EPiC Series in Computing
Volume 106, 2025, Pages 199–209
Proceedings of the 20th Asia Joint Conference on Information Security

No Anonymity in Metaverse: VR User Identification Based on DTW Distance of Head-and-Arms Motions

Koki Miura[1] and Hiroaki Kikuchi[1]

Meiji University, Nakano, Tokyo, Japan
cs252037@meiji.ac.jp, kikn@meiji.ac.jp

Abstract

In recent years, the adoption rate of virtual reality (VR) technology has been on the rise, and the metaverse is attracting attention as a next-generation form of internet usage. VR offers a variety of applications and content, such as education, gaming, and tourism, where users can remain anonymous and behave as fictional characters. However, there is a possibility that individuals in the real world can be identified from motion data that records VR users' head-and-hands movements in detail, represented in time-series data. Nair and Lieber demonstrated that publicly available replay data from the VR rhythm game "Beat Saber" can identify individuals with over 90% accuracy. Nevertheless, the features that had the greatest impact on identification accuracy were static attributes such as height and arm length. Therefore, in this study, we attempt to identify individuals in VR domain based on dynamic features such as users' distinctive ways of moving their arms by employing the DTW (Dynamic Time Warping) distance derived from motion data recorded during VR experiences.

1 Introduction

In recent years, virtual reality (VR) technologies and metaverse platforms have seen rapid growth and widespread adoption across entertainment, education, and professional collaboration [15]. These immersive environments allow users to interact with one another through avatars, often without revealing their real-world identities. This anonymity has been widely perceived as a core feature and appeal of VR spaces, fostering freedom of expression, creative experimentation, and privacy-conscious participation. Users are generally assumed to be unidentifiable, as their interactions are mediated solely through motion, voice, and digital representations rather than direct personal information.

Despite the perceived anonymity of VR environments, recent studies have revealed that users may be uniquely identifiable based on their behavioral patterns. In particular, Nair et al. [1] demonstrated that over 50,000 VR users could be accurately identified using only head and hand motion data collected during gameplay in the rhythm-based VR game *Beat Saber* [10]. Their hierarchical classification model achieved high identification accuracy—even with just 10 seconds of motion data, raising serious concerns about the privacy risks inherent in sharing such motion data. These findings suggest that even seemingly innocuous motion traces in VR can act as biometric signatures, potentially enabling persistent user tracking [7], profiling [9], or de-anonymization across sessions or platforms [8].

However, despite the impressive scale and accuracy of Nair et al.'s identification method, their study also reveals a potential limitation in its reliance on static features. According to their analysis (Figure 16 in [1]), *the most influential features used for identification were static* in nature, such as the maximum Y-coordinate of the headset, which effectively reflects a user's height. These static attributes accounted for approximately 23% of the model's decision-making. While such features are easy to capture and effective in short-term identification, they are also easily manipulated. For instance, users could intentionally alter their posture or device positioning to obfuscate their identity. This vulnerability limits the applicability of static-feature-based approaches for long-term tracking or persistent identification in dynamic VR settings.

To address these limitations, our study proposes a user identification method based on Dynamic Time Warping (DTW) [14], which focuses on *dynamic* rather than static features. This constitutes the key novelty of our approach. DTW computes a distance metric that is robust to variations in the length and timing of time-series data, making it particularly well-suited for analyzing natural motion patterns in VR environments. By capturing temporal dynamics instead of relying on fixed attributes, DTW-based identification has the potential to provide more stable and resilient performance—especially in long-term or behaviorally adaptive scenarios—compared to prior methods that emphasize static characteristics.

In this paper, we make the following contributions. First, we apply DTW-based user identification to motion data collected from real VR devices, including head-mounted displays (HMDs) and hand controllers. Through experiments using four-beat conducting gestures and gameplay sessions from the popular VR title *Beat Saber*, we demonstrate that our DTW-based method can effectively distinguish between users based on their natural motion patterns. Second, we quantitatively compare our method against prior approaches, including those based on static features and Random Forest classifiers. The results show that our method achieves higher identification accuracy and greater robustness over time, especially in scenarios where motion characteristics evolve gradually. These findings suggest that DTW offers a practical and privacy-relevant alternative to existing VR identification techniques.

