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

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Abstract. In this paper, we provide an approach for authenticating users in virtual reality (VR) environments by tracking the behavior of users as they perform goal-oriented tasks, such as throwing a ball at a target. With the pervasion of VR in mission-critical applications such as manufacturing, navigation, military training, education, and therapy, validating the identity of users using VR systems is becoming paramount to prevent tampering of the VR environments, and to ensure user safety. Unlike prior work, which uses PIN and pattern based passwords to authenticate users in VR environments, our approach authenticates users based on their natural interactions within the virtual space by matching the 3D trajectory of the dominant hand gesture controller in a display-based head-mounted VR system to a library of trajectories. To handle natural differences in wait times between multiple parts of an action such as picking a ball and throwing it, our matching approach uses a symmetric sum-squared distance between the nearest neighbors across the query and library trajectories. Our work enables seamless authentication without requiring the user to stop their activity and enter specific credentials, and can be used to continually validate the identity of the user. We conduct a pilot study with 14 subjects throwing a ball at a target in VR using the gesture controller and achieve a maximum accuracy of 92.86% by comparing to a library of 10 trajectories per subject, and 90.00% by comparing to 6 trajectories per subject.

1 Introduction

Head mounted virtual reality (VR) systems, such as the HTC Vive, Oculus Rift, and PlayStation VR, while traditionally used for recreational purposes, are now rapidly permeating a variety of mission critical applications ranging from therapy [16, 25, 35], manufacturing [4, 6], flight simulations [26], military training [5, 28], and education [9, 19]. It is becoming increasingly important to authenticate the identity of people using mission-critical VR systems in order to prevent tampering of virtual training environments and to guarantee the safety of users working in single- and multi-user VR environments. Unfortunately, work in the area of VR authentication has been limited. Existing approaches to authenticate users in VR environments rely on personal identification number (PIN) or pattern matching [?, 37] similar to mobile authentications systems [3], and do not allow continual seamless authentication. Head motions and blink patterns [29], head movements to music [14], and bone conduction of sound through the skull [30] have been used to authenticate users wearing Google Glass. However, these approaches have limited scalability for continuous authentication in large user groups due to the restricted degrees of freedom in the analyzed actions.

In this paper, we provide the first approach to authenticate users from natural goal-oriented tasks in VR environments by tracking 3D trajectories of VR gesture controllers. Due to their experience with the real-world, humans develop innate consistencies in average everyday tasks such as throwing a ball, lifting a chair, lowering a potted plant, swinging a golf club, or driving a car, which when translated to VR environments can provide a unique signature for a person. Unlike approaches that perform authentication using cameras by tracking the trajectories of a large group of points on the body of a person [1, 2, 11, 12, 24, 36], our approach uses a sparse point set from a single trajectory corresponding to the gesture controller, which can prove insufficient for authentication. To address the sparseness, our work draws inspiration from behavior-based authentication systems in mobile devices [7, 34] and matches complex multi-part actions, e.g., lifting a ball, poising it above the shoulder, throwing it at a target, and returning the hand back to neutral. Over multi-part actions, each user shows unique spatial placements of the gesture controller and temporal durations of controller motions, enabling multi-part actions to be specific to the user.

While approaches exist to authenticate users in real-world environments from sparse trajectories obtained using body-mounted or non-invasive sensors, these approaches require single actions [18], use user-dependent signatures [15, 18], or perform recognition based on gait [8, 13, 22, 23, 32, 38] or device shaking [27]. Unlike these approaches, our work on using multi-part goal-oriented actions can be used to perform continual authentication in VR environments where users perform a large number of tasks. Our challenge is that multi-part actions contain natural unavoidable differences in wait times between various segments of the actions. For instance, successive throws by a ball pitcher may show variations in the amount of time the pitcher holds a knee lift before pitching the ball. These variations prevent matching using a simple distance metric between corresponding trajectory points. Our approach addresses this challenge by identifying nearest neighbors between 3D points on a query trajectory and 3D points on a library trajectory, and using Euclidean distance between the nearest neighbors to match the trajectories.

