MR Device-Based Remote Medical Support System With Object Recognition

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***Abstract*—The field of digital healthcare is rapidly evolving due to advancements in artificial intelligence technologies, particularly deep learning. This study aims to explore new possibilities in telemedicine by applying mixed reality (MR) technology to emergency medical situations. The primary goal of this research is to develop an MR device-based remote medical support system that utilizes MR devices and high-speed wireless communication to transmit onsite conditions to medical control rooms, enabling emergency responders to provide treatment under remote guidance. The system leverages Microsoft's HoloLens 2 to capture and transmit patient biometric information and surrounding environments, utilizing deep learning algorithms for human skeleton recognition and object alignment. The generated 3D avatars and content are then used in remote medical consultations. This article highlights the potential medical applications of HoloLens 2, a cutting-edge consumer electronics device, demonstrating how this system can provide innovative medical solutions through consumer technology and open up new possibilities in the healthcare field.**

The field of digital healthcare is rapidly evolving, driven by advancements in artificial intelligence, particularly deep learning technologies. Deep learning-based object recognition has become a cornerstone of medical innovation, supporting applications ranging from clinical decision-making tools to patient management and diagnostic assistance. Its scope of application continues to expand, highlighting its

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transformative impact on healthcare. Meanwhile, mixed reality (MR) technology is emerging as a next-generation tool, blending the physical and virtual worlds to enable real-time interaction and support in medical environments.

The recent COVID-19 pandemic has significantly accelerated the adoption and utilization of telemedicine, establishing it as an essential component of modern healthcare systems. As of 2023, the global telemedicine market was valued at approximately $97.15 billion, with projections indicating it will grow to $107.52 billion by 2024.[1] This growth is driven by the need to provide healthcare services in underserved areas, improve patient convenience, and reduce medical costs, thereby addressing critical societal demands.

According to Boppana,[2] telemedicine platforms have increased patient satisfaction to 92% in rural areas, with patients in South Dakota particularly appreciating the convenience of accessing specialists remotely, which was previously unavailable. In addition, a study on diabetic patients demonstrated significant benefits of remote monitoring, including a reduction in HbA1c levels and a 30% decrease in emergency room visits due to hypoglycemia and hyperglycemia.[2] These findings highlight telemedicine's potential to bridge healthcare gaps in rural areas and improve long-term health outcomes.

Ezeamii et al.[3] further analyzed key studies on telemedicine adoption and patient outcomes, reporting that Singh et al.[4] found a reduction in emergency care visits and an annual cost saving of $201,583 through telemedicine. Similarly, Toriola et al.[5] demonstrated that telemedicine services reduced emergency room visits by 44% and hospital admissions by 69%.

These statistical insights underscore telemedicine's efficacy in cost reduction, improving healthcare accessibility, and its applicability even in regions with challenging communication environments. The proposed remote medical support system leverages these strengths and is designed to address critical needs in military and underserved areas, potentially making significant social contributions.

Against this backdrop, this study proposes a remote medical support system utilizing MR devices and high-speed wireless communication technologies. The proposed system captures biometric data from patients using the HoloLens 2, employing deep learning-based object recognition algorithms to generate aligned 3D biometric objects. The generated data are transmitted via low-bandwidth wireless communication to a medical control center, where medical professionals analyze it to provide real-time guidance to emergency responders.

This study incorporates the ViT-Pose algorithm, which enables efficient and accurate pose estimation even in complex environments, and validates its performance using the Max Planck Institute for Informatics (MPII) dataset. Experimental results demonstrate a matching accuracy of 99.54% and an average processing speed of 31 frames per second (FPS), confirming the feasibility of real-time remote medical support even in constrained environments.

The key contributions of this study are as follows.

1) The integration of MR technology and deep learning-based object recognition for designing an MR-based emergency medical support system.
2) Enabling communication in low-bandwidth environments through efficient data transmission.
3) Experimental validation of the proposed system, demonstrating its high reliability and practicality.

The rest of this article is organized as follows. It covers "Related Works," "Proposed Method," and "Experimental Results" sections. Finally, the "Conclusion" section concludes this article, highlighting the practical potential and applications of a telemedicine system that integrates MR and deep learning technologies.

RELATED WORKS

This study focuses on developing a remote medical support system based on MR devices, utilizing MR technology and high-speed wireless communication to address emergency medical challenges through the innovative application of consumer electronic advancements. Accordingly, this section will describe

TABLE 1. Widely used HMDs and their characteristics.

HMD	Developer	Features and uses	Key applications
NVIS nVisor HMD[6]	NVIS	Professional simulation-focused HMD, designed for precise and accurate applications.	Simulation, training
Google Glass HMD[7]	Google	Lightweight AR device providing simple information overlays, designed for everyday use.	Information display, simple AR
HTC Vive HMD[8]	HTC	VR-focused device offering immersive virtual environments with high interactivity.	Gaming, entertainment, education
Microsoft HoloLens 2 HMD[9]	Microsoft	MR device with optical see-through technology, supports real-time interaction.	Healthcare, manufacturing, education, collaboration
Oculus Rift HMD[10]	Oculus (Meta platforms)	High-quality VR experience with strong immersion for virtual environments.	Gaming, simulation
Oculus Quest 2 HMD[11]	Oculus (Meta platforms)	Standalone wireless VR device with high usability and support for diverse VR content.	Gaming, education, virtual collaboration

studies related to MR devices and research on remote medical systems.

