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RESEARCH ARTICLE

Enhancing Exercise Monitoring and Guidance Through Mobile Augmented Reality: A Comparative Study of RGB and LiDAR

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ABSTRACT Augmented Reality (AR) technology for motion tracking is often used on mobile devices with an RGB front camera or LiDAR sensor rear camera. While there are various AR applications for exercise, there is a lack of comparative studies investigating the specific effects of these technologies on the AR exercise experience. This study evaluated the performance and usability of using the RGB camera and the LiDAR sensor for exercise monitoring with a mobile AR application. We examined their performance in different environmental room conditions: a solid wall, a glass wall, and a wall with objects. Focusing on a marching-in-place use case, we assessed accuracy and usability across participants with varying body mass index (BMI). Our application provided display and audio notifications for correct posture compared with validation by an expert physical therapist. The results indicated that differences in BMI did not significantly affect accuracy. Algorithm 1. The LiDAR provided higher accuracy in various environments, while the RGB camera provided higher scores in usability. The results suggested that standing position affected the detection both RGB and LiDAR cameras had better accuracy when standing at a 45-degree angle than directly facing the camera. This study showed the potential of both technologies for telehealth scenarios, emphasizing the significance of practical usage in households and ease of use to support exercise monitoring and empower users to achieve fitness goals and telehealth.

INDEX TERMS Augmented reality, mobile applications, human activity recognition, telemedicine, cameras.

I. INTRODUCTION

Monitoring and correcting exercise forms, particularly in rehabilitation settings, requires specialized expertise usually offered by physical therapists to assess effectiveness and avoid the risk of injury [1]. Physical therapists often use specific evaluations such as goniometry, inclinometer, and gait analysis to identify these issues [2], [3], [4]. However, access to in-person physical therapy can be limited by cost, availability, and location. This creates a challenge for users who need consistent guidance to perform exercises safely and effectively at home. While wearable devices can track some aspects of physical activity [5], [6], they often cannot provide real-time feedback on specific movements or posture [7], [8], [9]. This highlights the need for accessible, technology-based solutions that empower users to self-monitor their exercise form at home, potentially reducing the need for frequent in-person assessments while promoting safe and effective movement practices.

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Mobile devices equipped with cameras and Augmented Reality (AR) capabilities offer a solution to this problem. By visually overlaying guidance and feedback, AR applications on mobile devices have the potential for users to self-monitor their exercise form in real-time [10], [11], bridging the gap between in-person therapy and unsupervised home-based exercise. There are two main approaches to camera-based exercise tracking. First, RGB cameras have been used for exercise recognition and assessment [13], [14]. The front RGB camera is a key feature, allowing users to see themselves in real-time for self-monitoring and form correction. However, variations in lighting or cluttered backgrounds can reduce their accuracy. Second, RGB-depth cameras, like the LiDAR sensor in smartphones provide richer 3D information [15]. This enables more precise tracking for posture correction and is particularly valuable in rehabilitation and exercise [16]. However, the rear camera lacks real-time feedback since it cannot immediately display captured movement, potentially impacting usability. Consequently, investigating the differential performance of these two tracking approaches is fascinating, particularly when considering their implementation in diverse home environments and the varying positions and orientations of users.

The study required the development of an application for detection purposes. Therefore, we decided on uncomplicated and commonly employed physical postures to analyze as a case study. Marching-in-place is a multifunctional exercise that improves physical function, balance, muscle strength, and general wellbeing. This exercise is frequently employed as a therapeutic activity for individuals struggling with chronic diseases [17]. The correct form involves maintaining an upright posture with feet positioned at a width equal to the hips, lifting knees alternately toward the chest, and synchronizing the movement with the swinging of the arms. The thigh should be parallel to the ground or slightly below, encouraging hip flexors and core engagement while ensuring stability. Correct joint mechanics are crucial, as the hip and knee usually bend up to an angle of 90-degree [18]. Marching-in-place is a useful workout posture to use as a case study. It can be applied to monitor physical activity for individuals with chronic diseases. Given these potential benefits, developing a mobile AR application could offer innovative exercise guidance and monitoring tools, especially within home-based settings.

This study proposes to investigate the comparative performance of the RGB camera and the LiDAR sensor on a mobile device, focusing on a specific case study of the marching-in-place posture. We designed the experiment by evaluating the accuracy and usability across varied body mass index (BMI) groups and comparing the results with physical therapist assessments. The objectives of this study are to design and develop a real-time motion tracking approach using markerless AR on mobile, based on the marching-in-place case study, allowing users to evaluate their exercise against expert standards. A second objective is to examine the accuracy of using the RGB camera and the LiDAR sensor for motion tracking during exercise and how environmental factors (body mass index, room conditions, standing positions) influence the tracking performance. Finally, the objective is to assess the usability differences between using a front camera (RGB) and a rear camera (LiDAR) for exercise with a mobile AR application and overall user experience.

The remainder of this paper is structured as follows. Section II focuses on literature reviews and related works about AR applications for telehealth. Section III shows the AR application development, which includes system architecture, calculation, algorithm, device, and implementation. Section IV presents the research approach for designing the experiment, which is based on the marching-in-place case study. Section V assesses the effectiveness of this method by conducting experiments and presenting the results. Section VI provides a comprehensive examination of the results and subsequent discussions, while the conclusion is presented in Section VII.

