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WorldAuth: Real-World Authentication Using LiDAR on Mobile Devices

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Abstract: With the increasing number of spatial computing and LiDAR-enabled mobile devices, 3D spatial mapping has enabled novel security applications. In this work, we propose WorldAuth, a LiDAR-based authentication method that leverages the unique 3D geometry of a user's room as an authentication factor. We implement our system entirely on an iPhone, capturing room geometry via the built-in LiDAR scanner and representing the scene as a point cloud. We evaluate several point cloud registration methods and similarity metrics, including ICP, FGR, and learning-based approaches, to compare genuine scan pairs and impostor scan pairs. Experimental results across diverse environments demonstrate promising performance, achieving an F1-score of up to 0.8558 and an Equal Error Rate (EER) of 0.0432, even under moderate changes in viewpoint and scene clutter. A user study complements the performance evaluation by assessing usability and real-world feasibility, suggesting that real-world-based authentication is both intuitive and privacy-preserving on modern mobile devices.

Keywords: Authentication, LiDAR, Point Cloud, Mobile Devices, Real World

1. Introduction

Authentication systems have evolved significantly as digital interactions become increasingly central to daily life, yet fundamental challenges persist across all established authentication paradigms. Knowledge-based credentials suffer from memorability constraints and vulnerability to theft; possession-based tokens introduce risks of loss or unauthorized transfer; and biometric methods raise concerns about template irrevocability and privacy implications. These persistent limitations underscore the need for authentication approaches that balance security robustness with user accessibility and privacy preservation.

We propose real-world authentication as a fundamentally new authentication paradigm that introduces "surrounding real-world environment" as a fourth authentication factor, distinct from the traditional triad of knowledge, possession, and inherence. This approach leverages the inherent uniqueness of physical spaces, where 3D geometric structures captured as point clouds serve as spatially-bound credentials. Unlike conventional authentication factors that verify attributes intrinsic to or possessed by the user, real-world authentication exploits the principle that each physical space possesses unique geometric characteristics. This spatial uniqueness enables dual verification capabilities: confirming user identity while simultaneously validating physical presence at a specific location.

Recent advances in consumer mobile technology have made this authentication paradigm practically viable. The integration of LiDAR sensors in devices such as the iPhone Pro and iPad Pro series [1] enables precise capture of room-scale geometry through high-resolution 3D scanning. These devices can robustly map spatial environments regardless of lighting conditions or surface textures, transforming physical spaces into reliable authentication credentials. The accessibility of this technology on widely-deployed mobile platforms creates opportunities for authentication systems that require minimal user interaction while maintaining strong security properties.

The usability advantages of real-world authentication are particularly significant for inclusive design. Traditional authentication methods often impose cognitive, physical, or sensory demands that exclude certain user populations. Password systems require memorization capacity; biometric systems may fail for users with certain physical conditions; token-based approaches necessitate carrying additional devices. In contrast, real-world authentication requires only the natural action of holding a mobile device and performing a simple scanning gesture. This minimal interaction paradigm reduces cognitive load, eliminates memorization requirements, and accommodates users with diverse abilities, advancing authentication accessibility without compromising security.

In this work, we present WorldAuth, a practical imple-

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mentation of real-world authentication using the LiDAR sensors integrated in iPhone Pro and iPad Pro devices. Building upon our previous exploration of this authentication paradigm's potential [2], we develop a complete system that captures and processes room-scale 3D geometry for authentication purposes. WorldAuth represents physical environments as point clouds, enabling users to authenticate by scanning their surroundings and matching against previously registered spatial templates. The system operates entirely on-device, ensuring privacy preservation while maintaining compatibility across all LiDAR-equipped iOS devices.

