Analysis of Marker and SLAM-based Tracking for Advanced Augmented Reality (AR)-based Flight Simulation

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Abstract. Augmented reality (AR)-based flight simulation reshapes how pilots are trained, offering an immersive environment where commercial and fighter pilots can be trained at low cost with minimal use of fuel and safety concerns. This study conducts a pioneering comparative analysis of marker-based tracking and SLAM technologies within the Microsoft HoloLens 2 platform, mainly focusing on their efficacy in landing manoeuvre simulations. Our investigation incorporates an experimental setup where marker-based tracking overlays interactive video tutorials onto a simulated cockpit, enhancing the realism and effectiveness of landing procedures. The experiment demonstrates that marker-based systems ensure high precision within 5 cm and 15 cm from the HoloLens 2 camera, proving indispensable for procedural training that requires exact overlay precision. Conversely, the native SLAM algorithm, while lacking the same level of precision, offers flexibility and adaptability by accurately mapping the cockpit and superimposing virtual information in dynamic, markerless conditions. The study juxtaposes these technologies, revealing a trade-off between precision and adaptability, and suggests an integrative approach to leverage their respective strengths. Our findings provide pivotal insights for developers and training institutions to optimize AR flight simulation training, contributing to advanced, immersive pilot training programs.

Keywords: Augmented Reality · Marker-based Tracking · SLAM-based tracking · Flight simulation · Microsoft HoloLens 2.

1 Introduction

Augmented Reality (AR)-based flight simulation is reshaping how pilots are trained, offering an immersive environment where commercial and fighter pilots can be trained at low cost with minimal use of fuel and safety concerns.

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Also, the continuous quest for enhanced pilot training methodologies is crucial in the aviation industry, where safety and proficiency are paramount. Traditional flight simulation has long been a cornerstone of pilot training, offering a controlled environment to hone essential skills. However, these conventional methods, including Full-Flight Simulators (FFS) and Computer-Based Training (CBT), often lack the dynamic and immersive qualities of real-world flight, potentially impacting the effective transfer of skills to trainee pilots and their overall engagement [1]. This gap underscores the need for innovative training solutions to provide more realistic and engaging training environments.

Augmented Reality (with its ability to overlay digital information onto the real world) emerges as a promising technology to bridge the gap in traditional flight simulators, offering a dynamic and immersive environment to train pilots. By enhancing the realism of flight simulation through AR, training programs can simulate complex flight scenarios in a risk-free environment, fostering improved situational awareness and decision-making skills among trainees [2].

The adoption of AR in flight simulation leverages advanced tracking technologies such as marker-based tracking and Simultaneous Localization and Mapping (SLAM) tracking, each with distinct advantages and limitations regarding accuracy, flexibility, and applicability in diverse training scenarios.

Despite AR technologies' potential benefits, a comprehensive comparison of marker-based and SLAM tracking methods in the context of AR flight simulation training effectiveness still needs to be discovered. This study's main contributions are summarised as:

- We aim to fill this gap by introducing a novel comparative analysis of these tracking technologies within the Microsoft HoloLens 2 platform. We specifically focus on the distinct impacts of marker-based and SLAM tracking on AR flight simulation training quality, aiming to develop more immersive and effective training programs.
- We further contribute to the field by carrying out an experiment to track video on markers for a landing tutorial, a critical manoeuvre in pilot training. This experiment explores the practical applications of marker-based tracking in enhancing the realism and effectiveness of landing simulations, thereby addressing an essential aspect of pilot training.
- By systematically evaluating marker-based and SLAM tracking in Hololens 2 through a mixed-methods approach, we address crucial research questions regarding accuracy, user experience, training effectiveness, and cost-effectiveness.

Our findings aim to empower developers and training institutions to select the optimal tracking solution for their specific needs, thereby contributing to the development of more immersive and compelling pilot AR training programs. In light of the limitations of existing training methods and the potential of AR to enhance pilot training, our study not only addresses a significant gap in the literature but also proposes a practical experiment with direct implications for training effectiveness. Through this comprehensive approach, we seek to contribute to the ongoing evolution of pilot training methodologies, ensuring they

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are both practical and engaging in preparing pilots for the complexities of modern aviation.

