
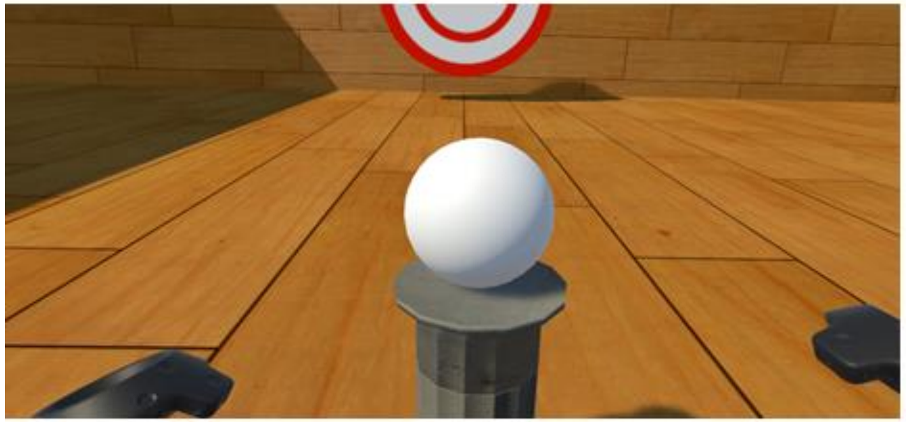

Task-Driven Biometric Authentication of Users in Virtual Reality (VR) Environments

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Virtual Reality (VR) in Mission Critical Environments

Virtual reality (VR) is pervading mission-critical environments such as military training, flight simulation, and health care.

Biometric authentication of individuals in mission-critical VR-based systems is important to prevent unauthorized access, avoid compromising of system integrity, and ensure safety of individuals using the systems.

Related Work on VR Authentication

Personal Identification Number (PIN) and 2D patterns

George et al., 2017

3D patterns: password is a particular ‘arrangement’ or configurations of elements in the VR space.

Yu et al., 2016

Issues With Existing Approaches

Once an intruder determines the PIN or pattern, the system is immediately compromised.

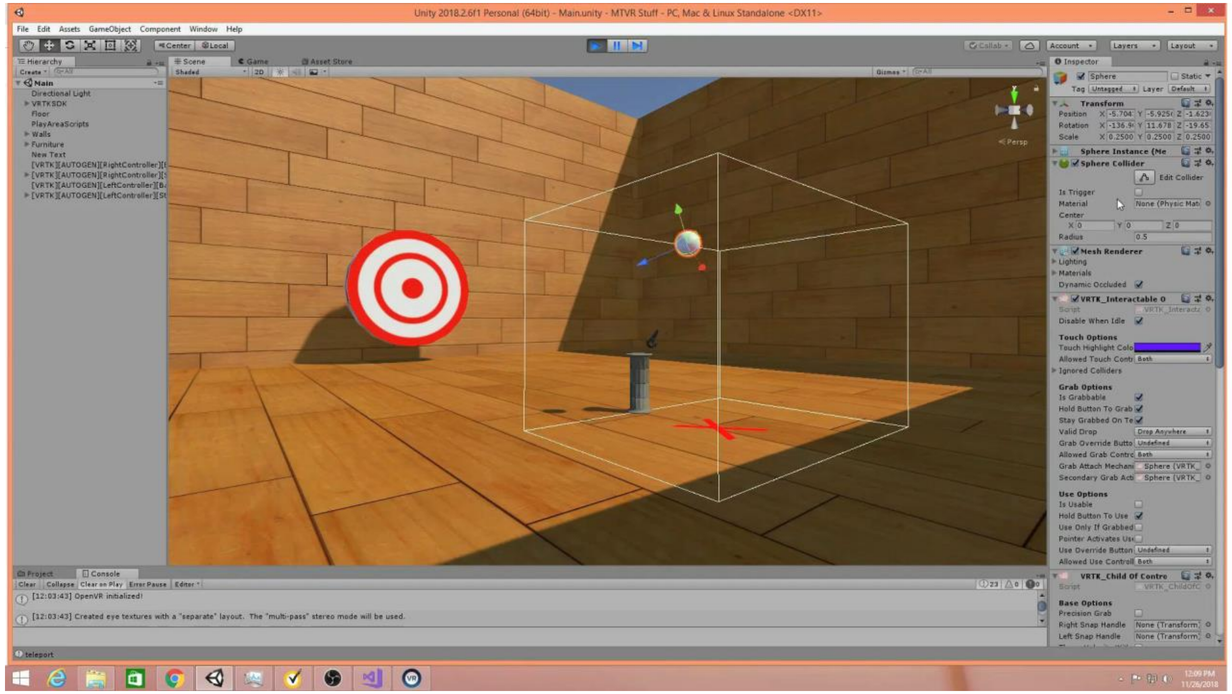
Prevent continual authentication, as they require the user to stop their on-going activity.