We evaluate WorldAuth through comprehensive technical assessment and user studies to establish its viability as a practical authentication method. Our technical evaluation examines both classical and learning-based point cloud registration algorithms, including ICP [3], [4], RANSAC [5], FGR [6], PointNetLK [7], FMR [8], and DeepGMR [9], to identify optimal approaches for room-level authentication. Through experiments across diverse real-world environments, we demonstrate that room geometry provides sufficient discriminative power for authentication, achieving an Equal Error Rate of 0.0432 and F1-score of 0.8558 under practical conditions including viewpoint variations and environmental changes. Our user study with 11 participants validates the system's usability, revealing high user acceptance (SUS score of 83.25) and confirming that the scanning interaction is intuitive and accessible.

In summary, our contributions are as follows:

- We introduce WorldAuth, a LiDAR-based authentication system that establishes "surrounding real-world environment" as a novel fourth authentication factor, demonstrating the feasibility of using physical spaces as authentication credentials.
- We comprehensively evaluate classical and learning-based point cloud registration methods for authentication purposes, identifying optimal approaches for balancing accuracy and computational efficiency.
- We validate the system's inclusive design through user studies, confirming that spatial authentication provides an accessible alternative to traditional authentication methods.
- We analyze practical deployment considerations for spatial authentication on mobile devices, including on-device processing requirements and privacy preservation strategies.

This work demonstrates that physical spaces can serve as effective authentication credentials when captured through mobile LiDAR, offering a privacy-preserving, user-friendly authentication method that leverages the inherent uniqueness of our surrounding environments. We discuss the implications of spatial authentication for future security systems and identify directions for enhancing robustness and expanding application domains.

2. Background and Related Work

This section aims to explain the concepts and methods related to this paper's development process, namely authentication, the LiDAR sensor, and point cloud registration methods.

2.1 Authentication

Authentication is the process of validating or confirming that something is real, true, or what someone claims it to be [10]. To ensure that unauthorized users cannot access a system, an authentication mechanism is crucial. According to IBM, there are three primary categories of authentication factors: knowledge, possession, and inherence. While widely adopted, these methods have limitations: passwords are prone to reuse and theft, tokens can be lost or stolen, and biometrics raise irrevocability concerns [11], [12], [13]. This has motivated the exploration of novel authentication factors that are user-friendly, privacy-preserving, and resistant to spoofing.

The system developed in this research aims to add a new factor for authenticating a user: the real-world location or surroundings. Spatial computing technologies such as Augmented Reality and Virtual Reality have been gaining popularity recently [14]. Therefore, it is possible to develop a new authentication method based on room or environmental layout that authenticates the user only if they are able to scan a specific location.

2.2 Light Detection and Ranging (LiDAR)

Light Detection and Ranging (LiDAR) is a sensor that measures the distance between itself and the environment by emitting laser light toward objects and calculating differences in laser return times, signal strength, frequency variation, and other parameters. Based on these differences, the three-dimensional shape of an object can be estimated and reconstructed [15].

LiDAR in smartphones was introduced in late 2021 by Apple in its iPhone Pro series and later in its iPad Pro series [16]. This advancement enabled high-resolution 3D scanning on smartphones. Most applications include environment mapping and object reconstruction, demonstrating the feasibility of capturing accurate environmental geometry in real-world conditions [17], [18].

Since Augmented Reality can be utilized by developers through the ARKit or RealityKit libraries, there is an increasing number of apps that use the LiDAR sensor for features such as IKEA Place, Pokémon GO, and many others. However, leveraging this capability for authentication purposes remains largely unexplored. There are only a few applications of authentication using LiDAR, such as employing unique hand gestures for user verification and applying 3D motion tracking to authenticate users in both immersive virtual reality and real-world environments [19], [20]. This work aims to develop a new authentication system based on LiDAR that utilizes real-world features as a means of authentication. LiDAR's ability to capture detailed room layouts from point clouds makes it a perfect fit for the authentication system proposed in this research.

2.3 Point Cloud Registration Methods

A point cloud is a collection of spatial points represented as 3D coordinates. The data can be used for various purposes, such as mapping environmental features [21].

Point cloud registration, the process of aligning two or more 3D point clouds into a common frame, is a fundamental task in 3D data processing [22]. Traditional methods, such as Iterative Closest Point (ICP), optimize point correspondences iteratively but are sensitive to noise and initialization [3], [4]. RANSAC is an iterative method widely used in machine learning and computer vision to robustly estimate model parameters from data containing outliers [5]. Fast Global Registration (FGR) enhances robustness and convergence speed through global optimization strategies [6].