We present results from a pilot study in which we capture 14 male and female subjects ranging in age from 18 to 37 years throwing a ball at a target in VR. To prevent over-fitting to trajectories, the test dataset actions for a particular user are captured on a different day from the library dataset actions for the same user, with 10 trajectories per user captured on each day. Our accuracy averaged over 10 trajectories from the second day is 92.86% when we use a library of all 10 trajectories from the first day, and 90.00% when we use a reduced library of 6 trajectories from the first day. Our results demonstrate that the accuracy of matching converges within 6 trajectories indicating that user behavior becomes consistent in 6 captures. Our work enables seamless authentication without requiring the user to stop their activity and enter specific credentials, and can be used for continual authentication.

2 Related Work

Current approaches in VR authentication largely extend traditional pattern and PIN-based techniques to VR environments. Yu et al. [37] provide users with 3D patterns, 2D sliding patterns, and PINs to authenticate themselves in a virtual environment. They determine 3D patterns to be most effective through a user study involving 15 participants. In George et al. [10], the authors use various virtual input surface sizes with both pattern and PIN based authentication systems to regulate in-game purchases in a 25 participant user study. However, these approaches require the user to stop their activity and interact with a virtual PIN pad or pattern entry surface. Our approach provides continual interaction by using the user actions to authenticate users.

Several approaches have attempted to use the hardware on Google Glass to perform user authentication. Rogers et al. [29] capture blink and head movements of users viewing a series of rapidly changing images using the infrared, gyroscope, and accelerometer sensors built into the Glass device. Similar to the PIN and password based authentication, this approach diverts users from their natural interactions. Li et al. [14] track head movements of users in response to external audio stimuli. Their approach depends on the variation in properties such as frequency and amplitude for periodic motions in response to music. Head movements in goal-oriented tasks such as throwing a ball or swinging a golf club may have limited diversity for use in continual identification of users in VR systems. In Schneegass et al. [30], the authors use the integrated bone conduction speaker and an external microphone to collect data on transmission of white noise through the skull of a user in a noise-free environment, which is unrealistic in a typical VR environment consisting of varying audio input. Unlike these approaches, our approach identifies users using actions such as lifting and throwing a ball that are natural in everyday environments, without constraints on their gestures.

Our work is related to authentication of users using bodily motions in real-world environments. There exists a large body of work in using cameras to authenticate users from their real-world motions. However, several of these approaches rely on the presence of a dense set of spatial points on the body of the person [1, 2, 11, 12, 24, 36]. While work exists on using sparse samples from a single body-mounted sensor, most approaches focus on authentication based on gait [8, 13, 22, 23, 32, 38], which is not suitable for continual authentication using gesture controllers in VR environments, since users spend a large portion of time performing tasks such as picking, throwing, shooting, or exploring, and the hand controllers have more recognizable tracks during non-walking actions. Okumura et al. [27] perform authentication on users shaking a smartphone, while

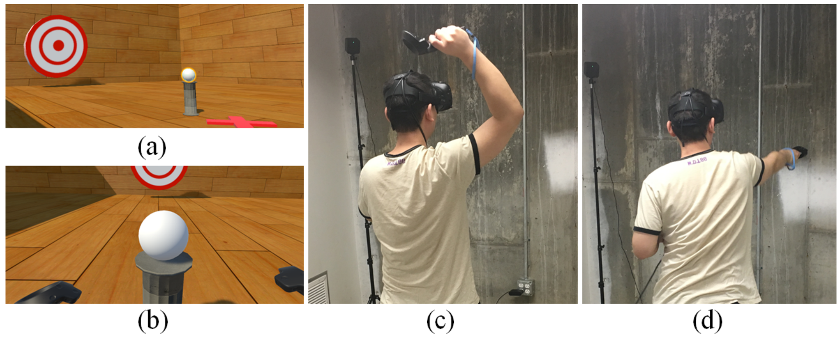

Fig. 1. (a) Ball throwing game showing target, ball on pedestal, and red 'X' on the floor for subject to stand on. (b) Perspective view from a subject preparing to pick up the ball. (c) Subject wearing the HTC Vive headset preparing to throw the ball. (d) Subject after completing the ball throw.

Mendels et al. [18] and Liu et al. [15] use free-form gestures to perform authentication using user-dependent signatures. Device shaking [27] and user-dependent signatures [15, 18] cannot be used for uninterrupted continual authentication.