Our Work:

First Approach to Use Natural User Behavior to Authenticate Users in VR

Natural behavior obtained by tracking 3D trajectory of dominant hand gesture controller

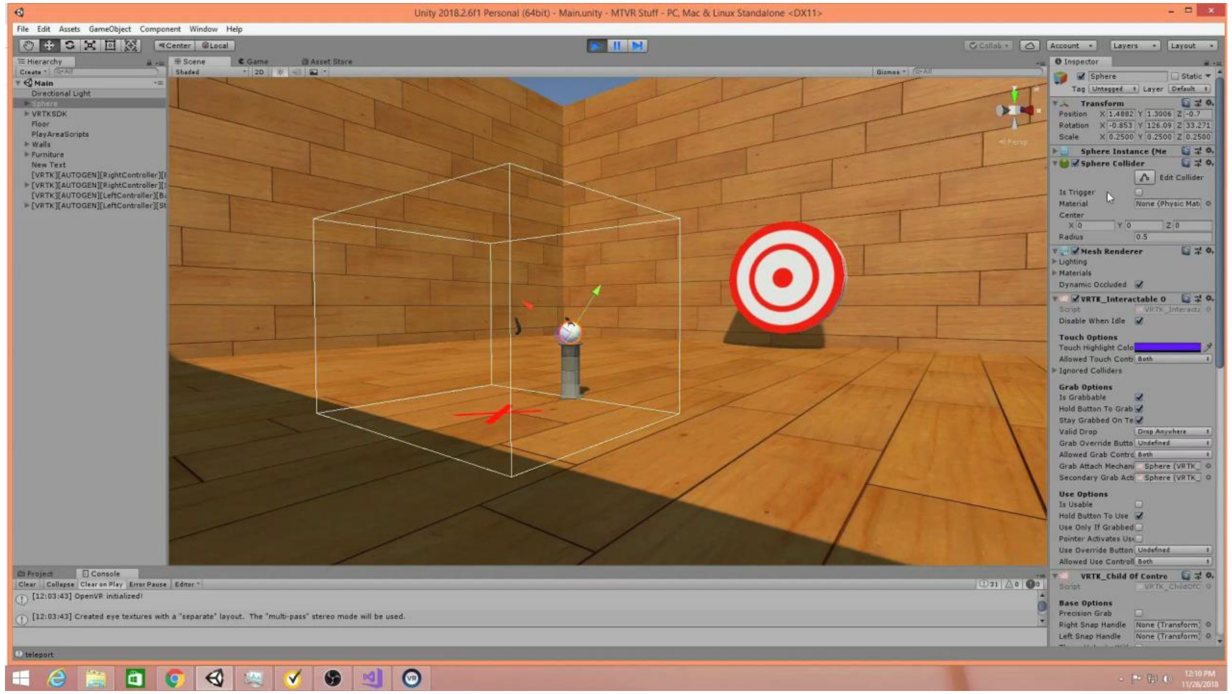
Tracking User Behavior For Ball-Throwing



View of Ball Throwing VR Environment

View of Subject Performing Ball Throwing

Tracking User Behavior For Ball-Throwing



View of Ball Throwing VR Environment

View of Subject Performing Ball Throwing

Advantages of Tracking Natural User Behavior

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Harder to spoof: intruder must precisely match the genuine user actions throughout the trajectory.

Collection of Data on User Trajectories

14 subjects throwing a ball at a target in VR.

Each subject provides 10 trajectories on Day 1 for the training dataset.

Each subject provides 10 trajectories on Day 2 for the test dataset.

Collection of Data on User Trajectories

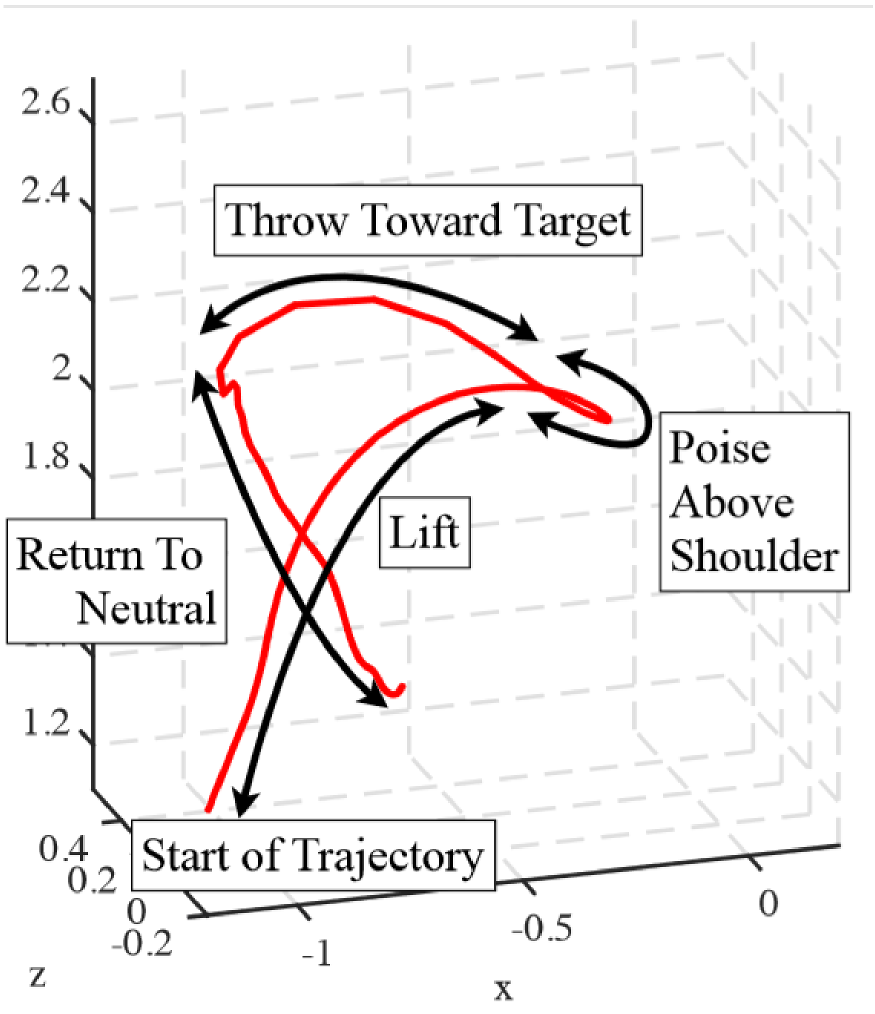
We show results of comparing trajectories for all subjects from Day 2 against trajectories from Day 1.