MR Devices

MR is an innovative technology that integrates the physical world with virtual environments, enabling users to interact with virtual and physical objects in real time. MR combines the strengths of augmented reality (AR) and virtual reality (VR), allowing users to manipulate and interact with virtual objects while remaining in a physical environment. Extended reality (XR) serves as an umbrella term that encompasses AR, VR, and MR, referring to all immersive technologies that bridge the physical and digital worlds. Within the context of this study, MR represents a subset of XR technologies, going beyond providing information or immersive experiences to enhance real-world tasks and foster novel collaboration methods. This positions MR as a significant technology in industries, such as healthcare, education, and manufacturing, addressing challenges in real-time data visualization and interaction that traditional technologies have failed to resolve.

Guo et al.[12] presented various use cases for MR devices. The specifications and features of each MR device are detailed in Table 1. A prominent example is the Microsoft HoloLens 2 head mount display (HMD),[9] which employs optical see-through technology to integrate real and virtual environments seamlessly. The importance of MR technology is particularly evident in applications, such as telemedicine, which require precise diagnostics and collaboration, even when healthcare providers are physically distant from patients.

This study leverages the potential of MR technology by utilizing the Microsoft HoloLens 2 HMD in telemedicine. While various HMDs exist, including NVIS nVisor,[6] Google Glass,[7] HTC Vive,[8] Oculus Rift,[10] and Oculus Quest 2,[11] the HoloLens 2 offers features particularly suited to medical applications. The HoloLens 2 provides an intuitive interface through hand gestures and voice commands, enabling healthcare providers to simultaneously observe a patient's real-world environment and visualize virtual data. This capability is especially valuable in telemedicine, where accurate information processing and real-time collaboration are critical. It enhances the quality of medical services while minimizing the limitations imposed by physical distance between patients and healthcare professionals.

MR technology is not merely a technical tool but a transformative enabler of collaboration and productivity in real-world settings. For instance, a system combining drones with AR devices achieved a 30% reduction in inspection time and over 95% accuracy in bridge inspections.[13] Such studies indicate that AR/VR technologies open new possibilities not only in industrial applications but also in the medical field. Moreover, studies on anatomy education leveraging XR and metaverse technologies demonstrated a 20% improvement in learning comprehension compared to traditional methods, positioning it as a viable alternative for remote learning during pandemics.[14] Long et al.[15] proposed an MR-based remote rendering method for real-time interaction with a 3D model of New York City, while Zhang et al.[16] introduced an AR approach for urban model visualization, enhancing data interaction. These findings confirm the effectiveness of AR-based real-time interactions facilitated by MR devices.

By harnessing the conceptual significance and technical strengths of MR, this study applies Microsoft HoloLens 2 in telemedicine, aiming to improve efficiency and precision in healthcare delivery. The ongoing development of MR devices continues to reshape traditional workflows, offering transformative tools for a wide range of applications across industries while opening new frontiers in healthcare.

MR Devices in Remote Medical Support System

The field of MR-based remote medical systems is rapidly advancing through the integration of cutting-edge technologies, with devices, such as Microsoft HoloLens, being widely adopted in telemedicine research. Pose-Díez-de-la-Lastra et al.[17] analyzed the use of HoloLens 1 and HoloLens 2 in orthopedic tumor surgeries, demonstrating that HoloLens 2 significantly improved ergonomic factors and task accuracy during surgeries. Similarly, Palumbo[18] reviewed studies on HoloLens 2 since 2019, highlighting its potential and limitations in applications, such as remote healthcare, remote control, and physical rehabilitation. HoloLens 2 has also been utilized in diverse medical studies[19,20,21] and AR-based educational applications, where it enables students to learn abstract concepts in an engaging visual format. Vidal-Balea et al.[22] further demonstrated the feasibility of applying HoloLens 2 in educational contexts.

In telemedicine, numerous studies have focused on integrating HoloLens with Internet of Things (IoT) sensors to develop remote medical systems.[23,24,25,26,27] These systems primarily leverage IoT sensors for real-time data collection and use smart medical devices for remote diagnosis and monitoring.

MR devices have also proven effective in remote surgery and diagnostics. For instance, Sugimoto and Sueyoshi[28] developed a method combining CT/MRI data with MR devices to convert them into STL/OBJ formats, improving surgical accuracy by 18% and enhancing collaboration efficiency by 25%. These examples illustrate how MR technology can significantly enhance the efficiency and precision of traditional workflows.

Reliability is a critical factor in telemedicine to ensure effective and accurate medical support. Relevant studies have shown the importance of addressing uncertainty in remote medical systems,[29,30] highlighting methods to reduce diagnostic errors and improve reliability. These findings emphasize the need for designing systems that address uncertainty, a challenge that the proposed system tackles by enabling efficient data transmission and accurate diagnosis in emergency scenarios.

In the domain of medical education and training, MR devices demonstrate high efficacy. Sivananthan et al.[31] utilized HoloLens 2 to reduce healthcare workers' exposure to infection by 79.5% and decrease the use of personal protective equipment by 83.3%, establishing it as an effective tool for remote education.