2 Related Works

2.1 Hierarchical Classification Model

In 2023, Nair et al. [1] presented the first study to demonstrate that highly accurate personal identification is feasible in virtual reality (VR) environments – settings traditionally believed to offer a high degree of anonymity. Their work revealed that head and hand motion data captured during VR interactions can pose a serious risk to user privacy.

Specifically, they proposed a method for identifying over 50,000 VR users based on motion data collected while playing the rhythm game *Beat Saber* [10]. Performing naive user identification with machine learning at such a large scale would require enormous computational and memory resources. To address this issue, Nair et al. developed a hierarchical classification model using multiple LightGBM models. The model was trained on a 232-dimensional hybrid feature set that combined motion statistics, i.e., position and rotation, with contextual information representing interactions between the user and in-game objects.

Their approach achieved an identification accuracy of 94.33% using 100 seconds of test data, and 73.20% with only 10 seconds of data, based on 5-minute training samples for each user.

2.2 Multiclass Classifier

In 2023, Liebers et al. conducted a remote field study [2] to evaluate the stability of behavioral biometrics in virtual reality (VR) environments and to examine how identification performance changes over time. Fifteen participants were asked to repeatedly play the same song in the VR rhythm game *Beat*

Saber over a period of eight weeks. Their motion data was analyzed using a multiclass classifier based on Random Forest.

The Random Forest model utilized 72 statistical features derived from each participant's movements, including the rotation (quaternions) of the HMD and both hand controllers, as well as the minimum, maximum, mean, and standard deviation of the relative positions of the controllers with respect to the HMD. Default hyperparameter settings were used.

When the model was trained on 80% of the data from the initial session and tested on the remaining 20%, it achieved an F1 score of 86%. However, when the model trained on the initial session was applied to subsequent sessions, the identification performance gradually declined over time, indicating temporal instability in behavioral biometrics.

The studies by Nair et al. and Liebers et al. both investigate user identifiability in VR environments, but from complementary perspectives.

Nair et al.'s work [1] demonstrated that highly accurate identification is possible in large-scale VR systems using only head and hand motion data. By introducing a hierarchical classification model with hybrid features, they showed that even short sequences of motion (e.g., 10 seconds) can reveal sufficient behavioral signals to identify users with high accuracy. Their findings raised early awareness of the significant privacy risks inherent in VR interactions, especially when motion data is retained or shared.

In contrast, Liebers et al. [2] focused on the temporal stability of behavioral biometric signals in VR. Through a remote longitudinal study, they showed that identification performance can degrade over time—even with the same VR task—highlighting that behavioral changes may reduce the reliability of static feature-based identification models. Their use of Random Forest classifiers and statistical feature engineering provided a practical baseline for measuring identification stability over weeks.

Together, these studies suggest that while motion-based identification in VR is highly feasible, it may also be subject to decay over time or improvements through task adaptation. This motivates the need for further investigation into robust, privacy-preserving methods for behavioral authentication in immersive environments.

2.3 Gait Recognition Using DTW Distance

In 2019, Mori et al. [5] proposed a method for accurate personal identification by applying DTW to time series gait data collected using a Kinect sensor. Their approach utilized the Kinect motion capture device to record 3D skeleton data from 25 body joints without requiring the user to wear any equipment. By analyzing the movement of specific joints and examining optimal combinations of features, they developed a method that enabled time-aligned similarity evaluation via DTW.

In their experiments with 31 subjects, they performed personal identification using integrated DTW distances between joints and achieved a high level of accuracy, with an equal error rate (EER) of 0.036. Multiple users identification was studied in [6].

2.4 User Authentication Using Controller Lift Gestures

In 2022, Suzuki et al. [4] proposed a gesture-based authentication method that utilizes users' natural movements for authenticating VR headset (HMD) users. While the present study aims to examine the potential for personal identification based on motion data—particularly through four-beat conducting gestures—and to highlight associated privacy risks, Suzuki et al.'s research focused on designing and evaluating a new gesture-based authentication system that balances usability and security in HMD login procedures.

Their experiment involved 10 participants who performed controller lift and pinch gestures commonly seen during HMD use. They evaluated the effectiveness of these gestures for user authentication

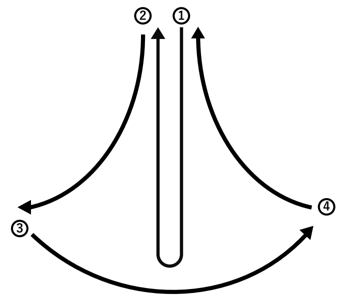

Figure 1: Example of four-beat conducting gesture

using three models: DTW, Support Vector Machine (SVM), and Random Forest. Among these, the SVM model achieved the highest accuracy, with an average authentication score of 0.991 for lift gestures and 0.989 for pinch gestures. In contrast, DTW yielded the lowest accuracy among the three models.