II. RELATED WORKS

The COVID-19 pandemic has accelerated the adoption of telehealth and telemedicine solutions [19] to ensure the continuity of healthcare services while minimizing in-person contact. The integration of AR into telehealth during the pandemic has presented opportunities to enhance remote healthcare experiences [20]. The intersection of telehealth and AR has garnered increasing attention as technology advances. Numerous studies are investigating how AR can improve and expand telehealth services. The use of AR for various healthcare purposes, monitoring on mobile devices, and remote monitoring and assessment with AR are aspects and potential recent works in this context.

A. AR FOR TELEHEALTH

AR technology in telehealth offers several benefits. It provided real-time feedback and motivation, making it suitable for home training programs. Cunha et al. [21] proposed guidelines for home-based rehabilitation systems. Using AR technologies, rehabilitation programs can provide efficient approaches to improve motor recovery and encourage participation in the rehabilitation process. Monge and Potolache [22] used a smart physical rehabilitation system that combines AR and serious games with wearable sensor networks to improve patient engagement during physical rehabilitation. These technologies can be used with wearable sensors and wireless sensor networks to capture kinematic and dynamic data associated with motion and muscle activation [23]. AR-based training programs have been found to have better subjective and objective outcomes compared to conventional methods for perioperative rehabilitation [24].

AR has been employed in conjunction with therapy to address several medical conditions. These include balance and fall prevention in elderly individuals, improved upper and lower limb functionality in stroke patients, alleviating pain in phantom pain syndrome, and assistance with turning in place for individuals with Parkinson's disease experiencing freezing of gait [25]. Additionally, AR is a suitable tool for rehabilitating patients after overcoming COVID-19, providing opportunities for comparing classical and modern approaches [26]. AR technology has a greater impact on patients' motivation to rehabilitate, especially when patients use it for the first time [27], [28]. These findings suggested that AR has the potential to enhance the effectiveness of telerehabilitation programs by providing interactive and engaging experiences for patients. Numerous studies have explored the effectiveness of AR telerehabilitation across various clinical conditions, comparing outcomes with those achieved through traditional, face-to-face interventions. The results suggested that telerehabilitation interventions can yield comparable results to conventional approaches [28], [29], [30], [31], [32], [33], particularly in physical therapy and chronic disease management.

Mobile devices, such as smartphones and tablets, are essential for the widespread adoption of AR in telehealth. Integrating AR into mobile platforms enables accessible and convenient rehabilitation solutions [34], [35]. By incorporating gamification elements, AR can transform exercises into engaging experiences, boosting patient motivation and compliance [25], [36], [37], [38], [39]. Studies examining the clinical outcomes of AR-supported rehabilitation provide valuable insights into its impact on functional outcomes, rehabilitation duration, and patient satisfaction [25], [28], [40], [41], [42], [43]. This growing body of evidence supports the integration of AR into telehealth protocols [28], [44]. While AR on mobile devices has significantly enhanced telehealth, further integration of user body detection capabilities into interactive exercises is still necessary. This allows for more personalized and targeted guidance within AR-based telehealth solutions.

B. MOTION TRACKING WITH AR

Motion tracking with AR on mobile devices has the potential to transform telehealth practices by offering personalized, accessible, and engaging interventions. Integrating AR with mobile platforms enabled real-time and markerless tracking of body movements, allowing for interactive and immersive rehabilitation experiences. Two primary approaches to markerless tracking using the RGB camera and the LiDAR sensor are available.

The RGB camera, prevalent in smartphones and tablets, relies on visual information captured through image processing for body tracking [45]. This well-established technology has demonstrated versatility, particularly in gesture-based interactions and basic body movement analysis [46], [47]. However, challenges like the sensitivity of lighting conditions and potential inaccuracies in in-depth perception may affect its performance in certain scenarios. On the other hand, LiDAR sensors integrated into modern mobile devices provide advanced depth-sensing capabilities, offering precise and instantaneous depth information [48]. This enhances the accuracy and robustness of body tracking, especially in scenarios where precision is critical [49], [50]. LiDAR technology is less affected by varying lighting conditions, providing a more reliable solution in diverse environments.

Despite the contributions of both RGB and LiDAR technologies to motion tracking, there's a lack of comprehensive studies directly comparing their performance in the specific context of telehealth exercise monitoring. Understanding their relative strengths and limitations in this domain is crucial for making informed choices when developing and optimizing AR-based telehealth solutions.

C. EXERCISE MONITORING AND ASSESSMENT

Exercise monitoring in telehealth uses technology to track and assess the progress of individuals receiving care from a distance or remote monitoring. This approach uses various tools and devices to collect information on patients' activities, movements, and health indicators. Key goals of remote monitoring in telehealth include improving accessibility, providing real-time feedback, and allowing healthcare professionals to adjust care plans remotely.

Usability assessment in telehealth evaluates how easy and effective it is for patients and providers to use telehealth systems. This can encompass system design, functionality, and the overall user experience [51]. Anil et al. [52] and Cavalcanti et al. [53] investigated how different feedback methods, such as text, images, and audio, impact the usability and effectiveness of telehealth interventions. Findings from usability studies can guide the development of more accessible and patient-friendly telehealth solutions.

Remote monitoring and assessment offer several benefits, including increased convenience for patients who can participate in care from home, reduced travel burdens, and the ability to provide personalized feedback based on real-time data [54], [55]. This approach enables healthcare professionals to track progress remotely, adjust treatment plans, and intervene quickly.