MR technology also excels in ultrasound diagnostics and remote collaboration. Maas et al.[32] applied HoloLens 2 with ultrasound probes, achieving a probe placement error reduction to 1.4 mm and improving real-time diagnostic accuracy with an average latency of 233$\pm$ 42 ms. Similarly, Yu et al.[33] utilized RGB-D cameras to increase surgical incision accuracy by 17% and enabled real-time collaboration among medical professionals through 3D modeling techniques.

AR/VR and MR technologies have been widely adopted to enhance diagnostic accuracy. Iwendi[34] integrated genetic algorithm, ant colony optimization, and particle swarm optimization with AR/VR devices to reduce diagnostic errors by 20% and improve diagnostic speed by 30%.

The integration of IoT and AI with MR-based remote medical systems has also gained

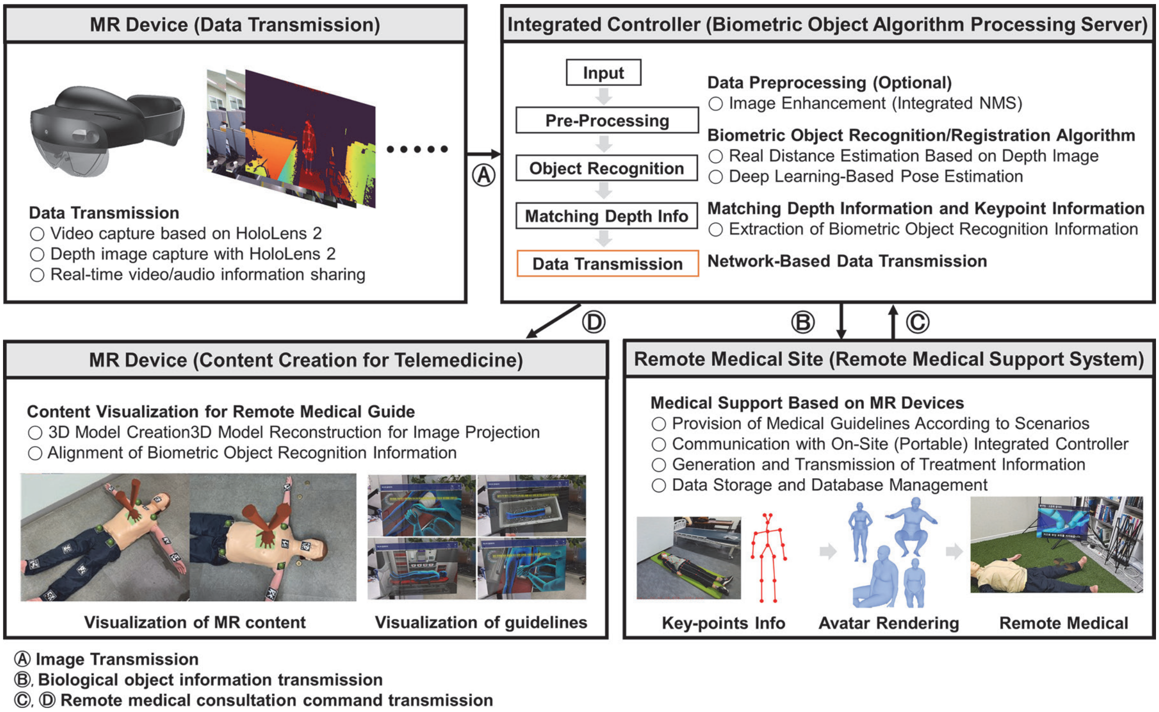


FIGURE 1. Conceptual diagram of the proposed remote medical support system.

traction. Senbagavalli and Singh[35] developed a wearable MR platform integrated with IoT sensors, achieving an anomaly detection accuracy exceeding 90% and validating the effectiveness of real-time data transmission. In addition, Lin et al.[36] utilized HoloLens 2 and Azure cognitive services to reduce healthcare worker exposure by 51.5% and enhance diagnostic efficiency in telemedicine.

These studies collectively demonstrate the transformative potential of MR technology in healthcare, education, and industry. However, limitations, such as real-time data processing constraints in low-bandwidth environments, and challenges in complex data integration remain. This study aims to address these challenges by developing a system that enables efficient data transmission and accurate medical support in emergency scenarios, paving the way for new possibilities in MR-based remote medical systems.

PROPOSED METHOD

This article proposes a remote medical support system utilizing MR devices. The conceptual diagram of the proposed remote consultation support system is illustrated in Figure 1. The system is primarily designed to provide realistic remote medical support to users based on MR devices. The MR devices capture depth and image information and transmit these data to a server for biometric object recognition. The server processes the received information through preprocessing for enhanced object recognition, depth estimation, and pose estimation for biometric object matching, and transmits refined data for content visualization. These refined data include information necessary for content visualization. Based on this information, the study generates 3D content and performs object recognition matching to be used in the HoloLens 2 application. The content for remote medical support is then transmitted to the remote medical support system. The remote medical support system provides a video system for telemedicine and displays medical guidelines on the HoloLens 2 screen, allowing users to perform remote medical procedures accurately.

Figure 2 illustrates the conceptual diagram for content visualization based on remote medical consultation. The content visualization process comprises three main components: 3D

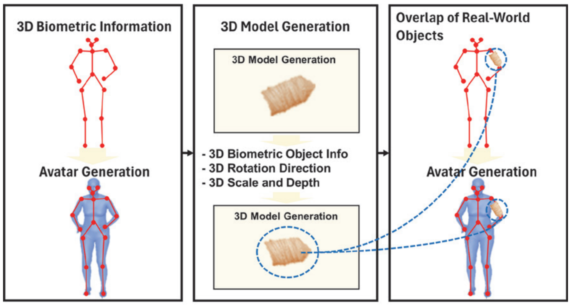


FIGURE 2. Concept diagram for biometric-based content visualization.