More recently, learning-based methods have emerged, leveraging deep networks to extract robust features and establish correspondences. PointNetLK integrates PointNet with the Lucas–Kanade framework; Feature-Metric Registration (FMR) optimizes registration in a learned feature space; and DeepGMR models point clouds as Gaussian Mixture Models for robust alignment [7], [8], [9]. These learning-based methods are predominantly trained on the ModelNet dataset, which consists of clean point clouds [23].

In this work, we evaluate both traditional and learning-based registration methods to assess their effectiveness for room-level authentication using mobile LiDAR scans.

3. Design and Implementation

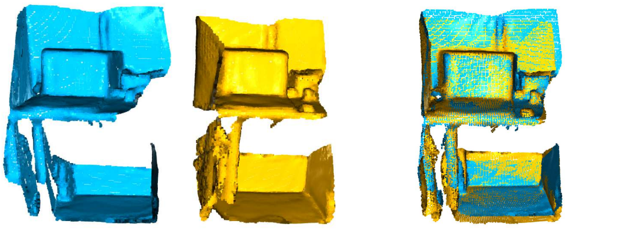
This section details the design and implementation of WorldAuth, our proposed LiDAR-based authentication system.

3.1 System Overview

WorldAuth enables users to authenticate by scanning their physical environment and comparing it with a previously registered room template. The system operates in two phases:

- **Registration**: The user scans their room with an iPhone, and the system stores the resulting point cloud as a room template for future authentication.
- **Authentication**: During authentication, the user scans a room. The system aligns the new point cloud with the registered room template, computes a similarity score, and accepts or rejects the attempt based on a predefined threshold. The point cloud alignment process is shown in Fig. 1.

The activity diagram for WorldAuth is shown in Fig. 2. The system is designed to be privacy-preserving (data are not shared with third parties and remain on-



(a) Unregistered point clouds. (b) Registered point clouds.

Fig. 1: Point cloud registration process.

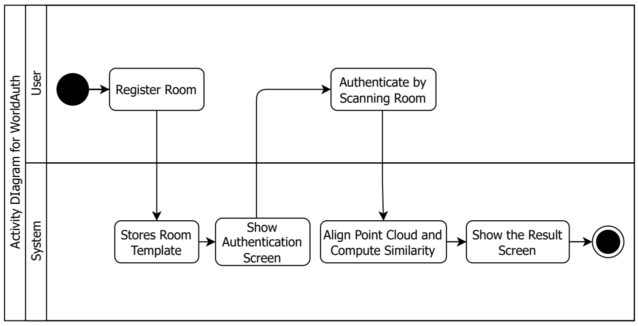


Fig. 2: Activity Diagram for WorldAuth.

device), compatible with all iPhone Pro and iPad Pro models, and robust to moderate environmental changes.

3.2 Similarity Measurement

We evaluate several registration methods, including RANSAC+ICP, FGR+ICP, PointNetLK, Feature-Metric Registration (FMR), and DeepGMR. In these experiments, ICP is combined with global alignment methods to ensure more robust results, as ICP performs best with good initialization. FGR is configured with 512 iterations and a maximum tuple count of 1,534 to better match real data.

In contrast, learning-based methods are not combined with global alignment, as they are designed to estimate transformations directly from raw, unaligned point clouds. Introducing a separate coarse alignment step can alter the input distribution, remove critical pose cues, and push the data outside the conditions under which they were trained, often degrading rather than improving performance.

Each method is expected to align the probe scan with the registered scan. The resulting alignment fitness is used as the similarity metric. Authentication is accepted if the score exceeds a predefined threshold of 0.5, based on each method's fitness criterion.