2 Related works

In this section, we present a state-of-the-art overview of marker and SLAM-based tracking technologies for AR systems. AR marker-based tracking uses distinct artificial markers for camera positioning and orientation. Systems employ various shapes and features: a)InterSense utilizes concentric rings, needing at least four for precision [3]. b)QR Codes are famed for fast scanning and high data capacity [4]. c)Visual Code identifies markers via image processing and databases [5]. d)Vuforia's customization feature allows for using any selected image as a marker, enabling personalized marker design for specific applications. Figure 1 depicts these markers.

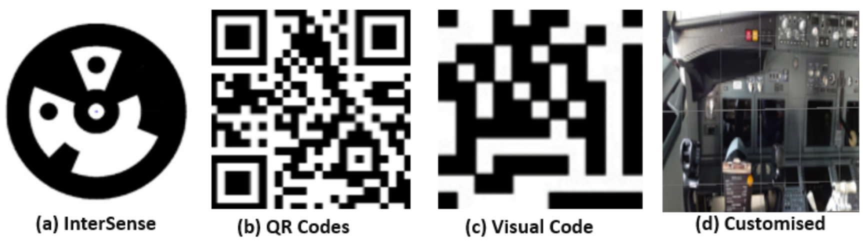

Fig. 1. Various AR Tracking Markers

Marker-based tracking offers high precision, making it ideal for accurately overlaying virtual elements onto real cockpits [6]. This approach can enhance realism and facilitate procedural training. Ribeiro et al.[7] demonstrate its application in UAV pilot training using printed markers and overlays, creating a cost-effective and accessible approach. Wallace et al. [8] leverage ArUco tags to overlay virtual gauges on a physical instrument panel, allowing immersive training while maintaining natural tactile interaction. However, marker setup and potential occlusion issues might pose challenges in dynamic scenarios [9].

SLAM-based tracking, on the other hand, adapts to dynamic environments but may face accuracy limitations compared to marker-based tracking, particularly during emergency procedures [10]. However, this adaptability eliminates setup requirements and facilitates training in unpredictable scenarios. Sun and Li [11] propose a system that translates user movements and control inputs into augmented visuals, eliminating the need for expensive physical mockups. Wang and Zhou [8] outline a system utilizing real-time data acquisition and intelligent identification of cockpit elements to enhance learning, reduce errors,

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and improve efficiency. A critical examination of existing studies reveals discrepancies in these technologies' effectiveness and implementation challenges. For instance, while Nwobodo et al. [12] review and evaluate SLAM methods for AR in flight simulators, emphasizing accuracy challenges in confined spaces and computational demands [13], it is crucial to acknowledge the broader context of technological and educational trends. Integrating adaptive learning technologies and gamification elements in pilot training could complement AR technologies, offering a more holistic approach to training that caters to diverse learning styles and enhances engagement and retention [14].

SLAM empowers robots and AR devices to autonomously build maps and track their location within them, eliminating the dependency on external markers or GPS. Leveraging a mix of sensors such as LiDAR, cameras, and Inertial Measurement Units (IMUs), SLAM technologies have advanced to meet specific application needs, significantly enhancing mapping and tracking accuracy [15]. AR devices like the HoloLens 2 utilize advanced SLAM technology, integrating IMUs and depth cameras to construct a detailed environmental model. This facilitates both navigational tasks and interactive user experiences, as depicted in Figure 4, with features like loop closure and object manipulation for a fully immersive AR experience.

A sophisticated hybrid approach appears promising for future flight simulation training in AR. This method would harness the precise capabilities of marker-based tracking for essential tasks requiring exactitude, such as instrument manipulation, while simultaneously utilizing the vast, dynamic environments afforded by SLAM technology. Such a multifaceted system would marry the best aspects of both technologies, extracting maximum benefit from the evolving hardware and software proficiencies of the HoloLens.

3 Materials and Methods

This section elaborates on the methodology applied in our study to assess the effectiveness of marker-based and SLAM-based tracking technologies in augmented reality flight simulation training using Microsoft HoloLens 2. We present the camera calibration procedure, which is essential for ensuring the accuracy of both tracking methods. We also present the design of markers and establish a mathematical relationship between the detection range and parameters of the Hololens 2 camera.

3.1 Camera Calibration

Practical AR simulation training necessitates accurate superimposition of virtual content, which hinges on robust camera calibration. As illustrated in Figure 2, calibration ensures the transformation of 3D world coordinates $\mathbf{E}_w$ into 2D image points $\mathbf{V}_c$, facilitating precise alignment of virtual and real elements. Understanding the intrinsic parameters—focal lengths f_x, f_y and the principal point x_0, y_0—and the extrinsic pose parameters $[R|t]$ is crucial for AR systems

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to track markers and reference points consistently. These parameters, including the marker size S_M and their distance D from the camera, along with the field of view (FOV), are instrumental in defining the tracking range. The image demonstrates this via the convergence of lines at the principal point, underscoring the geometric basis for optimizing detection thresholds for seamless AR integration. Incorporating these calibration parameters is vital for the realistic rendering of virtual content in pilot training modules, ensuring immersive and compelling skill acquisition.