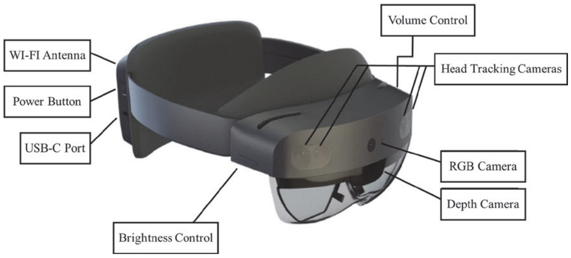


FIGURE 3. Basic hardware of Microsoft HoloLens 2.[37]

biometric object recognition information, 3D models for content visualization, and finally, the overlay of these 3D models. Initially, biometric object recognition information is extracted from images acquired by the HoloLens 2. Subsequently, to achieve object matching, a 3D model is reconstructed using information about the object's rotation, depth, and scale. This reconstructed 3D model is then overlaid onto the objects based on HoloLens 2, enabling a system where users can perform remote medical consultations under the guidance of a physician. The proposed system offers a practical solution by integrating advanced 3D reconstruction and overlay techniques, ensuring precise and effective medical support. Detailed explanations of the system's workings will be provided in this section.

MR Device-Based Remote Medical Support System Environment

This section describes the environment of the proposed MR device-based remote medical support system. The system utilizes HoloLens 2 to capture the patient's biometric information and surrounding environment. The HoloLens 2 is equipped with multiple sensors, including four visible light cameras for head tracking, two infrared cameras for eye tracking, a 1-MP time-of-flight (ToF) depth sensor, and an inertial measurement unit comprising accelerometers, gyroscopes, and magnetometers. It also features an 8-megapixel camera for photography and supports 1080p30 video recording.

The depth sensing functionality operates in two modes. The first is active-horizontal aperture time (AHAT) mode, which works at a high frequency of 45 FPS to provide precise information for hand movement tracking and delivers pseudodepth data to enhance accuracy. The second is long throw mode, operating at a lower frequency of 1–5 FPS, and is used for spatial mapping. These sensors and depth measurement capabilities enable the system to assess the patient's condition accurately and collect essential information for remote medical support.

The HoloLens 2 also uses its cameras to acquire RGB images and estimate depth. As shown in Figure 3, the RGB images captured by the device's built-in camera are transmitted to a server for pose estimation. This process is crucial for remote medical support in scenarios, such as limb amputations and AR-based battlefield emergency systems. In addition, the depth data from HoloLens 2 are mapped to the RGB camera's keypoint coordinates to generate a 3D avatar of the patient. Detailed explanations of the proposed system are provided in subsequent sections.

Object Recognition for Remote Medical Support Systems

The server employs deep learning-based object recognition algorithms on data acquired via HoloLens 2 to accurately identify patients' skeletons and other objects. The object recognition results play a crucial role in assessing the patient's condition. The pose estimation technique utilized in this system is based on the Vision Transformer for pose estimation (ViT-Pose). ViT-Pose is a model based on the vision transformer (ViT) approach for estimating poses. It is used to estimate the posture or pose of a person within an image and is one of the technologies gaining attention in the fields of

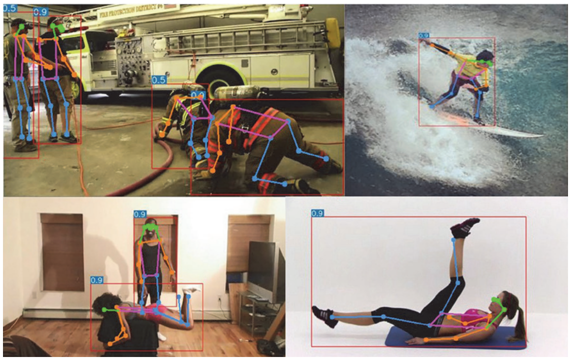
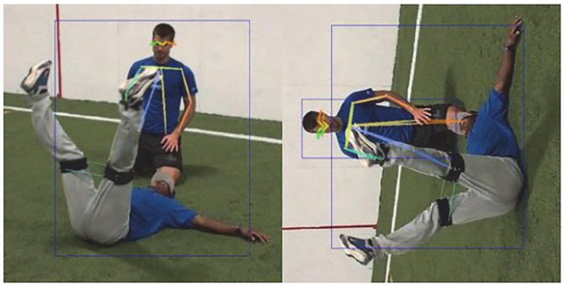


FIGURE 4. Example of object recognition using ViT-Pose.

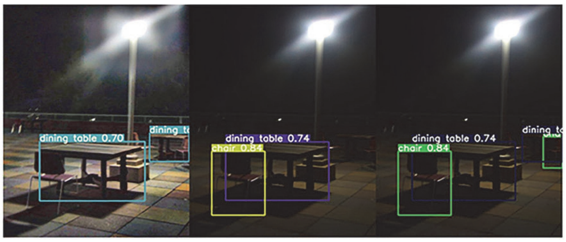
deep learning and computer vision. ViT-Pose,[38] which operates in a top–down approach similar to ALPHAPOSE,[39] OPENPOSE,[40] and DARK-POSE,[41] is among the algorithms that show superior performance in pose estimation methods, leveraging transformer-based algorithms.