3.3 Point Cloud Representation

Each scan is represented as a 3D point cloud $P = \{(x_i, y_i, z_i)\}$, where each point corresponds to a point on the surface of the environment. The scanned point cloud is saved in a PLY file represented in ASCII format, as shown in Fig. 3. We also perform the following preprocessing steps for every authentication process:

- Voxel downsampling to reduce noise and memory us-

```
ply
format ascii 1.0
element vertex 153222
property float x
property float y
property float z
end_header
0.61581117 0.6748693 -1.5978884
-0.27570745 -0.92233 -1.4378792
```

Fig. 3: Example of point cloud representation.

age.

- Statistical outlier removal to eliminate stray points.
- Normal estimation of point clouds (if applicable).

3.4 Implementation Details

We implemented WorldAuth using the following components:

- **Frontend**: iOS app built with Swift and ARKit for LiDAR scanning.
- Python with Open3D for point cloud processing and evaluation [24].
- **Hardware**: All experiments were implemented on a MacBook Air with an Apple M1 processor and 8GB RAM, while evaluations were conducted on the iPhone Pro and iPad Pro series.
- **Parameter settings**: maximum correspondence distance set based on FAR/FRR test results; voxel size set to 0.1 meters; statistical outlier removal and normal estimation with default settings; and learning-based methods trained with default weights and datasets provided by the respective authors.

4. Performance Evaluation

This section presents the performance evaluation of our proposed authentication system. We assess its effectiveness across different point cloud registration methods under real-world conditions, focusing on accuracy, reliability, and computational runtime.

4.1 Data Collection

We collected LiDAR-based room scans using the iPhone Pro series from 8 participants across 20 distinct rooms, with 5 scans per room. Users were instructed either to keep the phone still or to move it slowly to scan part of their room for approximately 1–3 seconds. The dataset was arranged by code for the FAR/FRR test as follows:

- Genuine pairs: scan pairs from the same room, taken at different times.
- Impostor pairs: scan pairs from different rooms.

The collected data are used to evaluate the performance of each method.

4.2 False Acceptance Rate/False Rejection Rate

The False Acceptance Rate/False Rejection Rate (FAR/FRR) test for each method is necessary to determine the optimal correspondence distance (threshold). Threshold is the maximum allowed distance between two points for them to be considered a valid match during point cloud registration. For each method, we compute the Equal Error Rate (EER) over the full range of thresholds.

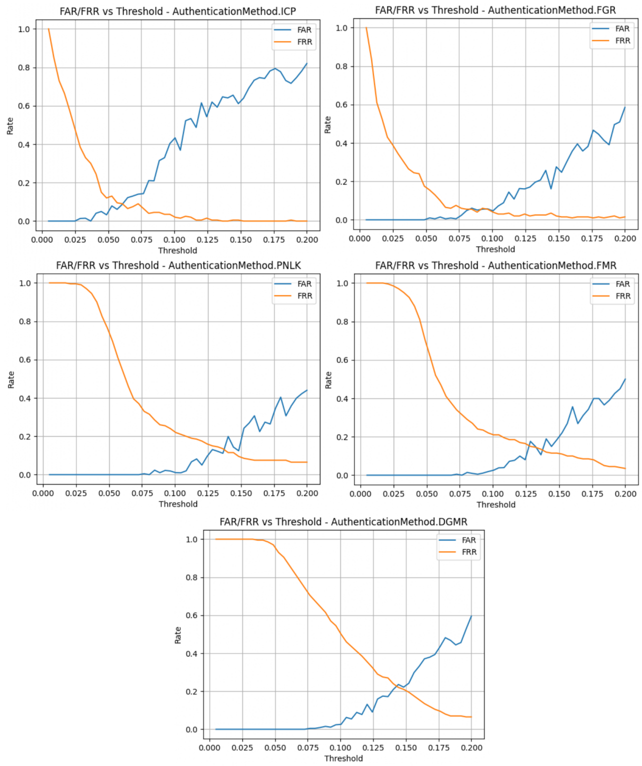


Fig. 4: FAR/FRR result for each method.

Table 1: Classification Performance Result (In Percentages).

