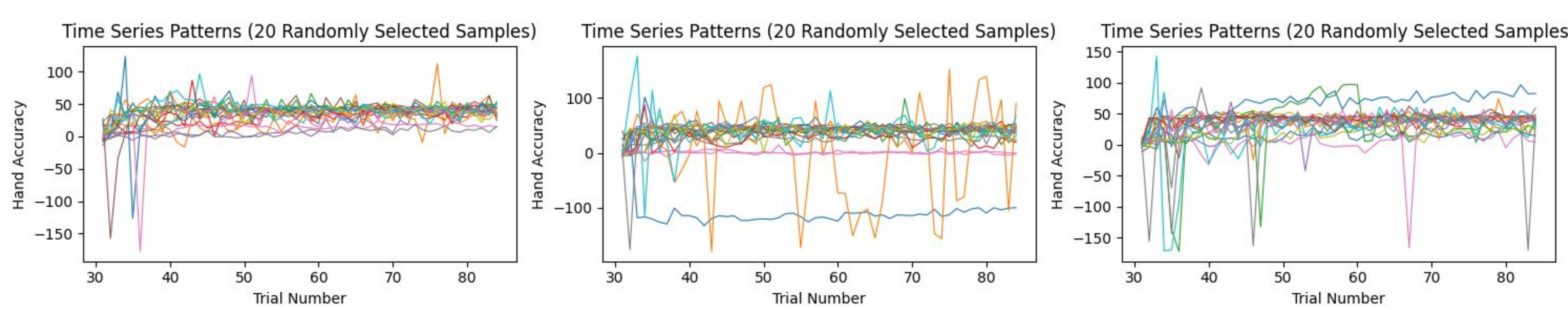

Fig 2. Subplots of Randomly Selected Time Series Samples

Methods

- Goal: The objective is to identify the most effective clustering technique for time series data by comparing different models.
- Challenge: The difficulty lies in accurately grouping time series data with inherent variability and identifying patterns within the data.
- Model 1: **K-Means Clustering** on time series models obtained from normalized interpolated univariate spline values (number of clusters: 5).
- Model 2: **Complete-linkage hierarchical clustering** on time series models obtained from interpolated univariate spline values with a cut-off distance of 1.6.
- Model 3: A **Gaussian Mixture Model** (GMM) to cluster time series models (number of clusters: 5).
- Model 4: Utilized **Dynamic Time Warping** (DTW) in combination with K-Means to cluster time series models (number of clusters: 4).

Results & Analysis

- The performance of the clustering methods is evaluated using a bootstrap method.

	Average Distance to Centroid
Spline + KMeans	597.606324
Spline + Hierarchical	219.709939
GMM	222.430133
DTW + KMeans	272.004011

- A lower average distance indicates that the method produces tighter, more cohesive clusters.
- The **Spline + Hierarchical clustering** method exhibits the lowest average distance, suggesting it performs **best** among the methods tested.