While Mendels et al. [18] also show authentication using user-independent gestures as analyzed in our work, their approach performs authentication using single-action gestures such as drawing a shape, which precludes continual authentication in VR environments where users change their tasks regularly. Additionally, while they collect samples for 18 users, they provide recognition in groups of 3 to 7 users, with an average recognition rate of 85% and lower for user independent gestures in groups of 4 or more users using 28 samples per shape. The approach of Matsuo et al. [17] requires 12 users to submit 30 to 100 samples per day for a six week period before performing authentication, which is unrealistic for immediate authentication in mission critical systems. In contrast, our approach provides recognition rates of 92.86% and 90.00% when run on all 14 users used in our work with smaller sets of 10 and 6 samples per trajectory from a single day tested against 10 samples collected on a second day.

In using data from a sparse set of time-samples to perform task-based authentication, our work resembles traditional behavioral biometrics, such as keystroke and gesture. Fixed password based keystroke dynamics relies on hold times and delay times for 26 alphabetic, 10 numeric, and 10 special character keys to generate the user model, with the number of samples per user depending on the length of the password [20, 21, 33]. Gesture based approaches for authentication use swipe behavior to authenticate users on smartphones [31,34]. In Serwadda et al. [31], the authors used 80 strokes to authenticate users, while in Syed et al. [34], the authors used 300 strokes per subject for authentication. Unlike traditional gesture-based biometrics in smartphones, we use 3D trajectories that provide higher constraints on matching due to the extra third dimension. Additionally, unlike mobile authentication approaches that require high prior device usage in

Table 1. Demographic and pre-interview summary of the 14 subjects tested.

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 throwing sports experience	8

order to develop consistency of behavior for authentication, our approach of task-driven authentication requires minimal prior use for high recognition accuracy due to the direct translation of everyday tasks to VR environments.

3 Data Collection

We gather our data by having users interact with a ball throwing VR experience developed in Unity for an HTC Vive headset and hand controllers. Figures 1(a) and 1(b) show views of the interaction. During the interaction, the subject picks up a white ball placed on a pedestal placed in front of the subject and attempts to throw it at a circular target on the wall directly in front. To reduce variability caused by the position of the subject in relation to the target, each subject is asked to stand on the red 'X' marked on the floor of the virtual space.

Our pilot study dataset consists of 14 subjects, both male and female, ranging in age from 18 to 37 years. Prior to data capture, we conducted a brief pre-interaction interview to solicit prior experiences with VR systems and throwing based sports. The following information was collected from each subject:

- Has the subject had prior experience with VR systems,
- If yes, what VR systems has the subject used,
- Has the subject had experience playing throwing sports,
- If yes, what sports has the subject played.

After interviewing the subject, we noted down their dominant throwing hand, gender, and age. The subjects in our dataset show varying degrees of familiarity with VR systems, with some subjects having never used a VR system before, and other subjects being regular users and owners of VR systems. The subjects in our dataset also show varying degrees of experience playing throwing sports, with some having never played a throwing sport, and others having actively played sports such as baseball or tennis. Due to the low prevalence of left handed subjects, all 14 subjects in our dataset were right handed. We summarize subject demographics in Table 1. As shown in the table, we maintain a near 50-50 split for gender, VR experience, and throwing sports experience, thus reducing biases due to these factors.