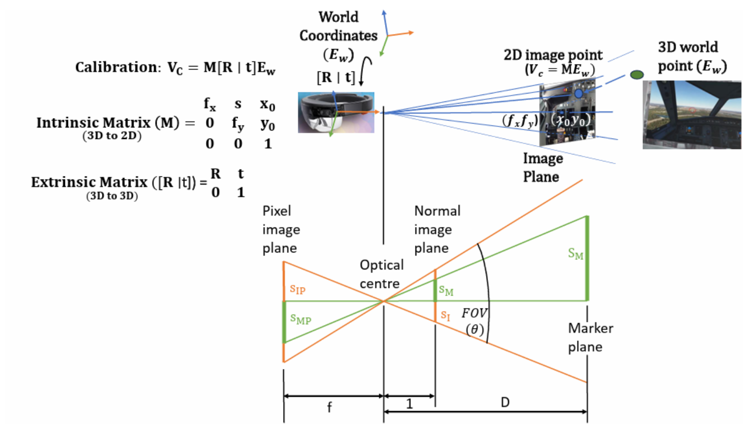

Fig. 2. The figure depicts the AR camera calibration, showing 3D world coordinates $\mathbf{E}_w$ projection onto 2D image points $\mathbf{V}_c$, including the camera's intrinsic matrix M and extrinsic parameters $[R|t]$. It also shows the principal point, FOV lines, marker size S_M, and distance D from the camera. (The lowest part of the figure is adapted from [16])

One of the calibration procedures is to estimate the optimal detection range of the camera. Marker-based tracking efficacy in AR devices like HoloLens 2 hinges on optimal detection range settings. This range, crucial for AR applications like flight simulation in cockpits, influences the required size of the printed, and it is given by [16]

$$D = \frac{S_M}{s_M} \tag{1}$$

where S_M is the printed marker size, and s_M is the normal image plane marker size at a distance $D = 1$ as shown in Fig. 2.

This expression establishes the fundamental relationship that determines the optimal placement of markers to the HMD's camera. This relationship is critical for the HoloLens 2 employed in flight simulation training to ensure that the markers fall within the device's field of view and are of a size that the onboard camera system can reliably detect. From equation (1) and Fig. 2, the detection

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range can be express as

$$D = \frac{S_M \cdot s_I}{s_{IP} \cdot s_{MP}} = \frac{S_M \cdot f}{s_{MP}} \quad (2)$$

where, $s_I = 2 \cdot tan\left(\frac{\theta}{2}\right)$, $s_{IP} = 2f \cdot tan\left(\frac{\theta}{2}\right)$. Also, f is the focal length of the camera, and θ is the field of view angle. Thus, for given parameters of the Hololens (f and s_{MP}), the detection range is proportional to the printed marker size, S_M. The parameter s_{MP} can also be obtained for a given type of Hololens.

Equations (1) and (2) are useful in the estimation of the detection range D and ensuring accurate AR marker tracking in the simulation environment. The practical application of these theoretical principles can be visualized through the marker-tracking process, as shown in Figure 3.

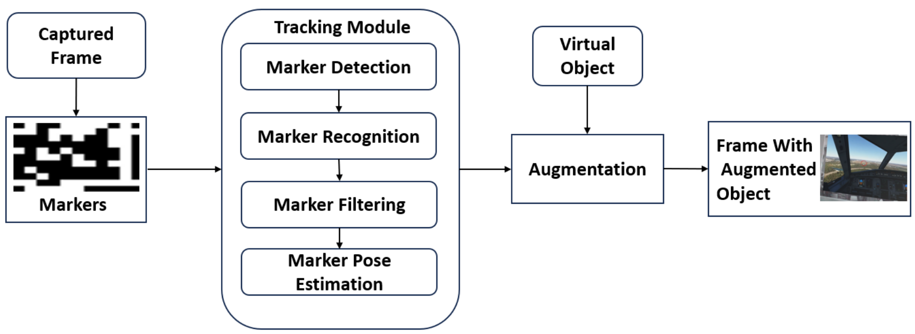

Fig. 3. Flowchart depicting the marker tracking process, from capture to augmentation.