D. RESEARCH GAP

The research gap exists due to the absence of direct comparisons between RGB and LiDAR specifically for exercise monitoring within a telehealth context. While the potential of AR for telehealth exercise guidance is well acknowledged, and the capabilities of both RGB and LiDAR have been explored, there is a lack of studies directly comparing their accuracy and usability within an AR exercise monitoring system designed for self-monitoring.

This paper introduced a self-assessment system that compared AR-based motion tracking using the RGB camera and the LiDAR sensor on mobile devices. The results of these technological differences support developers in further optimizing their use cases. The system's primary objective is to track users' postures in real-time, employing key metrics to evaluate the correctness of performed postures. The system provides users with exercise monitoring by notifying them of correctly performed postures and displaying when the posture drops outside the specified range. The system can also report the correct number of reps of each knee lift after the exercise.

III. APPLICATION DEVELOPMENT

The development of an AR application aimed to replicate the assessment techniques used by physical therapists to evaluate correct form during marching-in-place exercises. Specifically, it centers on the angle formed by the hip and knee joints while performing high knees as shown in Figure 1. Physical therapists traditionally use a goniometer to measure this angle, ensuring the thigh reaches a position approximately perpendicular to the body. Our application automates this process, making it possible for users to perform these assessments by the application.

The AR application used pose estimation frameworks with MediaPipe [56] for the RGB camera and ARFoundation [57] for the LiDAR sensor to track key anatomical landmarks [58] on the user's body. The positions of the hip and knee joints were continuously monitored, allowing the application to calculate the angle between them in real-time. Afterward, this data is used to determine whether the user is performing the correct high knee position and to offer visual and auditory feedback to guide their exercise posture.

This method employed live video analysis to monitor and quantify the high knee lifts performed during the marching-in-place exercise. It focused on monitoring the positions of the user's hips and knees, using pose estimation technology to extract anatomical landmarks from video frames. The algorithm applied iterative processes of video capture, landmark recognition, angle calculation, and high knee detection to facilitate the real-time monitoring of the user's exercise routine. By implementing this continuous input process, the application can result in responses to variations in posture.

A. SYSTEM ARCHITECTURE

The architecture of the system for real-time marching-in-place posture will be explained. The process begins with converting the user's motion data into digital information that can be read by a smartphone. This involves the following components: 1. Data Streaming, 2. Human Detection, 3. Joint Identification, 4. Movement Representation, and 5. Knee-Lifting Calculation, as illustrated in Figure 2.

The proposed system enables access to both the hip and knee joints to imitate the assessment performed by a physical therapist. Positional data is acquired using the capabilities of the Mediapipe framework, specifically its Joint Identification component. Mediapipe, an open-source framework developed by Google for real-time perception applications, incorporates a Pose Detection component that facilitates real-time estimation of the human body's pose. In the context of Human Detection and Joint Identification in computer vision, landmarks refer to specific points on the human body that are identified and tracked by an algorithm. The

FIGURE 1. Standing straight with the goniometer centered on the hip (left) and correct high knee position with the thigh approximately more than 90-degree perpendicular to the torso (right).

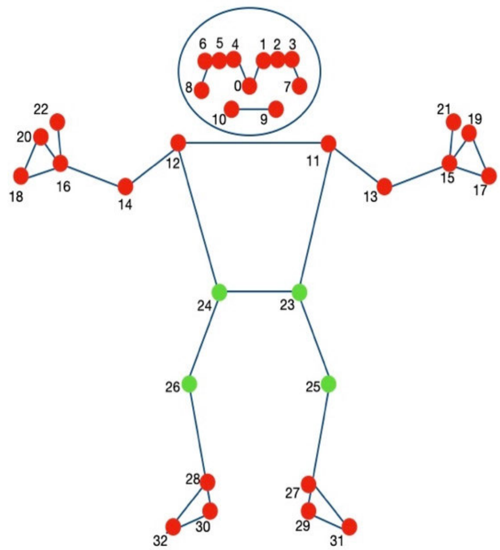

FIGURE 2. The pose landmarker model tracks 33 body landmark locations, representing the approximate location of the body parts. Highlight numbers 23-28 to show the hip, knee, and ankle joints used in this study.

Knee-lifting calculation component, designed to identify dynamic relationships between hip and knee landmarks, outputs data in vector form, allowing for the calculation of the degree of angle between defined pairs of landmarks. We used ARFoundation with human body tracking for the LiDAR sensor, employing a process similar to using RGB with Mediapipe, resulting in location values as landmarks. The key difference is the LiDAR's ability to capture three-dimensional spatial information, enhancing the depth and accuracy of the obtained data. This dimensional aspect contributes to a more comprehensive understanding of the physical environment