Keeping the training and test days separate helps minimize user priming.

User Demographics

Total number of subjects	14
Total number of male subjects	8
Total number of female subjects	6
Subjects with no VR experience	6
Subjects with VR experience	8
Subjects with experience in throwing sports	6
Subjects with no prior experience in throwing sports	8
Right-handed subjects	14
Left-handed subjects	0

Characteristics of 3D Ball-Throwing Trajectory

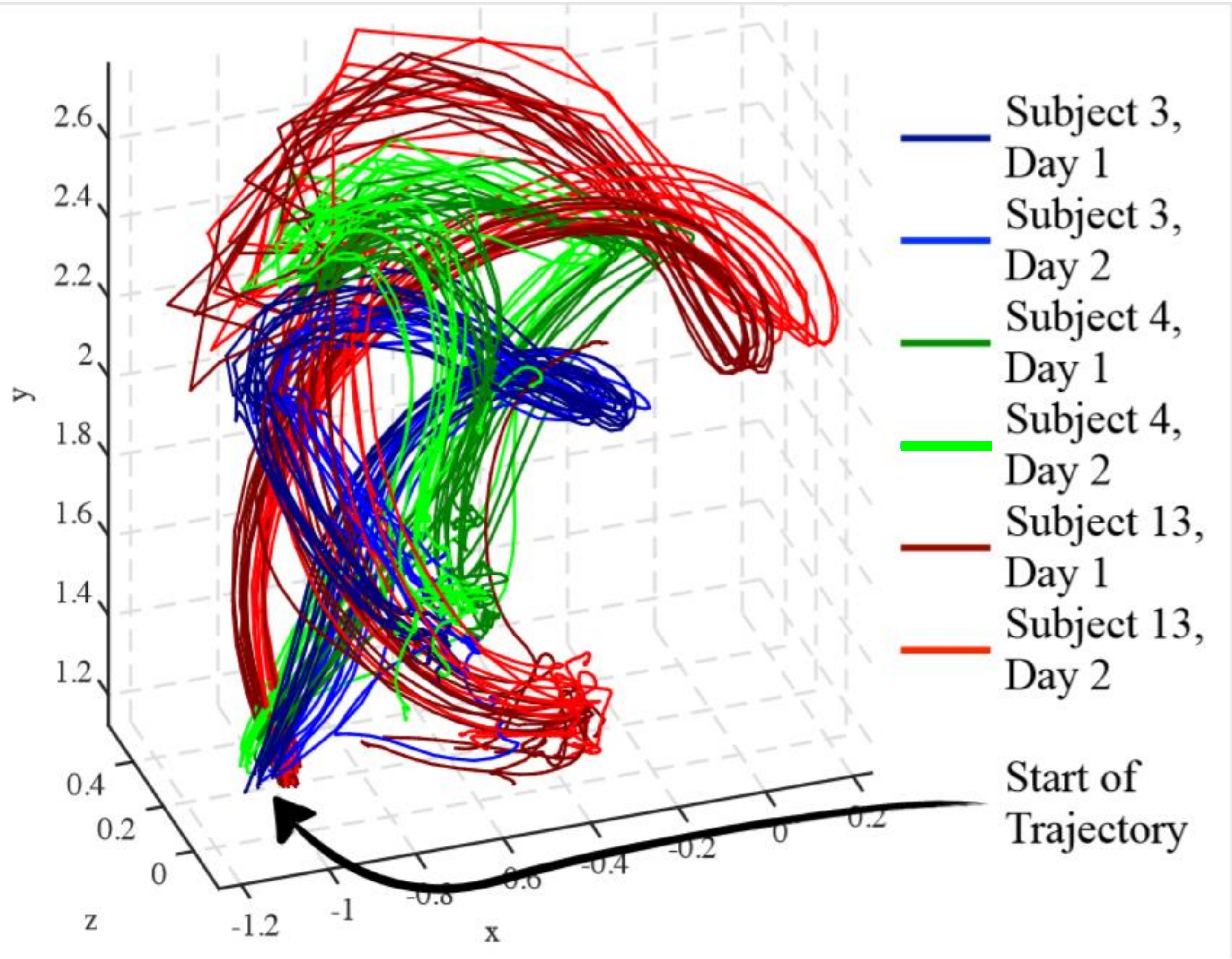


135 total points sampled at 45 fps.