The process begins with capturing a frame containing markers, which are then detected, recognized, and filtered by the tracking module. Following this, the pose of the markers is estimated, allowing virtual objects to be accurately overlaid onto the captured frame, resulting in an augmented reality experience. This sequence of operations is critical for ensuring that AR elements are appropriately aligned with the real world, providing an immersive experience for users, particularly in the demanding context of flight simulation training.

3.2 Experimental Setup

This study explores the profound impact of augmented reality (AR) technologies on flight simulation training, particularly in improving landing manoeuvres and comprehension of cockpit instrumentation using Microsoft HoloLens 2 and Unity software. The research involved developing an advanced AR flight simulation application integrating Unity's AR Foundation and the Mixed Reality Toolkit

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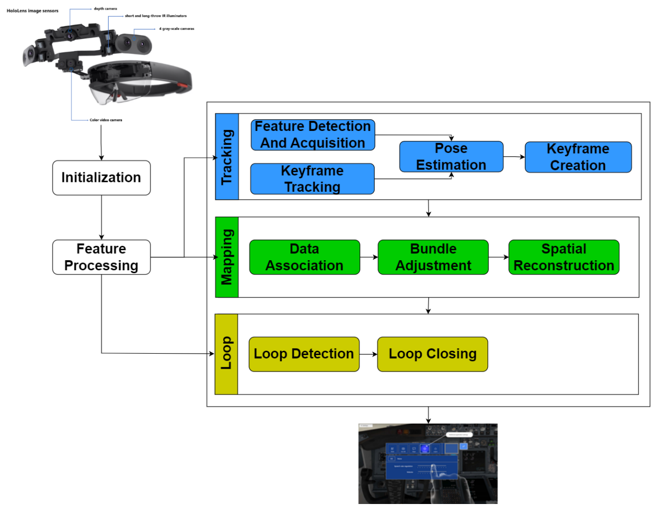

Fig. 4. A flowchart illustrating the SLAM process in HoloLens, including phases of initialization, feature processing, tracking, mapping, and loop detection.

(MRTK) to blend real-world cockpit settings with interactive virtual flight instruments seamlessly. Marker-based tracking technologies were employed, utilizing high-contrast QR codes and specially designed markers positioned within the optimal detection range of the HoloLens 2. This ensured maximum visibility and tracking stability, guided by precise spatial calculations. Calibration processes were conducted to adjust the interpupillary distance (IPD) for individual users, along with sensor optimization, to ensure accurate and stable tracking. The markers were printed in sizes of S_{M1}: 10 cm × 10 cm, S_{M2}: 16.2 cm × 16.2 cm, and S_{M3}: 29 cm × 20.4 cm, respectively.

During the experiment, the users were asked to wear the Head-mounted device (HMD) comfortably and suitably to track the markers in the cockpit. The localization speed, the predicted and actual positions of the markers, and the overlayed objects' positions were recorded as the user moved their head to track each marker in the cockpit. The experiment aimed to position the markers within optimal ranges in figure 6,7 to improve pilot training. Similarly, SLAM tracking was implemented to dynamically map the cockpit environment, with MRTK configurations meticulously adjusted to enhance environmental understanding and computational efficiency. This led to the projection of highly interactive flight instruments and instructional content directly into the user's field of view, significantly enriching the training environment. The evaluation of the study focused on the effectiveness of these tracking technologies in maintaining overlay accuracy and system responsiveness and providing an immersive, realistic experience. The primary goal was to enhance pilot training efficiency by integrating AR into flight simulation, representing a significant advancement in training methodologies and promising improved learning outcomes through en-

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riched, interactive experiences. Figure 5 depicts the experiment setup for marker and SLAM tracking in unity