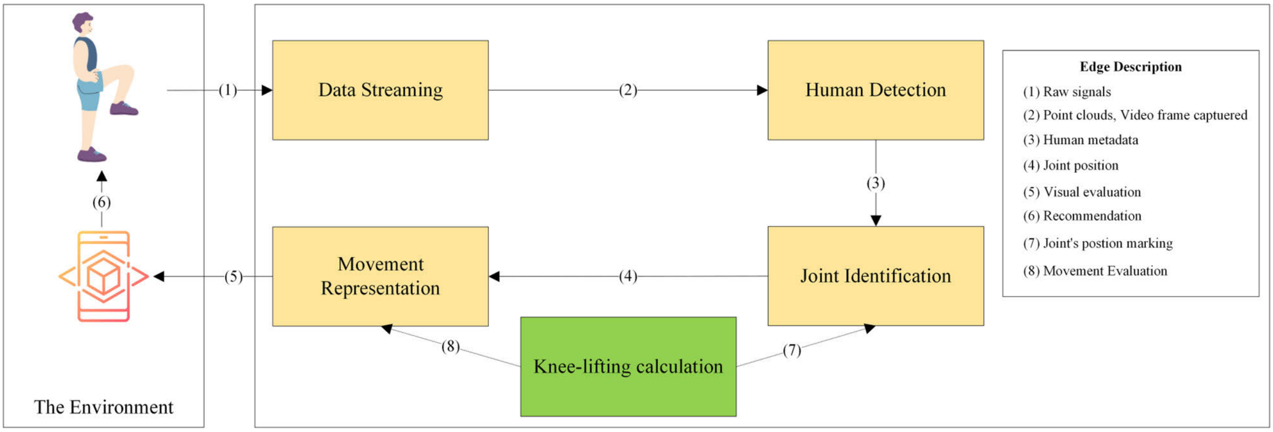

FIGURE 3. The overview architecture of the marching-in-place monitoring with a mobile AR application.

and further refines the precision of the assessment. These landmarks represent key anatomical features and define various body parts' spatial position and orientation. The graphical pose landmark model tracks 33 body landmark locations as shown in Figure 3.

B. CALCULATION AND ALGORITHM

The Knee-lifting calculation component is designed to identify the dynamic relationships between the hip and knee landmarks. Once the raw data for the hip and knee positions at landmarks 23 (left hip), 24 (right hip), 25 (left knee), and 26 (right knee), 27 (left ankle), and 28 (right ankle) is obtained, the subsequent step involves calculating the angle between specific pairs of landmarks. Specifically, these pairs are defined as 23, 25 and 27, as well as 24, 26 and 28. This angle θ represents the elevation of the thigh relative to the standing position. This calculation provides a quantitative measure of the angular relationship between these key anatomical landmarks, given by the formula (1), as shown at the bottom of the next page, where (x_1, y_1, z_1) and (x_2, y_2, z_2) represent the coordinates of the hip and knee landmarks respectively, while (x_3, y_3, z_3) represents the ankle landmark in the 3D coordinates captured by the LiDAR sensor using ARFoundation. This angle θ represents the elevation of the thigh from the vertical position. When standing upright, θ is close to 0°. As the knee is lifted, θ increases, with a correct high knee lift occurring when θ reaches or exceeds 90°. This method of angle calculation allows for precise tracking of the knee lift motion throughout the exercise. The formula calculates the angle θ between the vectors formed by the hip-knee and knee-ankle landmarks using the dot product and magnitude of these vectors.

This allows for a more accurate assessment of the knee lift angle, considering the depth information. In the case of 2D plane obtained from the RGB camera using MediaPipe, the landmarks are represented as (x_1, y_1), (x_2, y_2), and (x_3, y_3) for the hip, knee, and ankle, respectively. The same formula is applied, but no additional z-coordinate to calculate the angle θ in three-dimensional space.

Algorithm 1 Check Correct Knee Lift
Inputs: knee_coords, hip_coords, ankle_coords
Outputs: is_correct_lift (True or False), knee_angle (in degrees)

1. set is_correct_lift = False
2. set correct_angle = 90 degrees
3. set knee_angle = 0 degree
4. set threshold = 0 degree
5. (x_1, y_1, z_1) = hip_coords
6. (x_2, y_2, z_2) = knee_coords
7. (x_3, y_3, z_3) = ankle_coords
8. hip_to_knee_vec = $(x_2 - x_1, y_2 - y_1, z_2 - z_1)$
9. knee_to_ankle_vec = $(x_3 - x_2, y_3 - y_2, z_3 - z_2)$
10. hip_to_knee_mag = sqrt(hip_to_knee_vec[0]^2 + hip_to_knee_vec[1]^2 + hip_to_knee_vec[2]^2)
11. knee_to_ankle_mag = sqrt(knee_to_ankle_vec[0]^2 + knee_to_ankle_vec[1]^2 + knee_to_ankle_vec[2]^2)
12. dot_product = hip_to_knee_vec[0] * knee_to_ankle_vec[0]+ hip_to_knee_vec[1] * knee_to_ankle_vec[1] + hip_to_knee_vec[2] * knee_to_ankle_vec[2]
13. knee_angle_rad = acos(dot_product / (hip_to_knee_mag * knee_to_ankle_mag))
14. knee_angle = degrees(knee_angle_rad)
15. hip_error = sqrt($\Delta x_1 + \Delta y_1 + \Delta z_1$)
16. knee_error = sqrt($\Delta x_2 + \Delta y_2 + \Delta z_2$)
17. ankle_error = sqrt($\Delta x_3 + \Delta y_3 + \Delta z_3$)
18. threshold = const_k * (hip_error + knee_error + ankle_error)
19. **if** knee_angle > (correct_angle – threshold):
20. is_correct_lift = True
21. **return** is_correct_lift, knee_angle

For a correct knee lift, the knee must form an angle greater than or equal to 90-degree between the hip and the knee. To account for the potential error in MediaPipe and ARFoundation motion detection [59], [60], [61], the minimum acceptable angle for a correct knee lift is calculated with the threshold. The accuracy analysis of the knee lift meeting this criterion is then transmitted to the Movement Representation component for display, as illustrated by the algorithm for calculating both left and right knee lifts in Algorithm 1.