	Accuracy	Precision	Recall	F1-score
RANSAC+ICP	73.95	69.16	86.46	76.85
FGR+ICP	85.44	84.79	86.38	85.58
PNLK	74.11	82.71	60.98	70.20
FMR	74.11	82.13	61.64	70.43
DGMR	63.91	72.65	44.60	55.27

Table 2: Equal Error Rate, Area Under the Curve and Runtime.

	EER	AUC	Runtime (s)
RANSAC+ICP	0.0887	0.7828	0.5068
FGR+ICP	0.0432	0.5704	0.3559
PNLK	0.1097	0.3875	0.3064
FMR	0.1466	0.4430	0.2913
DGMR	0.2158	0.4674	0.2398

The results are shown in Fig. 4. Based on these results, ICP achieved the lowest optimal threshold, while FGR yielded the lowest Equal Error Rate (EER). Learning-based methods perform poorly on the collected dataset, as the LiDAR scans obtained from the iPhone are noisy and contain many feature spaces not captured during training.

4.3 Performance Evaluation Results

We evaluate the classification performance of each method using the F1-score, which is the harmonic mean of precision and recall [25]. Precision is defined as the ratio of true positives to all predicted positives, while recall (true positive rate) is the ratio of true positives to all actual positives. We also compare accuracy, defined as the ratio of all correct classifications (true positives and true negatives). Thresholds for binary classification are optimized per method to maximize the F1-score. Table 1 shows that FGR+ICP outperforms all methods in accuracy, precision, and F1-score, while RANSAC+ICP achieves the highest recall.

We also evaluate the Equal Error Rate (EER), Area Under the Curve (AUC), and average runtime of each method. EER corresponds to the point at which the False Acceptance Rate (FAR) equals the False Rejection Rate (FRR). AUC measures how well a method separates positive and negative instances across all thresholds. Average runtime reflects the mean processing time per authentication attempt, providing an indicator of efficiency.

Table 2 reveals clear performance trends across classical and learning-based registration methods. Classical pipelines that incorporate a global alignment stage before refinement generally outperform end-to-end learning-based methods in terms of accuracy. RANSAC+ICP achieves the highest AUC (0.7828) and a strong EER (0.0887), demonstrating that robust global initialization enables ICP to converge effectively. In contrast, learning-based methods such as PointNetLK, FMR, and DeepGMR, which operate directly on unaligned point clouds, produce higher EER values (higher than 0.1) and lower AUC scores. This suggests that the presence of unlearned feature spaces limit their robustness in complex room scenarios, despite their faster runtimes.

Among all methods tested, FGR+ICP achieves the most favorable balance of accuracy and efficiency, recording the lowest EER (0.0432) and a competitive runtime (0.3559 s). These characteristics make FGR+ICP the most suitable choice for WorldAuth, where both high precision and fast response times are essential. Although RANSAC+ICP achieves a higher AUC than FGR+ICP, AUC is primarily relevant when a dynamic threshold is used. Since WorldAuth employs a fixed threshold, the lower EER of FGR+ICP is more critical.

4.4 Implementation Feasibility

We evaluate the feasibility of implementing each method on-device. On-device implementation removes the need to transmit data to servers or third parties, thereby mitigating common HTTP-based attacks (e.g., man-in-the-middle and DDoS) and preserving user privacy by keeping data local.

For traditional methods such as RANSAC+ICP and FGR+ICP, on-device implementation is feasible because Open3D can be built from source on iOS, supplemented with LAPACK for the linear algebra operations required by Open3D. In contrast, learning-based methods are very difficult, if not impossible, to implement on-device. Only a limited number of deep learning frameworks are supported, and Apple's CoreML does not explicitly support the linear algebra operations required by Open3D [26]. The only learning-based method currently feasible on-device is DeepGMR using LibTorch with the RRI feature disabled. This configuration yields slightly worse performance than its RRI-enabled counterpart. Moreover, LibTorch is being replaced by ExecuTorch, a runtime designed for on-device inference [27]. Unfortunately, ExecuTorch faces the same limitations as CoreML, as neither explicitly supports the necessary linear algebra operations.