Each trajectory consists of lift, throw, and return phases. Before and after each phase, there are natural differences in wait times.

The only restrictions placed on the user are to stand close to an X on the floor, and to throw at the target.

Characteristics of 3D Trajectories for Multiple Users

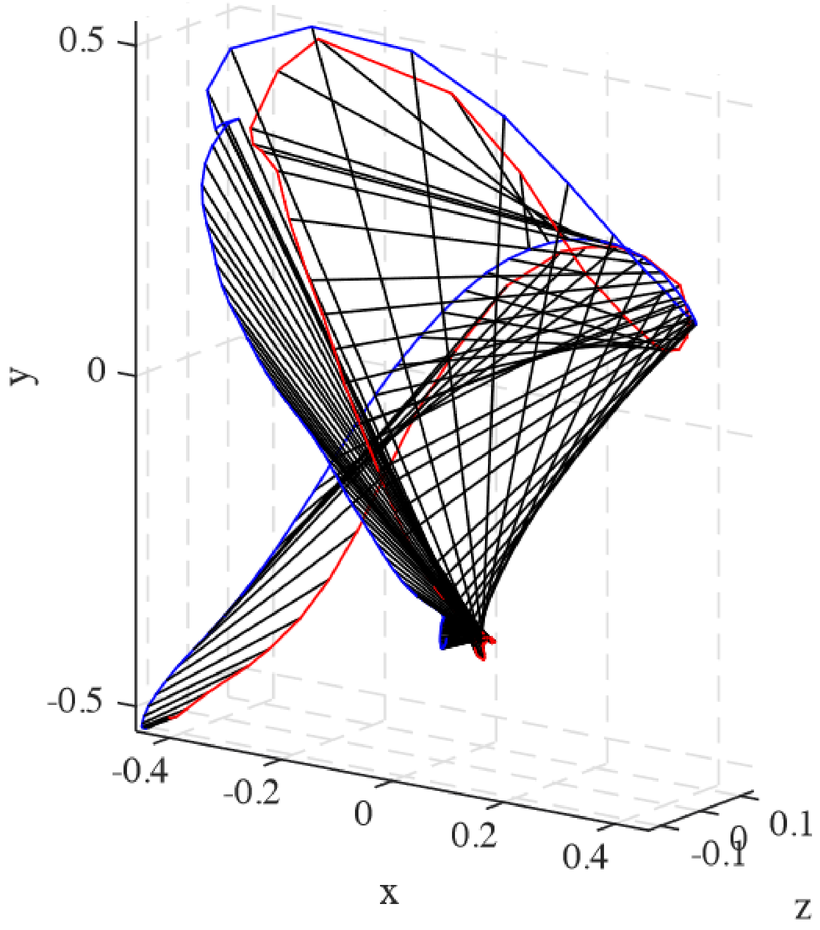


For each user, trajectories on Day 1 are similar to those on Day 2, demonstrating **consistency of action**.

For different users, trajectories have significant difference in shape, demonstrating **uniqueness**.

Comparing Trajectories

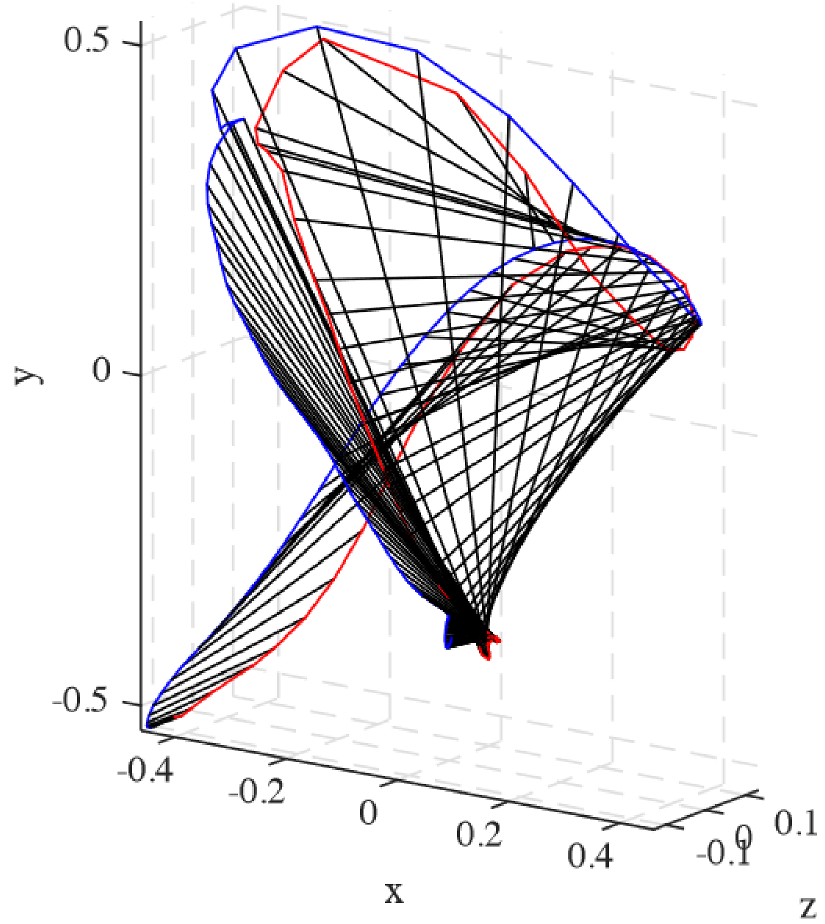
Corresponding points in two trajectories for the same user deviate from each other over time due to differences in wait times between action phases.