The Movement Representation component, as demonstrated in Figure 2, showcases the guidance for knee lifting through visual and auditory cues. It utilizes color changes on the screen and overlays virtual bones onto the user's body to indicate correct and incorrect knee lifting. Adding a countdown timer to this component can enhance the user experience by providing a clear indication of the remaining exercise time. When the knee is lifted correctly, the virtual bones turn green, and the background screen adopts a green hue, accompanied by an alert sound. Conversely, if the knee is not lifted or lifted incorrectly, the virtual bones will be colored orange, and the background screen will remain white. This multi-sensory feedback system aids users in understanding and performing the correct knee-lifting technique, even when they are unable to directly observe the screen. The countdown timer further empowers users to manage their exercise time effectively, ensuring they meet their fitness goals efficiently.

C. DEVICE AND IMPLEMENTATION

For the implementation and testing of our markerless AR exercise tracking system, we used the iPhone 13 Pro smartphone. This device was selected as it is equipped with both a front-facing RGB camera and a rear LiDAR sensor, which are the key hardware components required for our comparative study of RGB versus LiDAR-based motion tracking approaches. Preliminary tested on some Android smartphones equipped with RGB cameras showed promising results, comparable to the iPhone 13 Pro in terms of exercise tracking and fault detection.

The iPhone 13 Pro features a 6.1-inch Super Retina XDR display with a resolution of 2532 × 1170 pixels and 460 ppi pixel density. It is powered by Apple's A15 Bionic chip, a 6-core CPU with 2 performance and 4 efficiency cores, and a 16-core Neural Engine processor. The device has 6GB of RAM and runs iOS 17. To ensure consistent camera positioning and stability during data collection, we used a tripod to mount the smartphone.

IV. RESEARCH METHODOLOGY

This study employed a mixed-methods approach to investigate the comparative performance of RGB and LiDAR sensors within a mobile-based AR exercise monitoring application focused on the marching-in-place posture as a relevant case study for remote exercise guidance. We developed a mobile AR application that analyzes body movements during the marching-in-place exercise, providing real-time feedback on posture correctness based on physical therapist assessments.

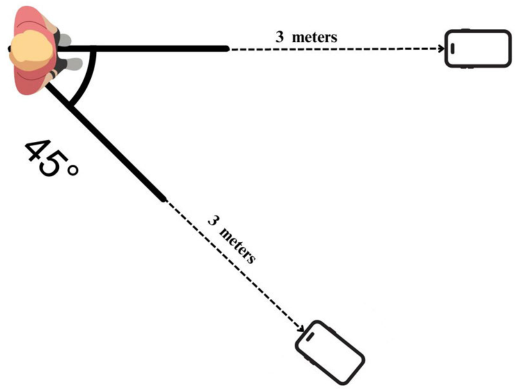

FIGURE 4. **The station was designed for capturing 3 meters away from different positions.**

We conducted controlled experiments for quantitative accuracy evaluation to measure the accuracy of both RGB and LiDAR in tracking exercise form. Key variables included environmental conditions, user BMIs, and standing positions. The System Usability Scale (SUS) was administered for qualitative usability assessment to gather participants' perceptions of the system's ease of use, learnability, and overall experience. We focused on differences in usability between the RGB (front camera) and LiDAR (rear camera) setups.

A. EXPERIMENT OBJECTIVES

This study aimed to evaluate the effectiveness of a real-time AR tracking application using the marching-in-place exercise as a case study. The accuracy of the system's outcome relies on its ability to recognize the high knee posture. Evaluation of marching-in-place exercise has three approaches: 1) expert-based approach, 2) RGB front camera approach, and 3) LiDAR rear camera approach. A physical therapist considered the expert-based approach provided a ground-truth assessment of correct posture (high-knee position) for comparison against AR application output, where a front-facing RGB camera and a rear-facing LiDAR sensor were used to count the number of high knees performed automatically. In addition, the investigation evaluated the variations in usability between the two methodologies within

$$\theta = arccos\left[\frac{(x_2-x_1)(x_3-x_1)+(y_2-y_1)(y_3-y_1)+(z_2-z_1)(z_3-z_1)}{\left(\sqrt{(x_2-x_1)^2+(y_2-y_1)^2+(z_2-z_1)^2}\right)\left(\sqrt{(x_3-x_1)^2+(y_3-y_1)^2+(z_3-z_1)^2}\right)}\right] \quad (1)$$

FIGURE 5. Two experiments simultaneously captured movement: standing parallel to the screen and standing at 45-degree, both 3 meters away from the screen. The experiment used the RGB front camera with display and audio notifications (left) and the LiDAR rear camera with only audio notifications (right).

FIGURE 6. The experiment used rooms with different environmental conditions: a room with solid walls (left), a room with glass walls (center), and a wall with objects (right).