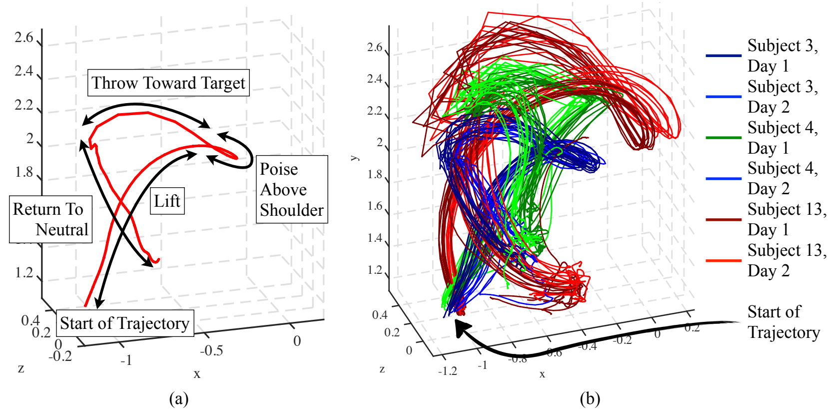

Fig. 2. (a) Description of trajectory for the right controller. (b) Right controller trajectories of ball throwing actions for Subjects 3 (blue), 4 (green), and 13 (red) for Day 1 (dark color) and Day 2(light color). Despite the lag in capture between the two days, subject still show consistent behavior, enabling gesture-based authentication.

For each subject, we capture two data collection sessions on two different days to enable cross-day analysis. To reduce priming, where a subject learns the objective of the interaction, we asked each subject to wait one or more days between each session. During each session, we captured 10 trajectories corresponding to 10 attempts made by the subject at hitting the target, similar to a carnival game. We captured the x, y, and z positional information for the dominant hand controller at 45 frames per second for 3 seconds to obtain a total of 135 samples per trajectory. As shown in Figure 2(a), each action consists of four parts: picking the ball, poising the ball above the shoulder, throwing the ball toward the target, and returning the controller to the neutral position. Example right controller trajectories for three of the subjects used in our analysis are shown in Figure 2(b). As shown by the figure, intra-class (i.e., within user) consistency in the pattern of the action is retained across the two capture days.

4 Trajectory Based User Authentication

While all trajectories start near a common spatial point, i.e., the location of the ball on the pedestal, differences in the extension of the arm of the user may induce translational offsets in the trajectories. To handle these offsets, we re-center each trajectory at the center of the bounding box for that trajectory prior to matching. While each trajectory contains an equal number of time samples, differences in time delays between multiple parts of an action (e.g., lifting the ball and throwing the ball toward the target) prevent the use of a distance metric between corresponding points of the trajectories. As shown by two trajectories for a single user in Figure 3(a), points earlier in the blue trajectory correspond

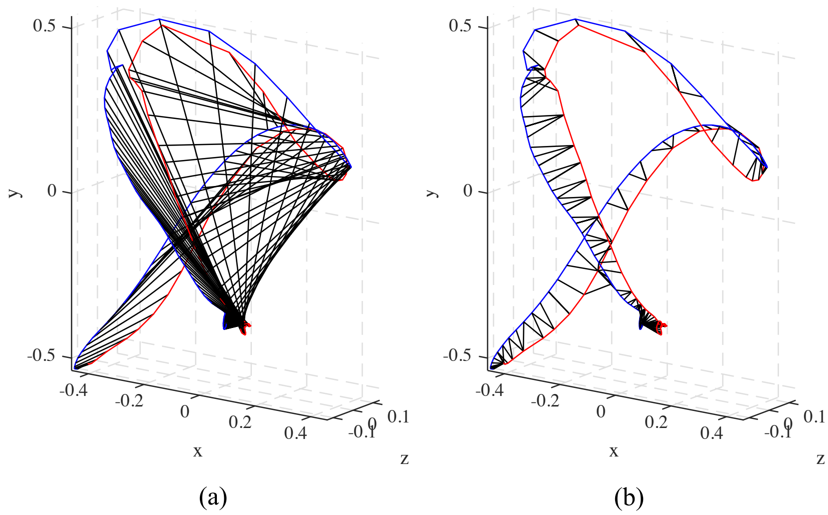

Fig. 3. (a) Corresponding points in two trajectories for the same user deviate from each other over time due to differences in wait times between actions, (b) Our approach handles the deviation by identifying nearest point neighbors between both trajectories.

to points further along in the red trajectory since the user is slower during the blue trajectory. Due to the differences in length of time for which the controller is poised over the shoulder, the deviation in correspondence increases over the latter parts of the trajectory. To address this issue, our approach computes the distance $d(\mathbf{T}_1, \mathbf{T}_2)$ between two trajectories $\mathbf{T}_1 \in \mathbb{R}^{N\times 3}$ and $\mathbf{T}_2 \in \mathbb{R}^{N\times 3}$ with N time samples as the symmetric sum-squared distance between nearest point neighbors given as

$$d(\mathbf{T}_1, \mathbf{T}_2) = \tfrac{1}{2}\textstyle\sum_{i=1}^{N} \min_j (\mathbf{T}_1(i) - \mathbf{T}_2(j))^2 + \tfrac{1}{2}\textstyle\sum_{j=1}^{N} \min_i (\mathbf{T}_1(i) - \mathbf{T}_2(j))^2. \quad (1)$$