In conclusion, the implementation feasibility of traditional methods is higher than that of learning-based methods, making them more suitable for WorldAuth's privacy-preserving design.

5. Usability Evaluation

To assess the practicality and user-friendliness of WorldAuth, we conducted a user study with participants in indoor environments. The study aimed to evaluate both authentication performance in real-world scenarios and user experience with the application.

5.1 Participants and Setup

A total of 11 participants took part in the user study via a guided survey that was designed in such a way that participants could complete it either on-site or remotely without difficulties. Each participant was asked to scan a part of a room (e.g., a desk setup) using an iPhone Pro/iPad Pro, which is equipped with a LiDAR sensor. The same device was later used for authentication in both successful and failed scenarios. Participants were given concrete instructions for each task to avoid accidents and to ensure that they understood what they needed to do.

Scans were completed by the participants in their own rooms with varying layouts, lighting conditions, and levels of furniture clutter. The participants scanned the room three times: once for registration, once for authentication of the previously scanned room, and once for a completely different room. This design ensures that the robustness of the system can be tested thoroughly without requiring specific room conditions, which could otherwise limit the scope of robustness testing for WorldAuth.

5.2 User Study Procedure

For the user study, participants were first guided to read the informed consent form so that they understood the aim of the study, that their data would be used solely for research purposes, and that WorldAuth was designed to be privacy-preserving. Afterward, participants were instructed to download the WorldAuth app from Apple's TestFlight. Once the app was installed, they were asked to briefly explore it and then begin the registration process by scanning a room of their choice using the WorldAuth mobile application. The resulting point cloud was stored as a room template. The design of the WorldAuth is

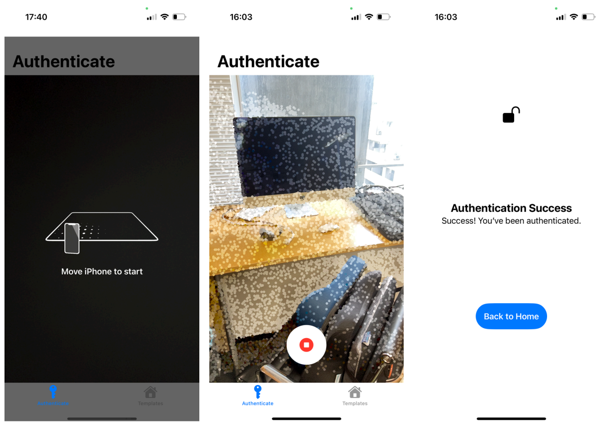


Fig. 5: The design of the WorldAuth application.

shown in Fig. 5.

After completing the registration, participants were asked to rescan the same room they had previously scanned, ensuring that WorldAuth could align the point clouds correctly and produce successful authentication as the expected outcome. To test the robustness of the authentication framework, participants were then instructed to scan a completely different room, ensuring that WorldAuth could recognize the difference from the previously registered room template and thereby produce authentication failure as the expected outcome. Finally, participants were asked to evaluate the overall system by completing the questionnaires provided in the survey.

5.3 Usability Metrics

We evaluated usability through both quantitative metrics (time taken to authenticate and success rate) and subjective feedback. The subjective feedback was collected using two standardized assessment tools: the NASA Task Load Index (NASA-TLX) [28] to measure cognitive workload during each authentication task, and the System Usability Scale (SUS) [29] to evaluate overall system usability.

For the NASA-TLX assessment, participants rated the following six dimensions immediately after completing each task using a 10-point Likert scale:

Q1: "How mentally demanding was the task?" (mental workload)
Q2: "How physically demanding was the task?" (physical workload)
Q3: "How hurried or rushed was the pace of the task?" (temporal workload)
Q4: "How successful were you in accomplishing what you were asked to do?" (performance workload)
Q5: "How hard did you have to work to accomplish your task?" (effort workload)
Q6: "How insecure, discouraged, irritated, stressed, and annoyed were you?" (frustration workload)

For the SUS assessment, participants evaluated the overall system at the end of the survey by indicating their level of agreement with the following ten statements using a 5-point Likert scale:

Q1: "I think that I would like to use this system frequently."
Q2: "I found the system unnecessarily complex."
Q3: "I thought the system was easy to use."
Q4: "I think that I would need the support of a technical person to be able to use this system."
Q5: "I found the various functions in this system were well integrated."
Q6: "I thought there was too much inconsistency in this system."
Q7: "I would imagine that most people would learn to use this system very quickly."
Q8: "I found the system very cumbersome to use."
Q9: "I felt very confident using the system."
Q10: "I needed to learn a lot of things before I could get going with this system."