Comparing Trajectories

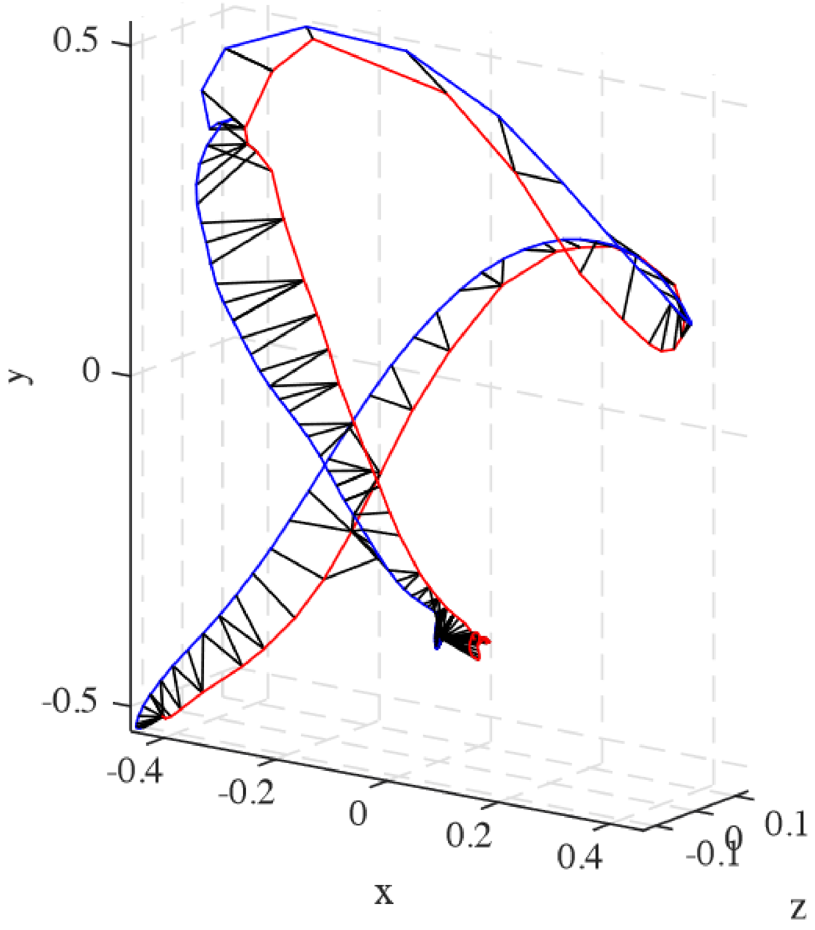
Corresponding points in two trajectories for the same user deviate from each other over time due to differences in wait times between action phases.

Thus a simple sum-squared distance between corresponding points cannot be used as a distance metric.



Comparing Trajectories

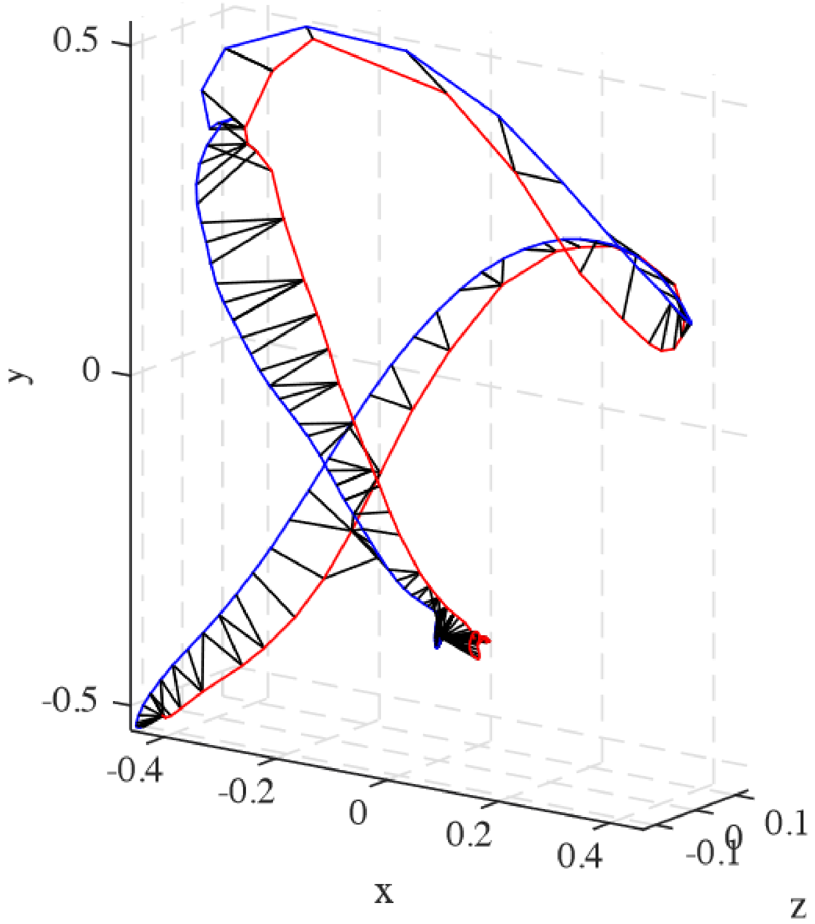
Our approach handles the deviation by identifying for every point on one trajectory, the nearest neighbor to the other trajectory.