ViT process images by dividing them into multiple small patches, which are then used as inputs to the transformer model. While transformers have been predominantly used in natural language processing, ViT adapts this model for image processing. ViT-Pose utilizes the structure of ViT to estimate the accurate pose of persons or objects within the image. This capability allows for the recognition of human actions and applications in various fields, such as sports analysis, gaming, VR, and healthcare. ViT-Pose can leverage global information more effectively than traditional convolutional neural network-based pose estimation models, thereby offering the potential for more accurate and detailed pose estimation results. In this research, we perform biometric object recognition for pose estimation based on the described ViT-Pose methodology. Figure 4 presents the pose estimation results obtained using ViT-Pose

Accurate pose estimation from 2D images was achieved using ViT-Pose, and the results were transmitted to the HoloLens 2 app, where they were mapped to depth images. This process enabled the creation of 3D avatars and the generation of content for remote medical consultations. ViT-Pose demonstrated its suitability for generating 3D avatars, even in dynamic situations. However, this article proposes a remote medical consultation system using MR devices in areas



(a)



(b)

FIGURE 5. Results of NMS-based operations for improved object recognition performance.

where medical support is not possible. In situations where medical support is difficult, such as in war zones, object recognition methods for low light and various poses are required. Therefore, this study applied Non-Maximum Suppression (NMS)-based integrated computations across multiple images to enhance object recognition performance in low-light environments and rotating images.[42,43] The NMS-integrated computation method improves object recognition in harsh conditions by performing object recognition on rotated and low-light enhanced images and then integrating anchor boxes from the original and improved images. Figure 5(a) shows an image where performance was improved through NMS calculations on rotated images. Figure 5(b) shows an image where performance was improved in low-light conditions by integrating NMS computations of low-light and normal images. In addition to the MPII training dataset, we also used a custom dataset to further train the model to improve object performance in simulated scenarios. These enhancement methods were able to improve object recognition success rates in various situations.

The identified object recognition results are transmitted from the HoloLens 2 to the server to support the remote medical support system by isolating the object identified as the patient.

TABLE 2. Sensor range specifications for depth estimation in HoloLens 2.

Range name	Minimum distance	Maximum distance
Depth camera	0.85 m (2.8 ft)	3.1 m (10 ft)
Hologram placement	0.1 m (4 inches)	Infinity
Optimal zone	1.25 m (4 ft)	5 m (16 ft)
Comfort zone	1.0 m (3 ft)	Infinity

In the proposed remote support system, the largest object centered in the user's field of view is designated as the patient, and only data from this object are transmitted. This method effectively prevents the misidentification and transmission of nonpatient objects by relying on the user's perspective. In addition, when partial occlusion occurs, the system can generate a partial 3D avatar of the patient. However, in cases of complete occlusion where object recognition fails, it is not possible to provide a 3D avatar. While estimated results, such as movement vectors or tracking data, could theoretically be transmitted, doing so in a medical context carries significant risks. Consequently, the system is designed to ensure accurate patient identification and reliable data transmission in remote medical support environments.

Furthermore, the proposed system significantly minimizes the data transmission volume to ensure seamless communication in low-bandwidth environments. For instance, only 204 bytes of data, comprising 17 keypoints of the patient, are transmitted during remote consultations. This is in stark contrast to transmitting a single 1920× 1080 image, which requires approximately 5.93 MB of data, over 30,000 times larger. By reducing the data size to such an extent, the system not only ensures efficient communication but also enables reliable operation in environments where bandwidth is severely constrained.

Based on these data, specific medical guidance and instructions can be provided to emergency responders. Medical professionals can assess the patient's condition in real time using information received through the HoloLens 2, enabling timely interventions and support. This system integrates and optimizes deep learning and MR technologies with advanced data processing and communication algorithms to ensure real-time accuracy in remote medical support systems. It has significant potential to enhance medical services in remote or inaccessible areas and emergency situations, offering accurate and reliable data to healthcare professionals. By doing so, it broadens the scope of remote medical support systems and improves access to essential medical services.

Depth Imaging and Distance Estimation Methods

In this section, we describe a method for depth estimation for biometric recognition based on MR. In this study, we use a 1-MP ToF depth sensor integrated into the HoloLens 2 for estimating the depth of objects. The range of the sensor used for depth estimation is given in Table 2.

HoloLens 2 supports two distinct modes, AHAT and Long throw, each designed for specific depth-sensing applications. The AHAT mode is optimized for hand tracking, providing high-speed (45 FPS) close-range depth detection. For distances beyond 1 m, it employs phase wrapping to deliver pseudodepth in the 0.2–1.0 m range. On the other hand, the Long throw mode is primarily used for spatial mapping, offering a lower frame rate of 1–5 FPS, but is well suited for detecting longer distances. This research focuses on extracting distances from depth-estimated images derived from camera images through actual distance mapping. The formula for estimating the actual distance is as described in the following equation:

$$\mathrm{Distance}_{\mathrm{Real}} = \frac{\mathrm{Pixel}_{\mathrm{Max}} \times \mathrm{Distance}_{\mathrm{Ref}}}{\mathrm{Distance}_{\mathrm{Max}} \times \mathrm{Pixel}_{\mathrm{Image}}}. \quad (1)$$

The process involves dividing the depth pixel values obtained from depth estimation by the maximum pixel value and then converting these to real-world distance units. In this context, $\mathrm{Distance}_{\mathrm{Real}}$ denotes the actual distance corresponding to a pixel value, and $\mathrm{Distance}_{\mathrm{Max}}$ represents the maximum distance value for conversion. $\mathrm{Pixel}_{\mathrm{Max}}$ is the maximum pixel value in the depth estimation image, while $\mathrm{Pixel}_{\mathrm{Image}}$ refers to the value from a single pixel in the image. This study progresses by correlating depth-estimated images with actual pixel values to estimate real distances.