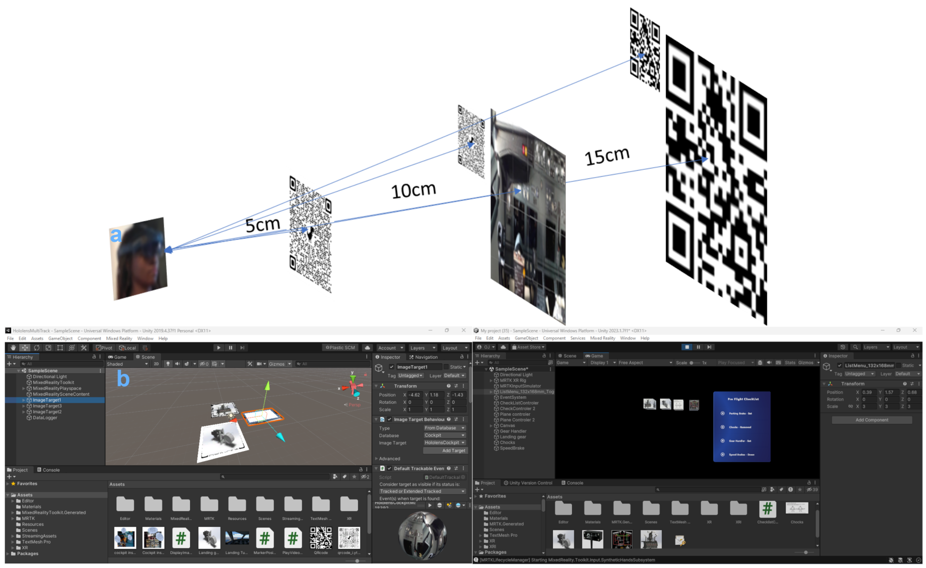

Fig. 5. a) Depicts markers at varying distances for HoloLens 2 tracking calibration.b) Shows a Unity interface setting up a simulated cockpit with marker detection and SLAM configuration for AR development.

4 Result And Discussion

This study conducted a comparative analysis of marker-based tracking and SLAM technologies within the Microsoft HoloLens 2 for advanced flight simulation training. Our systematic approach yielded nuanced insights into the performance and applicability of each system under varying detection ranges. The marker-based system demonstrated high precision within 5 cm and 15 cm from the HoloLens 2 camera in well-lit environments, ensuring reliability for procedural training requiring exact overlay precision. Including interactive video tutorials on landing manoeuvres, we further enhanced trainees' understanding of complex tasks, merging virtual learning with physical interaction.

In their study, Cheng et al. [17] highlighted that marker-based AR provides high positional accuracy, vital for precise overlays in flight simulation, as confirmed by our findings. They noted potential instabilities such as shakiness, which are linked to marker quality and AR SDKs and issues that are mitigated in our controlled simulation settings. Conversely, our results on SLAM reflect Cheng et al.'s observations on the adaptability of markerless AR. Utilizing GPS and

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gyroscopes offers flexibility without fixed markers, enhancing spatial awareness and cognitive skills in flight training scenarios despite its slightly lower accuracy. The marker-based tracking systems' dependency on sensor resolution and marker size is evident from our results and mirrors findings by Rabbi et al. [18], who noted that increasing marker size could significantly enhance detection ranges. However, our study extends this by quantifying how variations in marker sizes influence detection thresholds at different distances as demonstrated in Figs. 6 and 7, the detection range for marker-based tracking systems is significantly influenced by sensor resolution and marker size, which is critical for the precision and efficacy of marker-based tracking systems, affecting both the distance at which markers are recognizable and the sharpness of their identification as depicted in Figure 8.

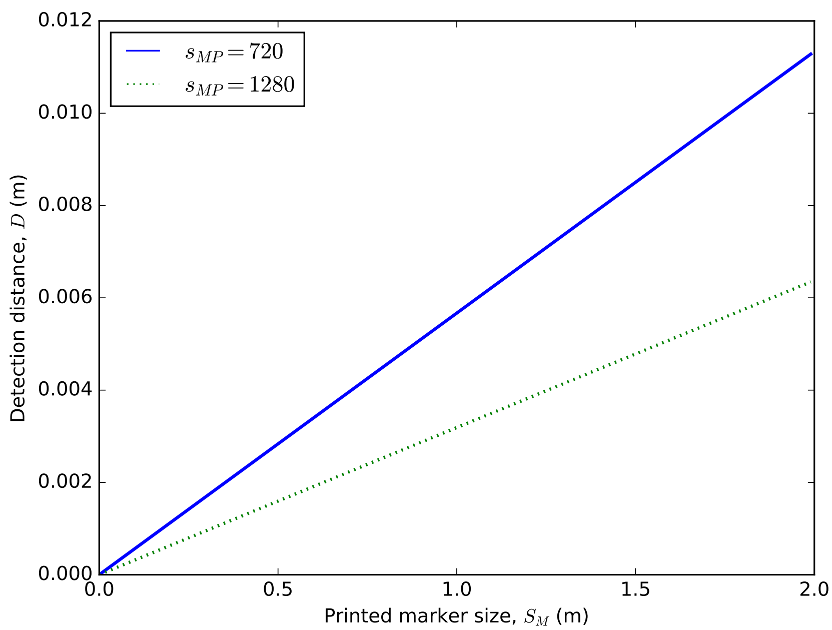

Fig. 6. Variation of minimum detection distance, D with printed marker size S_M for various marker size in the pixel image plane, s_{MP}.