The nearest neighbor in $\mathbf{T}_2$ to the i^{th} 3D point in $\mathbf{T}_1$ is represented by the argument of $\min_j(\mathbf{T}_1(i) - \mathbf{T}_2(j))$ in Equation 1, and vice versa. As shown in Figure 3(b), matches between the nearest point neighbors provides an accurate matching between the various parts of the two trajectories. While our approach shares features with bipartite graph matching, unlike bipartite graph matching, our matches are not bijective, i.e., a single point in one trajectory may match to multiple points in the other trajectory. We allow repetitive matches since a point in a short wait time phase on one trajectory may correspond to several points in a longer wait time phase on a second trajectory.

To obtain the results of user authentication discussed in Section 5, we match each trajectory for a user from the test set captured on the second day to all trajectories for every user in the library set captured on the first day using the symmetric nearest neighbor sum-squared distance. We label each test trajectory with the user corresponding to the closest library trajectory after matching.

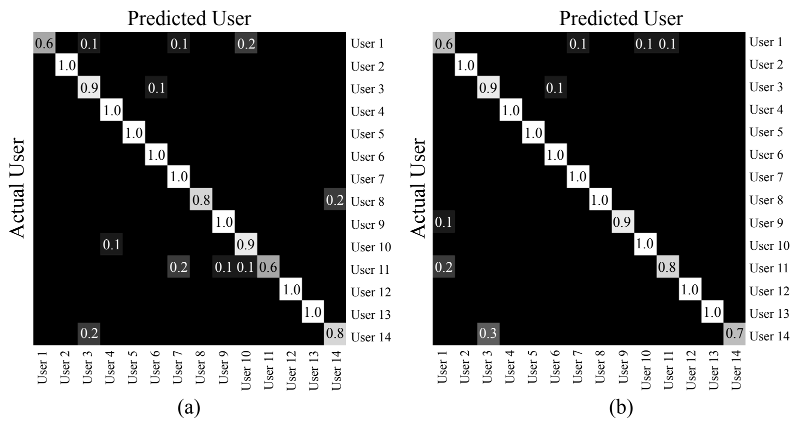

Fig. 4. Confusion matrices for classifying the trajectories of 14 users using (a) all 135 time samples, and (b) the first 95 time samples.

5 Results

Figure 4 shows the confusion matrices for performing authentication of 10 trajectories per user for 14 users using (a) all 135 time samples, and (b) the first 95 time samples. The average accuracy with all 135 time samples is 90.00%, while the average accuracy with the first 95 time samples is 92.86%. The higher accuracy with fewer time samples may be attributed to low information content toward the end of the trajectory as users' hands follow less predictable trajectories toward the end of the return phase. For instance, at the end of a return, the user may dangle their hand, or external factors such as gravity may induce the user to follow an alternative trajectory during the return.

Table 2 provides comparisons of our approach of symmetric nearest neighbor matching using trajectories re-centered around the bounding box center against 5 other matching methods for classifying using 95 time samples in the first column and 135 time samples in the second column. Results of our approach are provided in the first row. The second and third rows show classification results with re-centering of the trajectory using the centroid of the trajectory points, and without re-centering. As shown by the third row, without re-centering, the accuracy is low, indicating that users may change the location of the hand from the first day to the second. Despite the change in hand location, the higher accuracy of results in the first row demonstrates that the pattern of throw remains consistent within the user from one day to another.

The results in the second row obtained by re-centering using the centroid are lower than in the first row as the centroid is weighted toward regions of the trajectory with high point concentrations. The point concentration is higher in regions representing wait times during, for instance, the shoulder poise or the end of the return. Variations in wait times change the centroid position, due to which

Table 2. Accuracy with 95 time samples and 135 time samples using multiple matching approaches. We achieve the highest accuracy using of 92.86% using 95 points and re-centering around the bounding box center with symmetric nearest neighbor matching.