5.4 User Study Results

After conducting the usability test through a guided survey and analyzing the data obtained from the participants, It was found that the average time for on-device authentication was 1.56 seconds, with the system achieving 100% accuracy by correctly accepting all genuine attempts and rejecting all impostor attempts.

The workload scores for each task, as measured by the NASA-TLX, are presented in Fig. 6. Task 1 represents room template registration, Task 2 represents the authentication attempt using the same room as the one previously registered, and Task 3 represents the authentication attempt using a completely different room. The analysis of performance metrics across the three tasks highlights differences in workload and user experience. Task 3 consistently exhibited the lowest mental load (1.45) and physical load (1.73) scores, indicating that participants perceived it as the least cognitively and physically demanding, whereas Task 1 recorded the highest scores in these dimensions. Temporal load was also lowest for Task 3 (2.27), suggesting that it was perceived as the most time-efficient task. In terms of performance, Task 2 was rated most favorably, with a substantially lower score (1.09) compared to Task 1 (2.45) and Task 3 (2.09), indicating higher perceived effectiveness in completing the task. Effort followed a similar pattern, with Task 3 requiring the least perceived effort (2.64), followed by Task 2 (2.91) and Task 1 (3.36). Interestingly, frustration scores were lowest for Task 1 (1.27) and highest for Task 3 (2.00), suggesting that despite being easier and faster, Task 3 elicited slightly higher frustration.

Overall, Task 2 achieved the lowest average metric score of 1.95, indicating the most favorable overall experience,

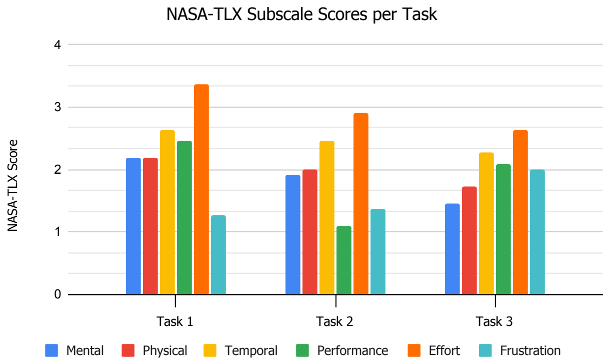


Fig. 6: NASA-TLX Subscale Scores per Task (Lower is better).

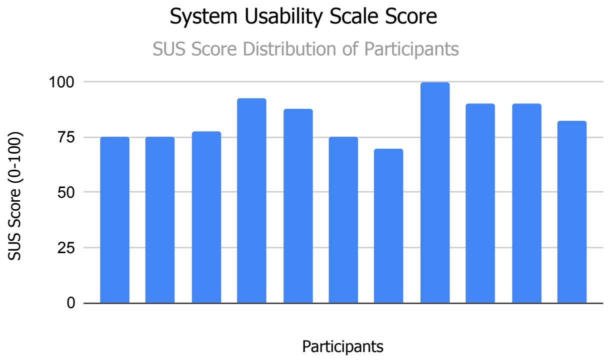


Fig. 7: System Usability Scale (SUS) Score Per Participant.

followed closely by Task 3 at 2.03, while Task 1 had the highest average score of 2.35, reflecting the greatest overall burden.

The SUS score for each participant is shown in Fig. 7. The SUS evaluation yielded a mean score of 83.25 (standard deviation = 9.93), which indicates high usability and corresponds to an "A" grade based on the SUS curved grading scale [30]. The relatively low standard deviation suggests consistent positive feedback among participants.