3 Proposed Method

3.1 Motion Features revaling individual differences

In this study, we measure the 3D coordinates of the head-mounted display (HMD) and both hand controllers obtained from the sensors of the VR device, and perform personal identification by calculating the DTW distance of the motion time series data. As the target motion, we adopt a four-beat conducting gesture. Fig. 1 illustrates the gesture. It is simple yet exhibits noticeable individual differences. Since the gesture involves repeated, rhythmic patterns, it is expected to yield stable and distinguishable features that reflect personal movement characteristics.

3.2 DTW distance

Dynamic Time Warping (DTW) [14] is a technique commonly used in waveform recognition, such as for speech signals, and is designed to measure the similarity between time series data of differing lengths (dimensions). DTW distance $d(P, Q)$ between two time series data $P = (p_1, p_2, \ldots, p_{n_p})$ of length n_p and $Q = (q_1, q_2, \ldots, q_{n_q})$ of length n_q is defined as $d(P, Q) = f(n_p, n_q)$, where $f(i, j)$ is computed as:

$$f(i, j) = \|p_i - q_j\| + \min \left\{ \begin{array}{l} f(i, j-1), \\ f(i-1, j), \\ f(i-1, j-1) \end{array} \right\}$$

with initial conditions: $f(0, 0) = 0, \quad f(i, 0) = f(0, j) = \infty$ and $\|p - q\|$ denotes the Euclidean distance between two 3-dimensional vectors.

Fig. 2 shows the result of applying DTW to the time series data of the x coordinates of the right-hand controller from different trials of subject (D). In the figure, the blue and orange lines show different time series. The dashed lines connect corresponding points as determined by DTW. In the figure, we observe that a single point in the orange time series is aligned with two points in the blue time series.

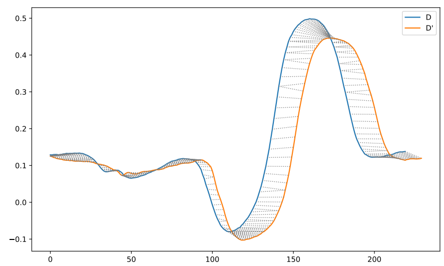

Figure 2: Example of DTW distance of the x coordinates of the right-hand controller from different trials of the single subject (D)

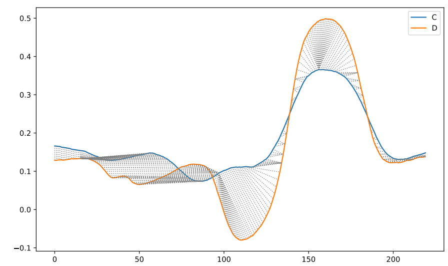

Figure 3: Example of DTW distance of the x coordinates of the right-hand controller from different subjects (C and D)

This alignment results from the fact that the blue sequence is slightly longer than the orange one. Such alignment behavior demonstrates the ability of DTW to flexibly map sequences of different lengths while preserving their temporal structure, thereby enabling robust similarity evaluation across variably sampled motion data.

Fig. 3 shows the results of applying DTW to the x coordinate time series data of the right-hand controller for different subjects, C and D.

In Fig. 2, although there are temporal shifts within the same subject, the gesture pattern of the four-beat conducting appears similar, suggesting a consistent hand motion. In contrast, Fig. 3 shows that the waveform shapes differs significantly between subjects C and D. Particularly, differences in the number and position of peaks can be seen, and the DTW alignment appears more complex. Subject D exhibits wider lateral hand movements compared to subject C.

3.3 Proposed DTW-based Method

We propose a template-matching-based user identification for VR motion data. Our proposed algorithm is given in Algorithm 1.

The method leverages the temporal similarity of motion patterns and is suitable for comparing sequences of varying length, which frequently occurs in VR use-cases.

4 Evaluation

4.1 Objective of Experiment

We aim to test whether the proposed method using DTW distance outperforms conventional techniques and to quantify the risk of user identification via motion data in virtual reality environments. To answer the following research questions, we will conduct two experiments with some subjects.