A method for estimating the actual values corresponding to specific points involves calculating depth values at designated locations. These extracted depth data are then utilized as depth information for corresponding locations in the RGB images. The pDepth image contains depth information obtained in the AHAT mode, representing the depth at each point in the environment, with each pixel carrying a depth value for its specific location. The pAbImage appears to include additional data, visualizing depth values extracted from certain points in the environment. Consequently, these extracted depth data are applied to RGB images for pose estimation (position and orientation). This process enables precise identification of the location and orientation of users or objects in AR or VR environments, facilitating interactions and pose estimation. For example, it can accurately track a user's hand movements or simulate interactions with objects within the environment.

EXPERIMENTAL RESULTS

In this article, we explore biometric object recognition and matching technologies for remote medical consultations based on HoloLens 2. This section conducts a performance evaluation to validate the proposed biometric object recognition technology and matching test. The evaluation of biometric object recognition rate and processing speed was carried out by connecting to a server, which stores the biometric object recognition algorithm and test images, via a local network from a test client. The test environment consisted of an OS Linux 18.04 LTS, H/W Intel i7-7700 K, 4.2 GHz, 128 GB memory, NVidia TITAN Xp, where the performance of the 3D biometric object recognition algorithm was assessed.

The evaluation of the biometric object recognition rate utilized the MPII Human Pose dataset to verify the recognition rate of the test subjects. Initially, 2729 images extracted from the MPII Human Pose dataset[44] were selected as validation data. These images served as a benchmark to verify the efficiency of the biometric object recognition algorithm. For the quantitative measurement of recognition rates, the average PCKh-0.5 value was used as the standard. PCKh-0.5 stands for the percentage of correct keypoints head, a metric measuring the ability to accurately detect the position and orientation of a person based on the size of the human head.

TABLE 3. Biometric object recognition results: Accuracy by body part.

Body part	Value
Head	97.61%
Shoulder	97.44%
Elbow	93.73%
Wrist	90.15%
Hip	92.40%
Knee	91.86%
Ankle	88.33%
Average	93.38%

The biometric object recognition algorithm was evaluated using validation data from the MPII Human Pose dataset. The PCKh-0.5 values obtained from each trial indicate the algorithm's recognition accuracy, serving as a measure of its consistency and reliability. Table 3 presents the performance evaluation results, demonstrating a recognition rate exceeding 90%, which provides sufficient reliability for keypoint recognition in remote medical consultations. The proposed system utilizes ViT-Pose for pose estimation, which currently offers state-of-the-art performance in 2D pose estimation, excelling in both accuracy and speed. The experimental results confirm that ViT-Pose performs exceptionally well with our dataset, making it highly suitable for real-world applications.

Utilizing the MPII Human Pose dataset, we measured the biometric object recognition processing speed of the test subjects. The same set of 2729 images extracted from the MPII Human Pose dataset, as used in the biometric object recognition rate evaluation, served as the validation data for this experiment. The processing speed was measured as follows: the average CPU time per image was calculated by dividing the total

TABLE 4. Recognition processing speed trials: Average CPU time and FPS.

CPU time (s)	CPU time/image (s)	Recognition speed (fps)
90.07	0.033	30.1
Average recognition speed:		30.1

CPU time (s) by the number of images used (frames). The recognition processing speed (fps) was determined by dividing 1 by the average CPU time per image (s/frame). The formula for calculating recognition processing speed is provided in the following equation:

$$\text{CPU time per image (s/frame)} = \frac{\text{Total CPU time (s)}}{\text{Number of images processed (frames)}}$$
$$\text{Recognition processing speed (fps)} = \frac{1}{\text{CPU time per image (s/frame)}}. \quad (2)$$

The proposed system was also evaluated using the MPII dataset employed in the performance assessment. The recognition processing speed was determined based on the measured CPU processing time and the number of images processed. The experimental results for recognition processing speed are presented in Table 4. Processing 2729 images took 90.07 s, resulting in an average CPU time per image of 0.033 s and a recognition speed of 29.9 fps. These results demonstrate the practicality of the proposed system in real-world environments. The ViT-Pose algorithm used in this system delivers state-of-the-art performance in terms of both accuracy and speed. By integrating an algorithm that excels in both areas, the proposed system is highly suitable for remote medical support systems.

In our proposed system, the patient's pose estimation algorithm is utilized to perform matching with a 3D body model. Accurate pose estimation-based biometric object recognition and visualization of content at corresponding coordinates of each biometric recognition point are essential for precise content visualization in remote medical support systems. To evaluate the system, we assess the matching accuracy and alignment processing speed required for content visualization. The evaluation data include object recognition results performed on the MPII dataset and an internally created 3D standard body model.