Figs. 6 and 7 demonstrate the relationship between the detection distance, D (in meters, m) and the printed marker size, S_M (in meters, m) for various values of the marker sizes in the pixel image plane, s_{MP} (in pixel). The focal length, f, of the device is obtained from the camera specifications, such as image width and height and the field of view angle, θ. The image size in the pixel image

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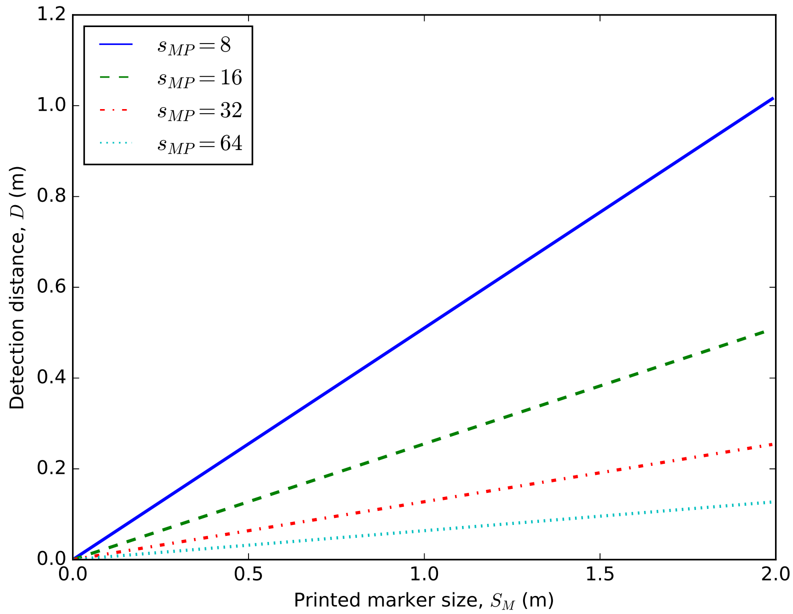

Fig. 7. Variation of maximum detection distance, D with printed marker size S_M for various marker size in the pixel image plane, s_{MP}.

plane, s_{IP} and the image size in the normal image plane can then be obtained from the camera specifications and thus, $f = s_{IP}/s_I$. In the plots in Figs. 6 and 7, we used the nominal values of the focal length and the Field of view angle of the Hololens 2 (e.g., $f = 1.08$ mm and $\theta = 96.1$ degrees). Thus, with given values of S_M, f, θ, and s_{MP} for a given device, the detection distance can be obtained from equations (2).

Aligning seamlessly with the physical markers, this intervention significantly enhanced trainees' comprehension of complex tasks while maintaining interaction with the physical cockpit, effectively bridging the gap between virtual learning and practical execution. However, SLAM rose to the challenge in the adaptability arena. Its ability to map and project virtual information onto any surface without relying on pre-placed markers offered an immersive, dynamic experience perfect for honing spatial awareness and broader skill sets, as shown in Figure 9. Our analysis revealed a sweet spot for each technology. Marker-based training, potentially leading to improved objective flight data, shines in focused skill development. SLAM, on the other hand, fosters real-world, transferable skills through its immersive and adaptable nature. Cost-wise, marker-based systems offer long-term savings for targeted training, whereas SLAM, despite higher initial costs, presents a scalable solution across different scenarios. Regarding user

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experience, marker-based tracking assures precision task confidence, and SLAM enhances cognitive skills and situational awareness through engagement.

Fig. 8. Various stages of augmented reality marker integration in flight simulator training, showcasing different marker placements and sizes for enhanced cockpit interaction and tracking accuracy.

4.1 Quantitative Assessment of Tracking Systems

The efficacy of the marker-based and SLAM tracking systems was quantitatively assessed through key performance metrics: accuracy, precision, and error rates, as encapsulated in Table 1. The accuracy and precision rates were calculated based on the proportion of correct detections.