RQ1. Does the four-beat conducting rhythm repeat accurately, and do individual differences emerge in the rhythm execution?

RQ2. Which does pose a higher risk to user identifiability, between the proposed DTW-based method and the conventional method using static features?

Algorithm 1 Identification of VR users

Require: A set of n users with VR devices.

1. (Template) For each user $i = 1, \ldots, n$, we measure a motion data y_i, consisting of 3D coordinates of the head-mounted display (HMD) and both hand controllers. It serves as a reference template representing the user's unique movement characteristics.

2. (Identification) Given a new motion data x_j for some (unknown) user j, we compute the DTW distance between x_j and each of the n reference template y_i and identify j^* estimated to be one of the template with the smallest DTW distance, as

$$j^* = \underset{i \in \{1,\ldots,n\}}{\operatorname{argmin}}\, d(y_i, x_j)$$

where $d(y_i, x_j)$ denotes he DTW distance between template y_i and the given motion data x_j.

Table 1: Experiment Environment

item	value
VR device	Meta Quest 3
development	Unity 2022.3.28f1
sampling rate	72 frame per second [fps]

Table 2: Subjects

item	value
age	20—50 years old
gender	11 male and 1 female
total	12

4.2 Experiment 1 (*Four Beat*)

4.2.1 Method

In this experiment, we evaluate the proposed identification method described in Section 3.3, along with the conventional method due to Liebers et al. [2], using four-beat conducting motion data.

Table 1 outlines the measurement environment. To collect time series data of 3D positions and rotations of the HMD and both hand controllers using the Meta Quest 3, we implemented a Unity-based application using C#.

Table 2 summarizes the participant information. A total of 12 participants performed the four-beat conducting gesture, and their motion data was recorded. Each participant was measured six times with both hands during the period from November 1 to 15, 2024. Since the initial position and orientation varied between subjects, we performed alignment to standardize both the starting position and facing direction across all data.

After data collection, the six trials per participant were divided into three groups. For each group, we treated it as the test set, while the remaining two groups served as reference templates. Both identification methods were applied accordingly. We compared their performances using the average accuracy, precision, recall, and F1 score across the three test rounds.

4.2.2 Results

We show the mean of the evaluation metrics—accuracy, precision, recall, and F1 score—are presented in Table 3. Additionally, the confusion matrices for the identification results using DTW and Random Forest are shown in Tables 5.

As seen in Table 3, the DTW-based method outperformed Random Forest in all evaluation metrics. Furthermore, the confusion matrices indicate that DTW successfully identified one more subject than

Table 3: Accuracies of identification using the proposed method (DTW) and the random forest

method	accuracy	precision	recall	F1 score
DTW	0.98	0.99	0.98	0.98
Random Forest [2]	0.97	0.97	0.98	0.97

Table 4: Confusion metrics using DTW-based method

true \ estimated	*A*	*B*	*C*	*D*	*E*	*F*	*G*	*H*	*I*	*J*	*K*	*L*
A	6	0	0	0	0	0	0	0	0	0	0	0
B	0	6	0	0	0	0	0	0	0	0	0	0
C	0	0	6	0	0	0	0	0	0	0	0	0
D	0	0	0	6	0	0	0	0	0	0	0	0
E	0	0	0	0	6	0	0	0	0	0	0	0
F	0	0	0	0	0	5	0	0	0	0	0	**1**
G	0	0	0	0	0	0	6	0	0	0	0	0
H	0	0	0	0	0	0	0	6	0	0	0	0
I	0	0	0	0	0	0	0	0	6	0	0	0
J	0	0	0	0	0	0	0	0	0	6	0	0
K	0	0	0	0	0	0	0	0	0	0	6	0
L	0	0	0	0	0	0	0	0	0	0	0	6

Random Forest.

These results demonstrate that the proposed DTW-based method slightly outperforms the Random Forest approach used in prior research [2], even in the context of a simple motion like four-beat conducting.

4.3 Experiment 2 (*Beat Saber*)

4.3.1 Method

In this experiment, we compare the proposed method and the method by Liebers et al. [2] using the publicly available Beat Saber dataset "BeatLeader" [11].

Liebers et al. conducted two experiments using the collected data:

1. *Single-session training:* The model is trained using only the data from the first session and tested on data from subsequent sessions.