Comparing Trajectories

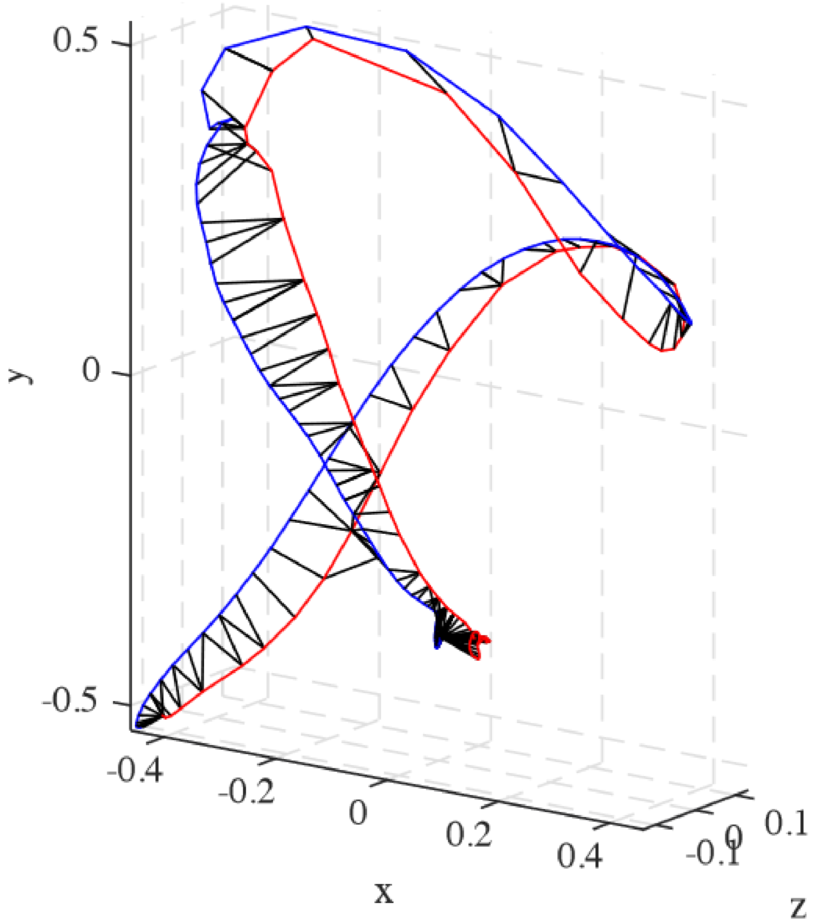
Our approach handles the deviation by identifying for every point on one trajectory, the nearest neighbor to the other trajectory.

The distance between two trajectories is obtained as the sum of squared distances between every point on one trajectory and its nearest neighbor on the other trajectory. For symmetricity, we halve the sum of the nearest-neighbor distances from each trajectory to the other.



Comparing Trajectories

Since natural user translation in the space may cause trajectories to be mis-aligned, we align trajectories by re-centering each trajectory so that its bounding box center lies at the origin.



Obtaining User Identification

For each user, we compare each trajectory on the second day to all trajectories from every user on the first day.

We obtain the trajectory with the lowest nearest-neighbor distance, and retain the user for that trajectory as the identified user for each query user.