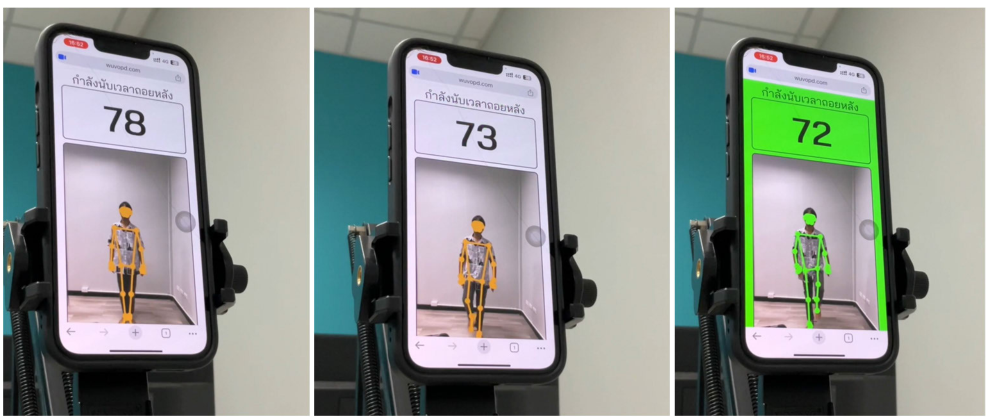

FIGURE 7. The AR application featured a timekeeper with both display and audio notifications: standing posture (left), incorrect high knee (middle), and correct high knee (right).

the context of an exercise carried out using a mobile AR application, contributing to a comprehensive understanding of the overall user experience.

B. PARTICIPANTS

Thirty participants, with an average age of 20.67, provided informed consent and were enrolled in the study, which was approved by the ethics committee (approval code WUEC-24-114-01). Participants were divided into three BMI groups (underweight, normal weight, and overweight) to investigate the potential impact of body composition on tracking accuracy.

C. EXPERIMENTAL SETUP

The experiment occurred at Informatics Studio, Walailak University. The environmental conditions in the three different rooms were diverse, encompassing trials conducted against various backgrounds. These backgrounds included a solid wall, which provided a consistent backdrop, a glass wall that introduced potential reflections and lighting challenges due to its transparency, and a wall with various objects, creating a more complex environment. Standardized capture stations were set up at two positions in Figure 4, directly in front of the participant and at a 45-degree angle (3 meters away). This allowed for testing tracking performance across different standing positions and viewing perspectives.

D. RESEARCH PROTOCOL

This study employed a repeated-measures experimental design to evaluate the accuracy and usability of using RGB and LiDAR cameras in an AR exercise monitoring application. We announced an online recruitment procedure to choose male and female volunteers to participate in the experiment. The volunteers were selected with three categories depending on gender: five individuals were classified as underweight, five as normal weight, and five as overweight. The distribution of males and females was equal.

The participants were recruited for the experiment over six groups, with five participants tested in each group. After receiving instructions regarding the research objectives and protocols, participants were required to provide informed consent before the beginning of the experiment. Each participant performed exercise tests at three distinct capture stations with different backgrounds. Participants completed two 120-second exercise sessions at each station for RGB front camera and LiDAR rear camera tracking. As a result, every participant completed a total of six test sessions.

This approach accounted for individual variations while evaluating performance under different environmental circumstances. We used a within-group design where each group of five participants completed six testing sessions in sequence. To control for fatigue, participants took breaks between sessions. Testing consisted of two rounds: the first with the RGB front camera and the second with the LiDAR rear camera (Figure 5). Participants exercised at three stations within each round: a solid wall, a glass wall, and a wall with objects, as shown in Figure 6. Each session lasted approximately 12 minutes, with a total experiment duration of roughly 1 hour and 15 minutes per group. After finishing, participants gave their evaluation of usability using the SUS questionnaire.

V. RESULTS

Our study investigated the accuracy of RGB front and LiDAR rear cameras for exercise fault detection within a mobile AR monitoring application. We examined performance under varying conditions to assess their potential for providing accurate exercise guidance. The average high knee lifts counted by each approach are presented in Table 1. Table 2 compares the average fault detections of RGB front and LiDAR rear cameras against physical therapist assessments. To ensure a comprehensive evaluation, fault detections included false positives and negatives. False positives referred to instances where the system incorrectly identified a fault, while false negatives referred to instances where the system failed to detect an actual fault.

A. ACCURACY RESULTS

The Kolmogorov-Smirnov test was used to assess the normality of the distribution of high knee lifts across various standing positions, indicating that the data were normally distributed. Following this, a paired samples t-test was performed to compare the performance of two camera systems: the RGB front camera and the LiDAR rear camera. The paired samples t-test was used to determine whether there were statistically significant differences in exercise fault detection between the RGB front camera and the LiDAR rear camera for marching-in-place exercise monitoring.

Our results showed the accuracy of camera-based exercise tracking systems, examining how camera type (RGB front vs. LiDAR rear), user positioning (0-degree vs. 45-degree angle), and background environments influenced performance. Table 3 shows that different cameras significantly impact accuracy across backgrounds, particularly with solid and glass walls at both 0-degree and 45-degree (p-value=.000). Similarly, the performance differed when standing 45-degree on a wall with objects (p-value=.018). However, when standing 0-degree directly facing a wall with objects, the performance of RGB and LiDAR cameras did not show a statistically significant difference (p-value=.146).

Table 4 shows the differences in accuracy between RGB front and LiDAR rear cameras when users stand in different positions across different backgrounds. The RGB front camera's accuracy significantly differed between standing positions on a glass wall (p-value=.006). There was no statistically significant difference across a solid wall and a wall with objects. The LiDAR rear camera's accuracy differed significantly between standing positions on a wall with objects (p-value=.012). No significant accuracy differences were observed across solid and glass walls.