2. *Multi-session training:* When testing on data from a given session, the model is trained using all sessions up to that point.

These experiments were conducted on two groups: those who submitted data for at least 8 sessions (N = 8) and those who submitted data for at least 4 sessions (N = 15). Since the number of recordings varied per session and participant, the weighted F1 score is used as the evaluation metric.

In our experiment, we apply DTW to the motion data of the 1.5 seconds starting from when the first score is recorded after a Beat Saber play begins. We compare the results with the results reported by Liebers et al. [2] where they trained Random Forest model using the motion data.

Table 5: Mean (Standard Deviation) of F1-scores of identification using DTW for multiple sessions

	Test data (sessions)						
Training data	2	3	4	5	6	7	8
1	0.69 (0.16)	0.74 (0.34)	0.70 (0.33)	0.62 (0.22)	0.70 (0.19)	0.72 (0.22)	0.66 (0.37)
1 – 2		0.86 (0.15)	0.85 (0.15)	0.58 (0.31)	0.74 (0.18)	0.78 (0.18)	0.74 (0.30)
1 – 3			0.91 (0.09)	0.76 (0.17)	0.77 (0.21)	0.83 (0.19)	0.80 (0.16)
1 – 4				0.80 (0.16)	0.85 (0.13)	0.83 (0.19)	0.80 (0.16)
1 – 5					0.89 (0.11)	0.86 (0.19)	0.85 (0.15)
1 – 6						0.92 (0.12)	0.85 (0.15)
1 – 7							0.85 (0.15)

Table 6: Mean (Standard Deviation) of F1-scores of identification using Random Forest for multiple sessions

	Test data (sessions)						
Training data	2	3	4	5	6	7	8
1	0.71 (0.33)	0.65 (0.41)	0.55 (0.41)	0.42 (0.37)	0.48 (0.41)	0.34 (0.44)	0.27 (0.39)
1 – 2		0.96 (0.08)	0.70 (0.34)	0.57 (0.39)	0.73 (0.34)	0.57 (0.40)	0.34 (0.40)
1 – 3			0.78 (0.33)	0.62 (0.39)	0.82 (0.34)	0.57 (0.38)	0.49 (0.44)
1 – 4				0.74 (0.33)	0.91 (0.19)	0.59 (0.42)	0.57 (0.48)
1 – 5					0.83 (0.35)	0.55 (0.42)	0.61 (0.51)
1 – 6						1.00 (0.00)	0.75 (0.46)
1 – 7							0.71 (0.44)

4.3.2 Results

Tables 5 and 6 show the identification results for the group $N = 8$. We show represents the mean and the standard deviation of F1 score for the combinations of training and test data with different durations (number of sessions).

In both the DTW and Random Forest methods, the F1 score of the test data generally improves as more training (template) data are given. However, while the F1 score for Random Forest tends to decline as test sessions progress, the DTW method maintains relatively stable F1 scores across all test sessions. This suggests that DTW is more robust against behavioral changes over time. Moreover, DTW also consistently shows lower standard deviations in the F1 scores compared to Random Forest, which implies that DTW proves better features to identify users for longer time.

From these findings, combining the above results, we conclude that regarding RQ2 the proposed DTW-based method poses a greater risk of user identifiability than conventional methods based on static features.

4.4 In-depth Analysis on DTW distances

To understand why the proposed DTW-based method outperformed previous approaches in identification accuracy, we conduct a deeper analysis of the distribution of DTW distances.

Fig. 4 shows the probability distribution of DTW distances between same-person pairs and different-person pairs. The DTW distances for same-person pairs are clearly concentrated at lower values compared to those for different-person pairs. Specifically, most DTW distances between the same person are distributed below a value of 50, whereas those between different individuals are more widely spread, with some still falling below 50. These intersection could be a source of false identifications. Note that the a crossover point occurs around a DTW distance of 50. After that, FRR decreases and FAR increases. This highlights a trade-off between FAR and FRR.