Results

Average accuracy over 14 subjects using 135 3D points: **90.00%**

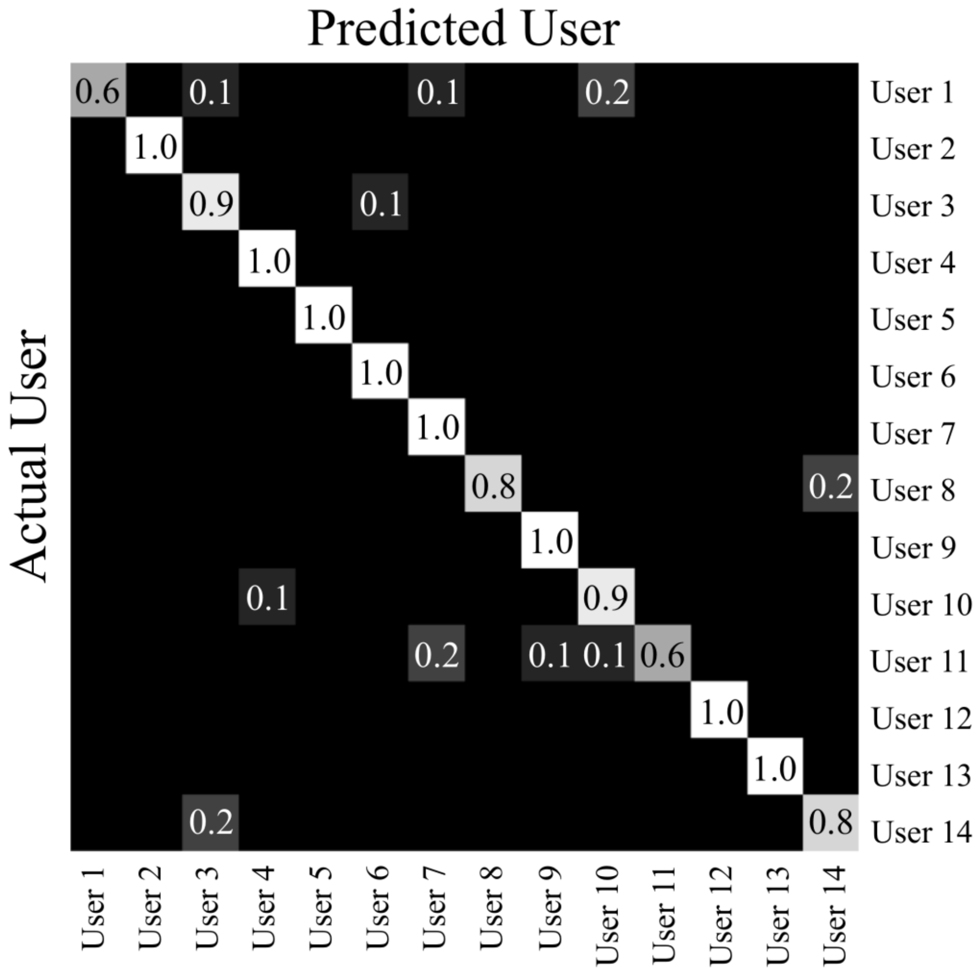
Higher accuracy obtained using 95 3D points: **92.86%**

Higher accuracy may be due to reduction in mismatches in the return phase where hand motions are less distinctive.

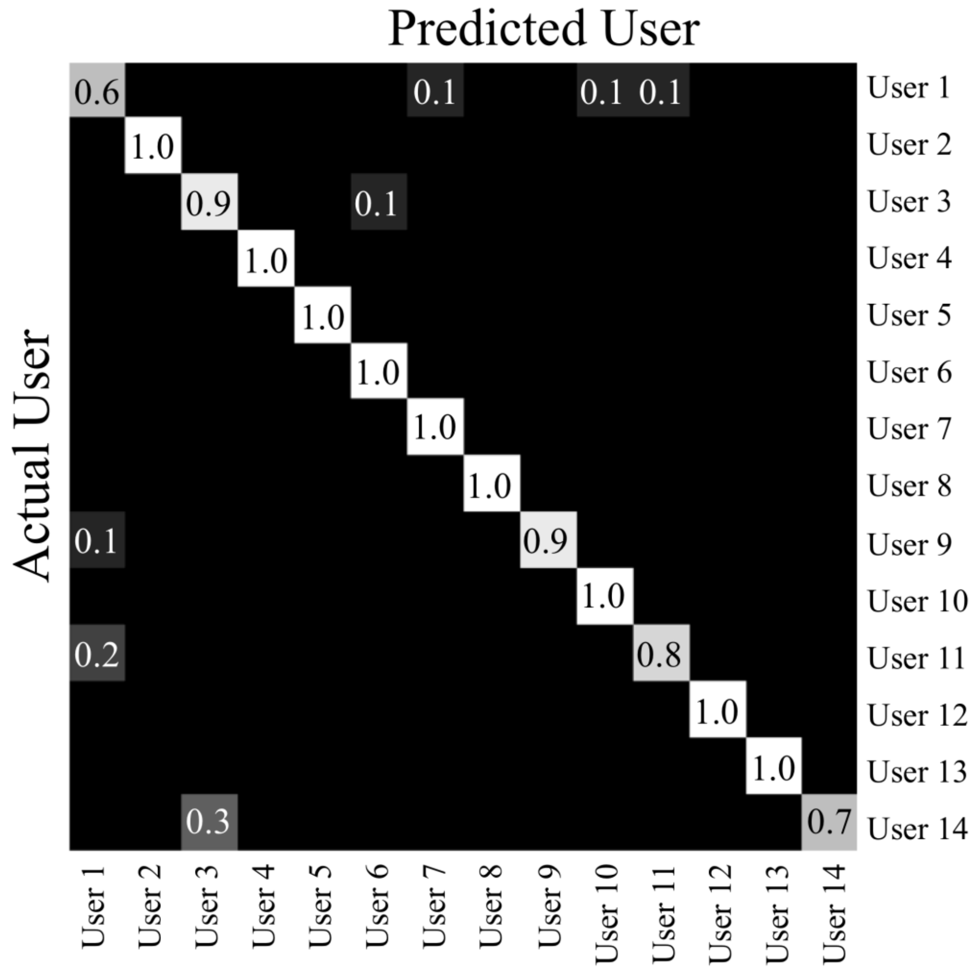
Results: Comparing Trajectory Re-centering Approaches and Distance Metrics