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

the translation offsets are not zeroed out. The last three rows in Table 2 provide authentication accuracies using matching of points at corresponding time samples between the two trajectories without identifying spatial nearest neighbors, i.e., using the correspondences shown in Figure 3(a). The matches are significantly lower due to the differences in temporal shift in the trajectories induced by the variations in wait times during the shoulder poise phase.

Figure 5 shows plots of average accuracy using increasing numbers of trajectory points ranging from the first 5 time samples to the complete set of 135 samples in steps of 5. Each plot represents classification using the first n library trajectories for each user, where n varies from 1 to 10. As shown by the figure, classification using 6 trajectories and higher approaches the classification using 10 trajectories. The plots demonstrate that we can authenticate users using a reduced set of trajectories, indicating that users use their natural interactions in the real world to rapidly develop consistency to actions in virtual environments. For all plots, increasing the number of time samples improves accuracy in the initial phase, after which the accuracy remains steady. For plots corresponding to matching with between 6 and 10 throws, peak accuracies are obtained at between 95 and 115 trajectory points, demonstrating that time samples later than 115 points, or around 2.56 seconds may contribute reduced information content due to the noise during the return phase. With 6 trajectories, we achieve a recognition accuracy of 90.00% within 115 points, which matches the recognition accuracy with 10 trajectories using all 135 points. Using 5 trajectories, we receive an accuracy of 87.14% within 105 points.

6 Discussion and Future Work

In this paper we provide the first approach for authenticating users using their natural behavior in VR environments using the 3D trajectories obtained from the dominant hand controller. Our approach does not require any external devices, such as RGB-D cameras or smartphones. Using our approach, users can

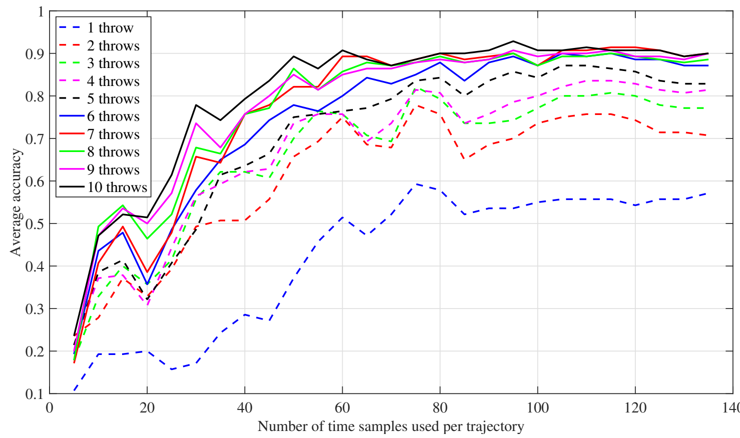

Fig. 5. Plots of the average accuracy of authentication against increasing numbers of time samples included per trajectory. Each plot corresponds to using the first n library throws, where n varies from 1 to 10 as shown by the legend.

continually authenticate themselves in VR environments without needing to stop their activity and enter credentials in a PIN or pattern based password system. We validate our 3D trajectory-based authentication approach by collecting data from a pilot study involving 14 subjects throwing a virtual ball at a target across two independent sessions. Using 135 3D trajectory points we achieve an overall accuracy of 90.00%, while using 95 points, we achieve an accuracy of 92.86%.

Our authentication approach relies on the notion that the trajectories of each user are unique. In future work, we will develop attack strategies that utilize trained actors to mimic the action trajectories of a genuine user to determine how long it takes an attacker to mimic the physical behavior of a genuine user. The authentication task used in our approach was a purely physical task with limited cognitive requirements. In future, we will create a broader range of authentication tasks ranging from physical tasks, such as swinging a golf club, to cognitive tasks, such as solving a puzzle. As part of these experiments, we will include changes in the position and orientation of the subject in the virtual space, and investigate matching techniques such as iterative closest point to address offsets in rotation and translation between user trajectories. Our current work focuses on the dominant hand gesture controller. As part of future work, we are interested in analyzing the influence of the subtle motions of the head and the non-dominant hand on user authentication.

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