The user study indicates that participants were generally comfortable with the process, and the authentication performance remained high across diverse conditions. Most participants completed the registration and authentication processes with minimal to no assistance, highlighting the system's ease of use and potential for real-world deployment.

However, several participants expressed concerns during the study. One participant was uncertain about how wide an area of the room should be recorded and which objects to focus on during scanning. Another participant questioned how this system could be applied in real-world scenarios, since the authentication framework currently functions only at a specific location. One participant reported a glitch during the first authentication attempt that prevented successful authentication, suggesting that WorldAuth still requires improvements and bug fixes. Additionally, another participant was curious about whether differences in scanning direction between the registration and authentication processes could affect the results.

6. Discussion

In this section, we will discuss the limitations, future work, and ethical considerations of this study.

6.1 Limitations

The system and methods used in this study have several limitations. First, during the performance evaluation, default settings were used in the learning-based methods to evaluate their robustness against real-world data containing many outliers. Second, only traditional methods could be implemented on-device for inference, since the currently available ML conversion frameworks remain limited in their capabilities. Lastly, the user study covered only general cases, such as registration, authentication using the same room, and authentication using a different room. There may be unexamined edge cases that could affect the overall accuracy of WorldAuth, such as scanning in dimly lit or completely dark rooms.

6.2 Future Work

There are several possible directions for extending this study. For instance, future work should explore methods for authenticating two similar rooms scanned from considerably different angles by determining room-intersection tolerance, which could improve authentication. Next, we recommend implementing a mechanism for incrementally updating the stored room template over time to ensure consistent accuracy in dynamically changing spaces. Furthermore, the previously tested learning-based methods could be refined to better adapt to real-world data containing noise. More recent learning-based methods may also be tested and evaluated for compatibility with Apple's CoreML conversion framework. It is also important to define the practical applications of this authentication approach so that the framework can be more widely adopted (e.g., for location-based access control). Lastly, WorldAuth could be extended to other devices and platforms that support LiDAR sensors, such as the Apple Vision Pro with its visionOS platform.

6.3 Ethical Consideration

The user study and data collection in this study were conducted in accordance with ethical research standards for human participants. Prior to participation, all individuals were informed about the purpose of the study, the procedures involved, and their right to withdraw at any time without consequence. Informed consent was obtained from all participants. Personally identifiable information was kept completely confidential, and all data were anonymized during processing. The scanned point cloud data collected using LiDAR were stored securely on participants' own devices and were not shared with the researchers or any third parties. The survey data were also not shared with any third parties and were used solely for the purposes of this research.

7. Conclusion

In this work, we presented WorldAuth and explored the feasibility of using LiDAR-based 3D room scanning as a novel authentication factor on mobile devices, particularly the iPhone Pro and iPad Pro series. By leveraging the iPhone's built-in LiDAR sensor and evaluating classical and learning-based point cloud registration methods—including Iterative Closest Point (ICP), RANSAC, Fast Global Registration (FGR), PointNetLK, Feature-Metric Registration (FMR), and DeepGMR—we selected the method with the best results and built a system capable of verifying whether a scan was captured in a previously authenticated location.

Our evaluation showed that traditional methods, especially FGR combined with ICP, achieved the highest accuracy and robustness against environmental changes. Meanwhile, learning-based methods showed promising speed advantages, but their reliability was limited due to the lack of adaptation to real-world point cloud data, which contains many outliers. Across various metrics, such as EER and F1-score, the system demonstrated promising potential as a real-world LiDAR-based authentication method, particularly for scenarios where spatial context is critical, such as location-based access control.

The user study further confirmed that participants found the system intuitive and easy to use. However, concerns about scanning procedures and real-world use cases indicate that further refinement is needed to improve long-term reliability and security.

In summary, this work establishes WorldAuth as a promising authentication framework that utilizes the environment as an authentication factor by scanning rooms using the LiDAR sensor embedded in the iPhone Pro and iPad Pro series. While the system has several weaknesses, further improvements are possible.

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