Mean Absolute error (MAE) and standard deviation of error (SD) were computed using the following standard formulas:

Mean Absolute Error (MAE):

$$MAE = \frac{1}{n}\sum_{i=1}^{n}|x_i - \hat{x}_i| \tag{3}$$

Where n is the number of measurements, x_i is the true position, and $\hat{x}_i$ is the predicted position.

Standard Deviation of Error (SD):

$$SD = \sqrt{\frac{1}{n-1}\sum_{i=1}^{n}(x_i - \bar{x})^2} \tag{4}$$

Where $\bar{x}$ is the mean of the observed errors.

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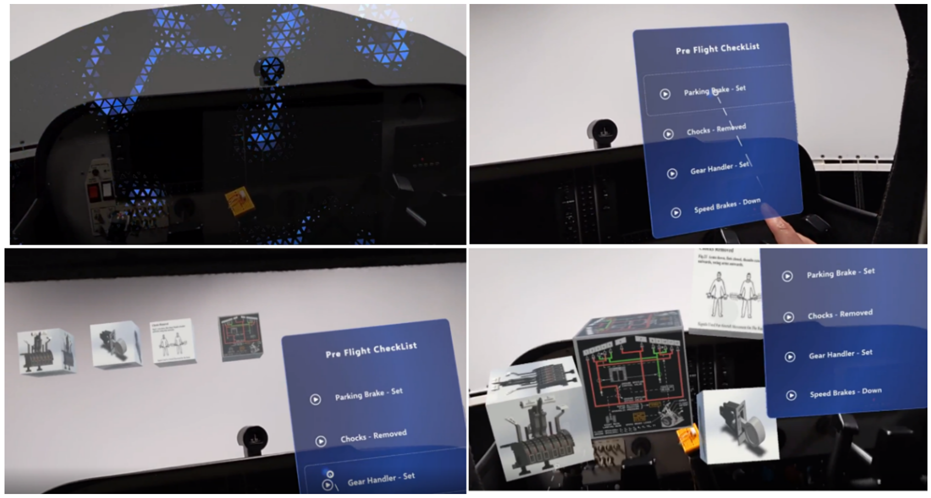

Fig. 9. SLAM tracking in AR for procedural training: showcasing interactive checklists and equipment diagrams to boost pilot understanding and interaction.

In our analysis, as depicted in Figure 10, the marker-based system reported an accuracy rate of 98.5% and a precision rate of 97.8%, with an MAE of 0.5 cm and an SD of 0.3 cm. The SLAM system had an accuracy rate of 96.2% and a precision rate of 94.5%, with an MAE of 1.2 cm and an SD of 1.0 cm. These show that the marker-based system outperforms the SLAM system regarding accuracy and precision, although the SLAM offers greater flexibility in dynamic environments. The derived error metrics underscore the trade-offs inherent to each system: marker-based tracking provides higher reliability in controlled settings. However, SLAM tracking's greater adaptability in changing conditions is evidenced by a broader error distribution and localization speed. While marker-based systems boast rapid localization speeds at 16 milliseconds, indicative of their efficiency in stable environments, SLAM systems demonstrate a notable proficiency with a localization speed of 30 milliseconds. This slightly increased time consumption is offset by its remarkable adaptability, enabling real-time responsiveness in dynamic scenarios. The versatility index in figure 10 displays the scenario versatility index, comparing the adaptability of marker-based systems, which excel at stable tasks such as precise video overlays for landing manoeuvres, to SLAM systems, which scale from essential instrument readings to complex, real-time interactions like equipment checks and adaptive navigation. Marker-based systems held a steady index of 1. In contrast, SLAM systems advanced from 1 to 5, gauging their performance by the users' accuracy in engaging with augmented content and their adaptability to dynamic scenarios.

The cognitive skills enhancement is quantified, showcasing that SLAM systems achieved a prominent boost in cognitive abilities with a score of 7, surpassing the marker-based systems, which scored 4 on a scale of 1 to 10. This

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Table 1. Performance metrics of marker-based and SLAM systems.

Metrics	Marker-Based Systems	SLAM Systems
Accuracy Rate (%)	98.5	96.2
Precision Rate (%)	97.8	94.5
Mean Absolute Error (cm)	0.5	1.2
Standard Deviation of Error (cm)	0.3	1.0
Localization Speed (Milliseconds)	16	30
Scenario Versatility Index (1 scenario)	1	1
Scenario Versatility Index (2 scenarios)	1	2
Scenario Versatility Index (3 scenarios)	1	3
Scenario Versatility Index (4 scenarios)	1	4
Scenario Versatility Index (5 scenarios)	1	5
Cognitive Skills Improvement Factor	4	7

was derived from objective data, such as response times and checklist accuracy, alongside users' self-evaluations of situational awareness and adaptability. Through normalization and weighting, these measures established SLAM's significant role in advancing pilot training with realistic, engaging simulations that align with modern aviation's complexities.