B. RESULTS ACROSS BMI GROUPS

This study investigated the impact of user BMI (underweight, normal weight, and overweight) on the accuracy of exercise fault detection using RGB front and LiDAR rear cameras. Following the confirmation of normality, a one-way ANOVA

TABLE 1. The result of the average number of high knee lifts during marching-in-place according to the AR application with RGB front camera, LiDAR rear camera, and physical therapist.

Environment	RGB front camera		LiDAR rear camera		Physical therapist
	0-degree	45-degree	0-degree	45-degree	
Solid wall	103.17	108.20	117.13	117.73	117.63
Glass wall	96.73	103.63	115.60	117.43	115.97
Wall with objects	105.73	108.00	109.17	112.97	119.87

TABLE 2. The result of the average number of fault detections from the AR application was determined using criteria provided by physical therapists.

Environment	RGB front camera		LiDAR rear camera	
	0-degree	45-degree	0-degree	45-degree
Solid wall	14.73	10.03	2.23	2.23
Glass wall	19.43	13.07	3.03	2.53
Wall with objects	14.20	12.13	10.90	7.30

TABLE 3. Paired samples t-test results of differences in fault detections between the RGB front camera and the LiDAR rear camera across different backgrounds.

Background	Mean	Std. Deviation	Std. Error Mean	t	df	Sig. (2-tailed)
Solid wall (RGB0°-LiDAR0°)	12.5	11.84308	2.16224	5.781	29	.000**
Solid wall (RGB45°-LiDAR45°)	7.8	8.65986	1.58107	4.933	29	.000**
Glass wall (RGB0°-LiDAR0°)	16.4	13.24204	2.41766	6.783	29	.000**
Glass wall (RGB45°-LiDAR45°)	10.53333	8.77981	1.60297	6.571	29	.000**
Wall with objects (RGB0°-LiDAR0°)	3.3	12.10058	2.20925	1.494	29	0.146
Wall with objects (RGB45°-LiDAR45°)	4.83333	10.57024	1.92985	2.505	29	0.018*

* p-value<0.05, ** p-value<0.01

TABLE 4. Paired samples t-test results of differences in fault detections between the standing positions 0-degree and 45-degree across different environments.

Environment	Mean	Std. Deviation	Std. Error Mean	t	df	Sig. (2-tailed)
Solid wall (RGB0°-RGB45°)	4.7	12.7662	2.33078	2.016	29	0.053
Solid wall (LiDAR0°-LiDAR45°)	0	2.43537	0.44464	0	29	1
Glass wall (RGB0°-RGB45°)	6.36667	11.63077	2.12348	2.998	29	0.006**
Glass wall (LiDAR0°-LiDAR45°)	0.5	3.25629	0.59452	0.841	29	0.407
Wall with objects (RGB0°-RGB45°)	2.06667	14.88098	2.71688	0.761	29	0.453
Wall with objects (LiDAR0°-LiDAR45°)	3.6	7.37002	1.34558	2.675	29	0.012*

* p-value<0.05, ** p-value<0.01

for independent measures was conducted to analyze whether user BMI influenced fault detection accuracy. Our results in Table 5 show no statistically significant differences in fault detection accuracy across BMI categories for either camera

TABLE 5. One-way ANOVA for independent measures results of fault detection from users' BMI (underweight, normal weight, and overweight) between RGB front camera and LiDAR rear camera across environmental conditions.

Camera	Environment	Sex	F	Sig.
RGB front camera	Solid wall 0°	M	2.5854	.1164
		F	1.8934	.1928
	Solid wall 45°	M	0.2758	.7636
		F	2.8993	.0939
	Glass wall 0°	M	0.5500	.5908
		F	2.52	.1219
	Glass wall 45°	M	0.7200	.5066
		F	1.9081	.1907
	Wall with objects 0°	M	0.121	8864
		F	0.3624	.7033
	Wall with objects 45°	M	0.1048	.9012
		F	2.398	.1329
LiDAR rear camera	Solid wall 0°	M	0.6607	.5342
		F	0.0241	.9762
	Solid wall 45°	M	0.1818	.836
		F	0.0638	.9384
	Glass wall 0°	M	0.1728	.8433
		F	0.0094	.9906
	Glass wall 45°	M	0.6019	.5634
		F	1.6065	.2408
	Wall with objects 0°	M	0.5276	.6030
		F	0.1018	.9039
	Wall with objects 45°	M	0.5624	.5841
		F	0.1434	.8677

* p-value<0.05, ** p-value<0.01

TABLE 6. Paired sample t-test results of SUS scores comparing the usability of the RGB front and LiDAR rear cameras.

Group	Mean	Std. Deviation	Std. Error Mean	t	df	Sig. (2-tailed)
RGB - LiDAR	23	6.2767	1.146	20.071	29	.000**

* p-value<0.05, ** p-value<0.01

system in male or female participants. This indicates that user BMI may not significantly affect the performance of these technologies within this context.

C. USABILITY RESULTS

Regarding usability assessment, we used the SUS questionnaire to investigate usability scores. The SUS scores showed the comparative usability of the RGB front camera with display and audio and the LiDAR rear camera with only audio and no display (Figure 7). The SUS questionnaire, administered after participants completed a marching-in-place exercise for two minutes, serves as a tool to assess user perceptions and preferences in the context of these distinct camera setups. The paired sample t-test results in Table 6 comparing SUS scores between the front and rear cameras indicated a statistically significant difference. The mean SUS score for the RGB front camera is 69.1667, while the LiDAR rear camera is 46.1667, with a p-value=.000. Interpreting the SUS scores, the average result for the RGB front camera is between 68 and 83, categorizing it as "Good." In contrast, the LiDAR rear camera's average score is less than 51, indicating an "Awful" usability rating.