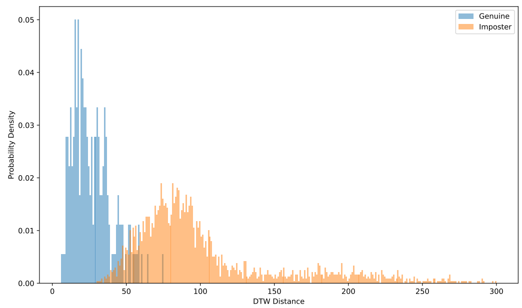

Figure 4: Distributions of DTW distance for same user (genuine) and different users (imposter)

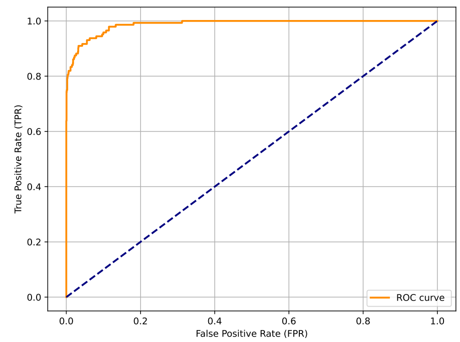

Figure 5: Receiver Operating Characteristic (ROC) curve

Furthermore, Fig. 5 presents the Receiver Operating Characteristic (ROC) curve. The Equal Error Rate (EER) was 0.0644, occurring at a DTW threshold of 52.49. These results suggest that the DTW distance effectively separates same-person and different-person pairs, and that threshold selection around 50–53 is particularly significant in balancing false acceptance and rejection.

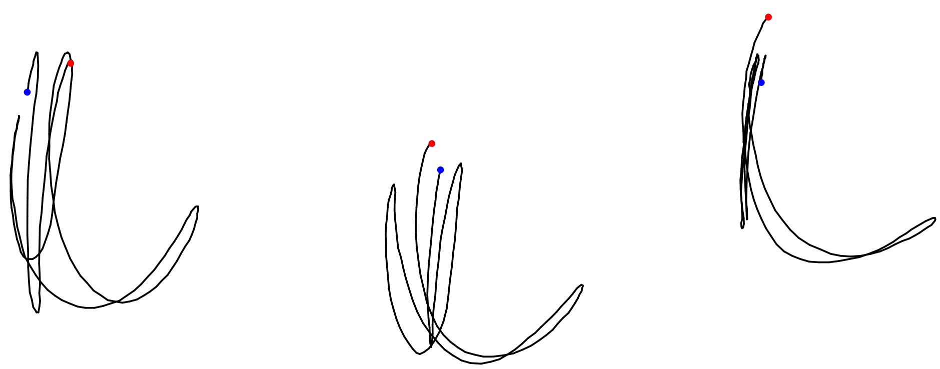

Figure 6: Trajectories of four-beat conducting motion for subject F_1 (left) F_4 (middle) L_3 (right)

4.5 Discussions

4.5.1 Misclassification in Experiment 1

To better understand the sources of identification errors, we examine specific users whose motion patterns led to misclassification. Furthermore, we discuss how temporal variation and motion individuality affect the performance of DTW-based identification.

As shown in Section 4.2.2 and Table 4, subject F was misidentified as subject L.

4.5.2 Robustness to Temporal Variation

In Section 4.3.2, we observed that DTW was less affected by temporal changes in user behavior than Random Forest. In Beat Saber, a timing is fixed for a given song and game difficulty, and players aim to slice target objects accurately to maximize their score. It is expected that players gradually improve their performance with repeated practice. Although this may introduce subtle timing shifts or changes in motion speed, DTW is robust to such variations even when the overall temporal structure remains consistent.

4.5.3 Individual Differences in Motion

In a prior study by Suzuki et al. [4], authentication using lift and pinch gestures showed that SVM achieved the highest accuracy, followed by Random Forest and then DTW. In contrast, our experiment using four-beat conducting revealed that DTW performed best.

This suggests that gestures like lift and pinch may exhibit less individual variability, whereas four-beat conducting allows for more expressive personal differences. Hence, DTW is more advantageous in our study due to the naturally diverse nature of the movement.

4.6 Mitigations

To mitigate the risk of user identification based on motion data in VR spaces, it is important not to share raw numerical motion data online. Instead, it is advisable to reduce detail by generalizing or coarsening the motion information to represent only the approximate movements consistent with the original gestures.

Lowering the data granularity, e.g., reducing the frame rate, can be expected to suppress individual differences in motion.

Additionally, injecting noise into motion data, e.g., differential privacy such as [13], may provide a defense against identification via statistical features extracted by machine learning models.