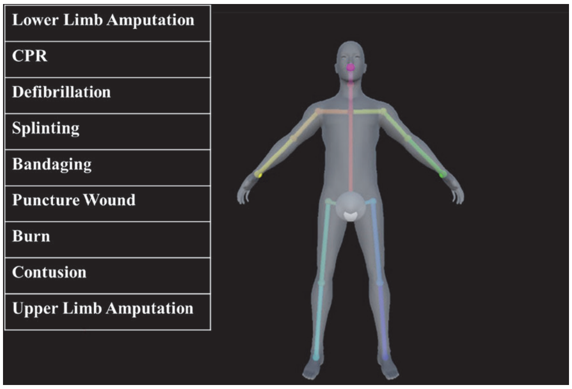


FIGURE 6. Program for evaluating biometric object matching accuracy.

A quantitative evaluation criterion was established to assess biometric object matching accuracy and processing speed. In this study, we set a target of achieving a biometric object alignment accuracy of over 90% and a processing speed of at least 15 FPS. To measure the matching accuracy and processing speed of biometric objects, the evaluation program shown in Figure 6 was executed. To begin the analysis, a specific treatment displayed on the left-hand side of the image was selected.

For the biometric object matching accuracy evaluation, the accuracy was calculated when the test subject was aligned with the standard 3D body model. The criterion for evaluating matching accuracy is based on predefined matching locations in the 3D model. The evaluation metric used was the intersection over union (IoU) between the predefined ground truth and object recognition results. IoU is a critical metric for evaluating object detection and alignment accuracy, quantifying the overlap between two areas. It is calculated using the following equation:

$$\text{IoU} = \frac{\text{Intersection}(\text{Predicted} \cap \text{GroundTruth})}{\text{Union}(\text{Predicted} \cup \text{GroundTruth})}. \quad (3)$$

The results of the biometric object matching accuracy evaluation are presented in Table 5. The matching performance exceeded 90%

TABLE 5. Biometric object matching accuracy results: IoU.

Procedure	Ground truths (pixels)	Matched results (pixels)	IoU (%)
Lower limb amputation	3932	3888	98.88
CPR	7077	7060	99.76
Defibrillation	7077	7068	99.87
Splinting	6099	6091	99.87
Bandaging	6770	6755	99.78
Puncture wound	3462	3403	98.30
Burn	1329	1323	99.55
Contusion	6416	6407	99.86
Upper limb amputation	2697	2696	99.96
Average			99.54

TABLE 6. Biometric object matching processing speed results.

Procedure	Trial 1	Trial 2	Trial 3	Average
Lower limb amputation	31	31	32	31
CPR	31	31	32	31
Defibrillation	32	31	31	31
Splinting	31	32	32	32
Bandaging	32	31	32	32
Puncture wound	31	31	31	31
Burn	31	32	31	31
Contusion	31	31	31	31
Upper limb amputation	32	31	31	31
Average				31

alignment across all metrics when compared to the ground truth data. In constructing remote medical support systems content through MR devices, the most critical factor is the alignment between the content and the actual image. The results confirm that the proposed system is sufficiently capable of visualizing the 3D content for remote medical support systems using MR devices.

The process of biometric object matching consists of the following steps: image transmission from HoloLens 2, depth estimation and object recognition, the transmission of estimated 3D data, and content visualization based on the results. The processing speed was measured in FPS, and the experimental results showed an average of 31 FPS. This significantly exceeds the initial target of 15 FPS, demonstrating that the proposed system is well suited for implementing remote medical interaction systems. Detailed results for each metric are summarized in Table 6. In addition, Figure 7 illustrates the remote medical support content visualized using key points obtained from pose estimation. This visualization confirms the feasibility of remote medical assistance using HoloLens 2, even in situations where direct interaction is challenging.

In conclusion, the experimental results validate that the proposed HoloLens-based remote medical system meets the benchmark criteria in both biometric object matching accuracy and processing speed. These findings highlight the system's capability to enable effective remote medical guidance and support.

Figure 7 illustrates the visualization of the 3D medical content through HoloLens 2. It visualizes the necessary emergency treatments on the MR device by receiving the remote medical support results from the physician at the remote site. The user of HoloLens 2 can perform

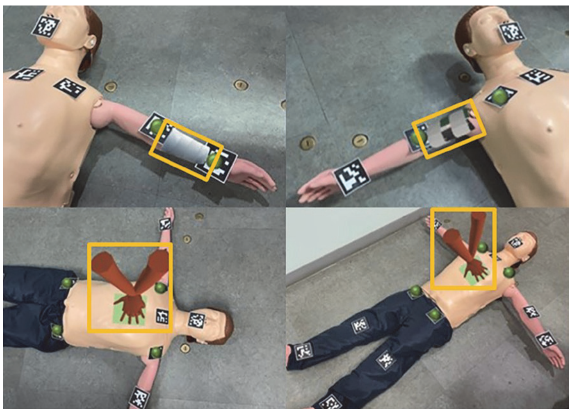


FIGURE 7. Processing speed results for biometric object matching: Average FPS.