VI. DISCUSSION

The key findings of this comparative study of RGB and LiDAR cameras based on a case study marching-in-place exercise are summarized in terms of performance, environment, position, and usability as follows:

A. CAMERA PERFORMANCE AND ENVIRONMENTS

The study revealed that the LiDAR rear camera outperforms the RGB front camera in detection. However, both cameras were influenced by environmental conditions differently. The RGB camera proved sensitive to background texture and reflectivity, with detection accuracy diminishing, particularly on glass surfaces. The glass wall seems to be the most challenging environment for the RGB camera (likely due to reflections and transparency). Conversely, the LiDAR camera demonstrated sensitivity to obstructing objects, which could interfere with depth perception and accuracy. The LiDAR camera's accuracy is primarily affected by objects in the background. Interestingly, neither camera's performance was significantly affected when facing a wall with objects. This suggests that under specific conditions, both technologies may be suitable.

B. BMI AND ACCURACY

No significant differences in accuracy were observed across different BMI groups (underweight, normal, overweight) for both male and female users. This suggests that variations in the user body may not significantly impact the performance of these tracking technologies. AR-based exercise tracking systems using these technologies may broadly apply across diverse body types. This removes a potential barrier to adoption and promotes inclusivity for exercise monitoring in telehealth programs. However, some fault detections may be attributed to the influence of overweight users' clothing, which may appear messier and result in less joint detection than users with normal or underweight. Since BMI appears less influential, research can focus on other factors that impact accuracy, such as lighting, clothing, or individual movement variations.

C. STANDING POSITION

Generally, standing at a 45-degree angle slightly improved accuracy for both camera systems. This could be due to reduced occlusion or improved perspective on the user's body. This observation needs further investigation. There are some potential explanations for reduced occlusion and perspective changes. When standing at a 45-degree angle, body parts may be less likely to block each other from the camera's view, improving tracking of key landmarks. The angled view could offer the cameras additional information about the 3D position of the user's body, supporting accurate movement analysis. There might be limitations in the field of view or calibration of the cameras that are partially mitigated by the angled position.

D. USABILITY

The SUS results highlighted a clear difference in perceived usability between the RGB front camera setup (including display and audio) and the LiDAR rear camera (limited to audio only). While the RGB front camera scored in the "good" range, both systems can be better usable. This underscores the need for significant improvements to enhance the user experience and achieve the "excellent" usability target of 80.3 or above. These recommendations are for improving feedback, assistance, and design. Focus on providing more intuitive and timely feedback on the exercise form. This could involve visual overlays, auditory cues, or other forms of guidance. Explore ways to offer more proactive assistance when the system detects errors or deviations from the correct exercise form. This could include real-time corrective cues or suggestions for improvement. Finally, users should be involved in the iterative design process to identify pain points and tailor the AR system to their needs and preferences.

E. IMPLICATION FOR PRACTICE

LiDAR's depth-sensing capabilities offer advantages for accurate exercise tracking, particularly in environments with complex backgrounds. However, RGB cameras, while less robust to environmental factors, may be more convenient for users due to their widespread availability and integration with displays. The lack of significant BMI influence implies that both camera technologies could broadly apply for exercise monitoring across different body types. The findings support AR-based exercise guidance systems, particularly those leveraging the RGB front camera for enhanced usability. Prioritize user experience when designing AR systems. Incorporating displays and intuitive feedback mechanisms is crucial, even when using less advanced camera technology.

F. LIMITATIONS

This study has several potential limitations to consider when interpreting the findings. Firstly, the focus on the marching-in-place exercise, while providing a well-defined case study, might limit the generalizability of the results to more complex exercises or movement patterns. Secondly, the sample size and participant demographics could influence the performance of the AR system. In particular, the age of participants should be consistent with the real use. A larger and more diverse sample would be needed to explore how user differences in body composition, physical ability, or technical proficiency might interact with the RGB and LiDAR technologies. Additionally, while preliminary tests on some Android devices showed promising results, the main experiment was conducted solely on the iPhone 13 Pro. Further investigation is needed to assess the generalizability of our findings across different device types and hardware specifications. Finally, while the study controlled for certain environmental factors, real-world telehealth settings may present additional challenges, such as dynamic lighting conditions or cluttered backgrounds that could affect tracking accuracy.

VII. CONCLUSION

Our study explored the potential of AR-based motion tracking for exercise monitoring and guidance. Results demonstrated that LiDAR-based systems generally outperform RGB cameras in accurately detecting exercise faults, especially in environments with complex backgrounds. Furthermore, our findings suggest that different BMIs may not significantly impact tracking accuracy, indicating the potential of these technologies for users across a diverse range of body types. Importantly, usability assessments revealed a clear preference for the RGB front camera setup, highlighting the crucial role of intuitive feedback and displays in successfully adopting AR exercise systems. Using the front camera can be a practical choice for real-world telehealth for AR applications on mobile.

While the results indicated that the system is functional, there is potential for further improvement and enhancement. Future research will focus on the investigation of adaptive guidance systems that can effectively adapt to individual capabilities. In addition, future research will explore the possibility of using recorded activity data to individualize future exercise routines. The mobile AR application for exercise monitoring has the potential to track physical activity, improve telehealth interventions, and empower users to efficiently attain their fitness objectives.

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