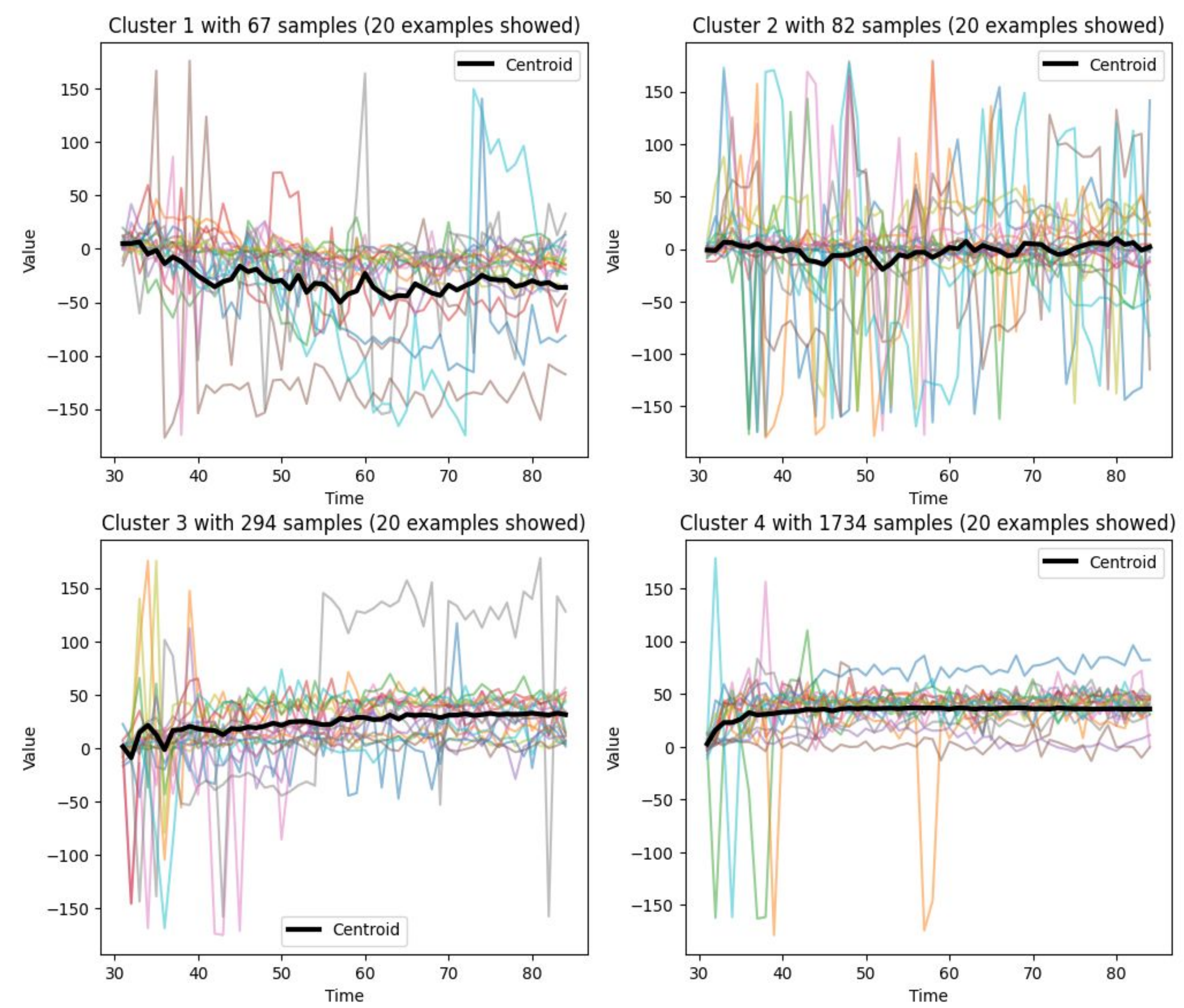

Fig 4. Clusters with Centroids Using Complete-linkage Hierarchical Clustering

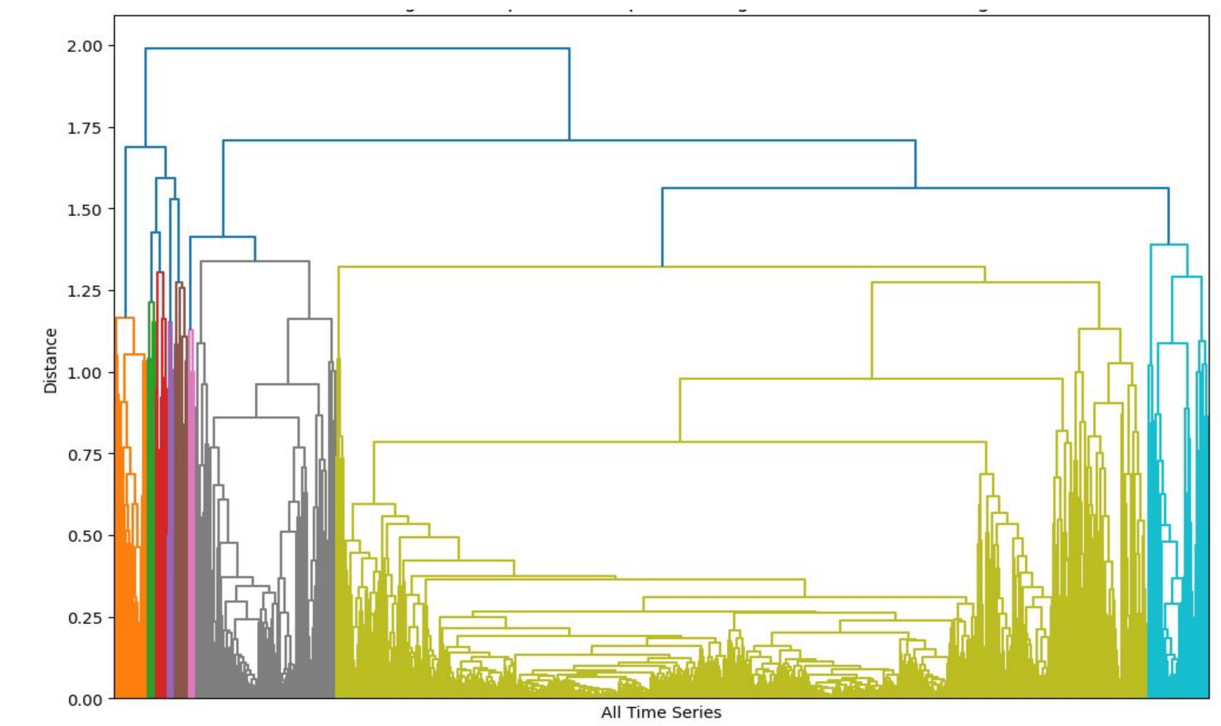

Fig 3. Dendrogram for Spline + Complete-Linkage Hierarchical Clustering

- Cluster 1 displays a general **downward** trend with significant volatility, as the individual time series frequently deviate from the centroid.
- Cluster 2 also exhibits a **downward** trend, with less volatility compared to Cluster 1 but still noticeable deviations from the centroid.
- Cluster 3 has a relatively **flat** trend, indicating more consistency in the time series data with fewer extreme deviations.
- Cluster 4, the largest cluster with 1734 samples, shows a very **flat** trend with the time series closely hugging the centroid, suggesting that the majority of the data follows a consistent pattern with minimal fluctuations.
- The presence of extreme values in all clusters indicates occasional anomalies or outliers. The majority of the data is captured by the more stable and consistent trends of Clusters 3 and 4.

Conclusion

- After testing multiple clustering techniques, hierarchical showed the most cohesive and interpretable groupings.
- Clusters 3 and 4 displayed stable adaptation patterns, suggesting potential pathways for personalized learning strategies in skill acquisition.

References

- Finazzi, F., Haggarty, R., Miller, C. et al. A comparison of clustering approaches for the study of the temporal coherence of multiple time series. Stoch Environ Res Risk Assess 29, 463–475 (2015). https://doi.org/10.1007/s00477-014-0931-2
- V. Niennattrakul and C. A. Ratanamahatana, "On Clustering Multimedia Time Series Data Using K-Means and Dynamic Time Warping," 2007 International Conference on Multimedia and Ubiquitous Engineering (MUE'07), Seoul, Korea (South), 2007, pp. 733-738, doi: 10.1109/MUE.2007.165.