5 Conclusion

Our comprehensive analysis provides critical insights into the comparative performance of marker and SLAM-based tracking within Microsoft HoloLens 2 for advanced flight simulation training. The results underscore marker-based systems' superior precision and reliability, which is particularly beneficial for procedural training where exact overlay precision is paramount. Interactive video tutorials further augment these systems, effectively enhancing comprehension of complex tasks by bridging the virtual-physical interface. Conversely, SLAM technology demonstrates remarkable adaptability and immersive capabilities, making it ideal for dynamic environments and broader skill development. Though SLAM may incur higher initial costs, its scalability and flexibility across varied training scenarios offer long-term benefits.

The findings of this study, while focused on flight simulation, resonate across AR education and training sectors. The high fidelity of marker-based systems is indispensable for tasks that demand high precision, particularly in controlled settings where the consistency of virtual overlays directly impacts learning outcomes. Conversely, the adaptability of SLAM shines in scenarios that benefit from less regimented, more versatile interaction. The balance between accuracy, precision, and error variability underscores the advantage of marker-based systems for stability. Nevertheless, it illuminates SLAM's broader educational promise, enhancing cognitive skills and situational awareness through its immersive nature.

For the future direction, the emerging trends in AR flight simulation training suggest a blended approach that merges the precision of marker-based tracking

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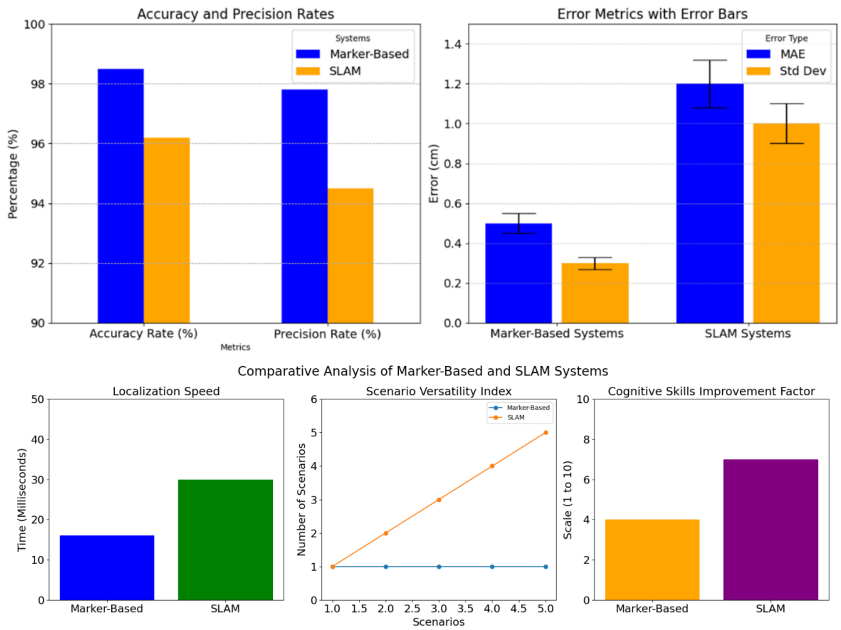

Fig. 10. A comparison of marker-based and SLAM systems highlighting differences in accuracy, precision, error, localization speed, adaptability, and cognitive impact.

for critical tasks such as instrument operation with the extensive environments enabled by SLAM technology. This dual system could leverage the advancing capabilities of devices like the HoloLens to enhance training efficacy. Integrating biofeedback tools such as EEG and GSR could offer deeper insights into trainees' psychological states, allowing the development of adaptive training that responds to individual learning needs. Imagine AR simulations that adjust complexity based on the user's biofeedback, creating a tailored training experience that optimizes skill acquisition and minimizes stress. Additionally, incorporating deep learning for better marker recognition and environmental mapping could enrich simulation training. Such technological progress, especially in wearable AR, is crucial for the comprehensive application of AR in aviation training. However, incorporating biofeedback raises ethical issues, particularly around data privacy. Strict anonymization protocols and informed consent are essential to maintaining ethical standards and respecting trainee privacy.

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Conflict of Interest
The authors declare no conflict of interest.

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