Approach	Using 135 points	Using 95 points
Re-center around bounding box center, symmetric nearest neighbor matching	90.00%	92.86%
Re-center around centroid, symmetric nearest neighbor matching	83.57%	83.57%
No re-centering, symmetric nearest neighbor matching	80.00%	82.14%
Re-center around bounding box center, corresponding points matching	63.57%	62.86%
Re-center around centroid, corresponding points matching	60.00%	57.86%
No re-centering, corresponding points matching	58.57%	56.43%

Results: Confusion Matrices

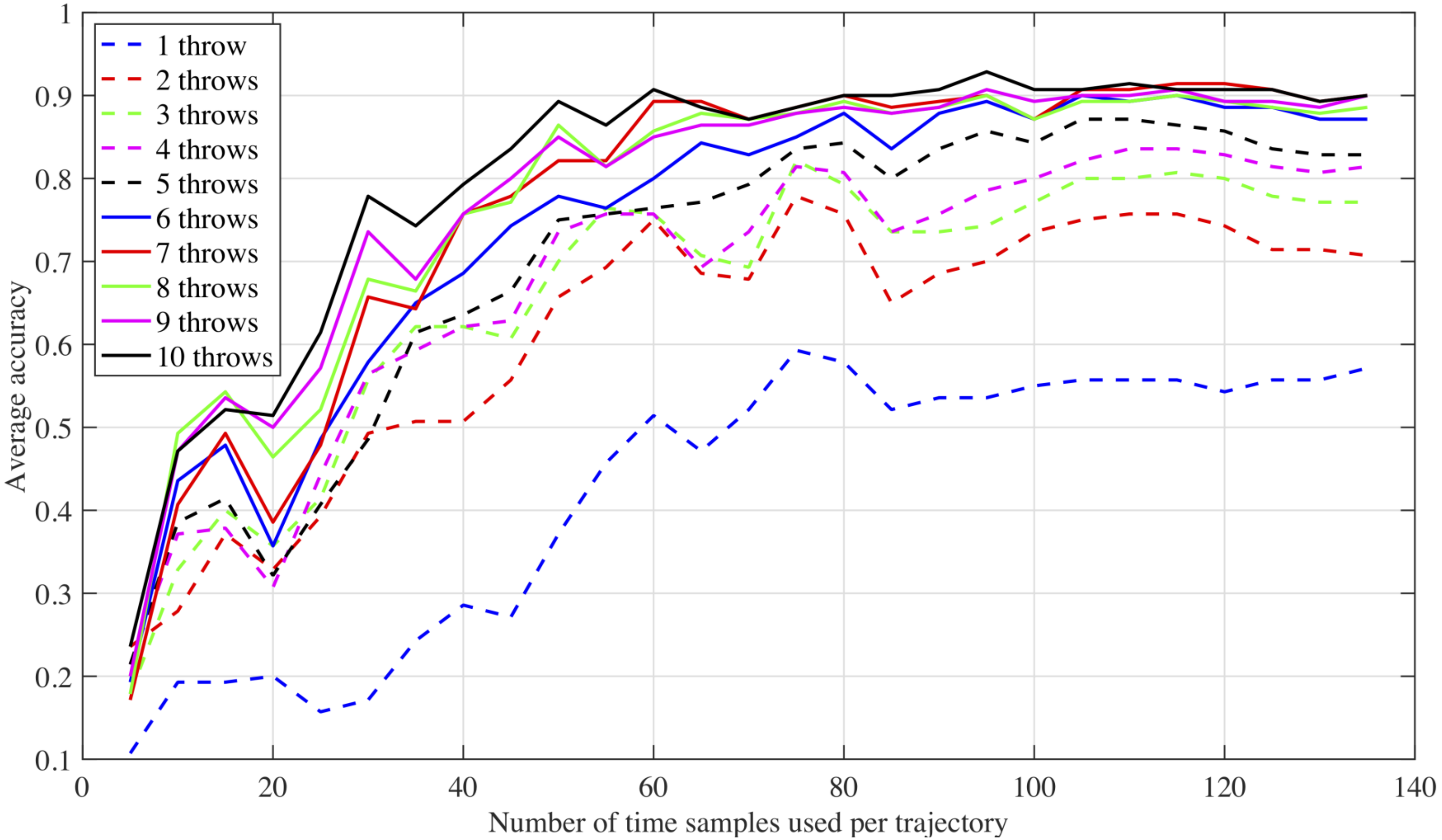


135 3D Points per Trajectory



95 3D Points per Trajectory

Comparison of Varying Number of Training Trajectories and Varying Number of Time Samples



With 6 trajectories and 115 points, accuracy is 90.00%

Future Work

Authentication by combining tracking of headset, dominant controller, and recessive controller.

Analyze effect of age, height, VR ability, and everyday dexterity.

Include more complex actions (e.g., cooking in VR, playing a game, rehabilitation motions in physical and occupational therapy).