5 Conclusions

In this study, we proposed a method for personal identification based on Dynamic Time Warping (DTW) distances using time series data of 3D coordinates from a head-mounted display (HMD) and both hand controllers in a VR environment.

We conducted experiments using time series data from 12 participants performing a four-beat conducting motion, as well as gameplay data from 15 participants playing Beat Saber. The proposed DTW-based method outperformed conventional approaches in most evaluation metrics.

We conducted in-depth analysis to reveal the source of misclassification and primal factors for making the identification more robust. We also discussed some possible mitigations for preventing privacy violation in VR applications, in metaverse.

For future work, we plan to expand the number of participants, investigate the impact of varying the number of frames per motion sequence, and explore combinations of DTW with machine learning techniques to further improve identification accuracy.

References

[1] Vivek Nair, Wenbo Guo, Justus Mattern, Rui Wang, James F. O'Brien, Louis Rosenberg and Dawn Song, "Unique Identification of 50,000+ Virtual Reality Users from Head & Hand Motion Data", the 32nd USENIX Security Symposium, pp. 895-910, USENIX, 2023.

[2] Jonathan Liebers, Christian Burschik, Uwe Gruenefeld, and Stefan Schneegass, "Exploring the Stability of Behavioral Biometrics in Virtual Reality in a Remote Field Study", Virtual Reality Software and Technology 2023, pp.1-12, VRST, 2023.

[3] Jonathan Liebers, Mark Abdelaziz, Lukas Mecke, Alia Saad, Jonas Auda, Uwe Gruenefeld, Florian Alt, and Stefan Schnee- gass, "Understanding User Identification in Virtual Reality Through Behavioral Biometrics and the Effect of Body Normalization," In Proceedings of the 2021 CHI Conference on Human Factors in Computing Systems, pp. 1–11, Yokohama Japan, May 2021.

[4] Mei, Suzuki, Ryo, Iijima, Kazuki, Nomoto, and Tatsuya, Mori, "Usable User Authentication Method for Head-Mounted Displays Using Natural User Behavior", IPSJ Computer Security Sympoisum, CSS 2022, pp. 667-674, 2022. (in Japanese)

[5] Mori, T. and Kikuchi, H., "Robust Person Identification based on DTW Distance of Multiple-Joint Gait Pattern," In Proceedings of the 5th International Conference on Information Systems Security and Privacy - ICISSP, ISBN 978-989-758-359-9, SciTePress, pp. 221-229, 2019.

[6] Toma, R., Yaguchi, T., Kikuchi, H., "Multiple Person Tracking Based on Gait Identification Using Kinect and OpenPose," In: Mobile, Secure, and Programmable Networking, MSPN 2023, Lecture Notes in Computer Science, vol 14482. Springer, pp. 175-187, 2024.

[7] D. Kim and S. Park, "A Study on Face Masking Scheme in Video Surveillance System", Tenth International Conference on Ubiquitous and Future Networks (ICUFN 2018), pp. 871-873, 2018.

[8] Creţu, AM., Monti, F., Marrone, S. et al., "Interaction data are identifiable even across long periods of time", Nat Commun 13, 313, 2022 (https://doi.org/10.1038/s41467-021-27714-6).

[9] European Parliament, Council of the European Union, "General Data Protection Regulation", 2016 (accessed from https://eur-lex.europa.eu/eli/reg/2016/679/oj).

[10] Beat Saber, https://beatsaber.com/

[11] Viktor Radulov, BeatLeader, https://www.beatleader.xyz/.

[12] Jan Wöbbeking, "Beat Saber generated more revenue in 2021 than the next five biggest apps combined", August 2022.

[13] T. Wang, N. Li and S. Jha, "Locally Differentially Private Frequent Itemset Mining," 2018 IEEE Symposium on Security and Privacy (SP), San Francisco, CA, USA, pp. 127-143, 2018.

[14] Berndt, D. J. and Clifford, J., "Using dynamic time warping to find patterns in time series", The Third International Conference on Knowledge Discovery and Data Mining, pp. 359-370, 1994.

[15] Q. ai-Powering a Personal Wealth Movement, "VR Headset Sales Underperform Expectations, What Does It Mean For The Metaverse In 2023?", Section: Money, Forbes, 2023. https://www.forbes.com/sites/qai/2023/01/06/vr-headset-sales-underperform-expectations-what-does-it-mean-for-the-metaverse-in-2023