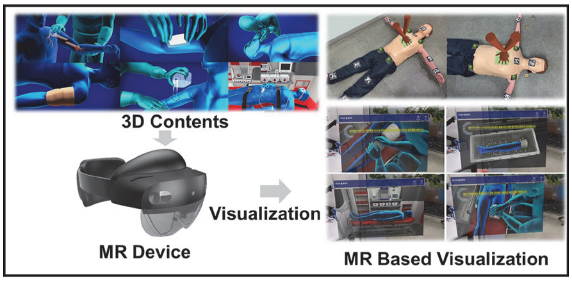


FIGURE 8. HoloLens 2-based guideline provision system for telemedicine.

emergency procedures based on the visualized 3D content, following the expert's guidance. Figure 8 displays content that provides medical instructions based on the patient's condition. The user performs emergency care for the patient by following the guidance visualized on the MR device. Therefore, the proposed remote medical support system enables efficient medical assistance by using visualized content on MR devices, guided by the physician's remote instructions. This system was developed based on the procedures outlined in Table 6, demonstrating its practicality and effectiveness in real-world scenarios.

The performance of the proposed method was evaluated using computer vision-based technologies to measure the biometric object recognition rate and processing speed in real-world applications. Both results indicated levels suitable for practical use. The matching rate and processing speed of AR images in remote medical consultations, based on biometric object recognition using Unity,[45] were also evaluated, and the results were deemed appropriate for telemedicine applications. The experimental outcomes demonstrate that the proposed system is well suited for remote medical consultations. In addition, the proposed telemedicine system, compared to existing systems, has shown the capability to perform remote consultations even under poor communication conditions by utilizing minimal bandwidth.

Comparison of MR Device-Based Remote Medical Support Systems

Table 7 provides a summary of various MR device-based remote medical support systems, highlighting their key technologies, performance metrics, and core contributions. This comparison is not intended to directly evaluate the superiority of one technology over another but rather to showcase how diverse approaches address specific challenges and contribute uniquely to remote medical systems. This section discusses the progression of MR-based remote medical systems, compares existing approaches, and emphasizes the distinct advantages of the proposed system. Existing studies have demonstrated significant advancements in MR-based remote medical systems. For instance, Shabir et al.[46] utilized MR technology for tele-ultrasound diagnostics, achieving improved probe placement accuracy with a latency of 233$\pm$ 42 ms, while Wersényi[48] evaluated 5G-enabled MR systems, reporting ultra-low latency between 42.5$\pm$ 27.5 ms. These findings underscore the importance of real-time interaction in remote medical applications. Similarly, Garcia et al.[50] demonstrated the integration of 5G with MR devices, achieving latency in the range of 402$\pm$ 90 ms. These systems highlight the potential of MR technologies to improve healthcare delivery in various scenarios. Further advancements include the application of MR devices for collaborative and educational purposes. Maas et al.[32] and Pregowska et al.[52] explored the role of MR systems, such as HoloLens 2, in improving healthcare training and interteam communication. Rufai et al.[51] showcased the feasibility of using digital twins for remote medical support, validating their utility in providing enhanced visualization and control. In addition, Yu et al.[33] developed a real-time modeling system for emergency neurosurgery, with a latency of 775$\pm$ 25 ms and a reconstruction speed of 15 fps. Despite these advancements, certain limitations remain. Research by Black and Salcudean[53] highlighted the challenges of achieving procedural precision in remote diagnostics, with a continuous tracking lag of 255$\pm$ 118 ms. Similarly, systems, such as those by Lo et al.[54] which utilized Holoportation and 3D visualization, required high-resolution data transmission, posing significant challenges in low-bandwidth environments. While these studies provide insights into the potential of MR for remote healthcare, their reliance on additional hardware or high

TABLE 7. Summary of MR research papers: Technologies, devices, and key contributions.

Authors	Used technology	MR device	Latency/ speed	Core contributions
Shabir et al.[46]	MR, virtual hologram, depth estimation	HoloLens	(Latency) 233± 42 ms	Validated MR's feasibility in tele-ultrasound diagnostics.
Lawson et al.[47]	MR, ICECAP error evaluation tool	HoloLens 2	N/A	Improved MR's accuracy in emergency medical contexts.
Wersényi[48]	MR, 5G connectivity	HoloLens	(Latency) 42.5± 27.5 ms	Showcased MR's performance in 5 G environments.
Franzò et al.[49]	MR, wearable sensors, unity	HoloLens 2	N/A	Explored MR's potential in remote health monitoring.
Garcia et al.[50]	MR, 5G network	HoloLens 2	(Latency) 402± 90 ms	Highlighted MR and 5 G integration for critical care.
Rufai et al.[51]	Holoportation, digital twin, Azure Kinect	HoloLens 2	N/A	Validated digital twins for remote medical support.
Maas et al.[32]	MR, real-time collaboration	HoloLens 2	low latency	Improved efficiency of MR-assisted diagnostic workflows.
Pregowska et al.[52]	HoloLens 2 with Unity, 3D modeling	HoloLens 2	N/A	Explored MR's role in medical education and training.
Yu et al.[33]	Microsoft Kinect, HoloLens, real-time modeling	HoloLens, Kinect	(Latency) 775± 25 ms (Speed) 15 fps	Improved accuracy and collaborative decision-making in emergency surgery.
Black and Salcudean[53]	HoloLens 2, haptic feedback	HoloLens 2	(Latency) 255± 118 ms	Improved procedural precision in remote diagnostics using MR.
Lo et al.[54]	Holoportation, 3D visualization	HoloLens 2	N/A	Showcased feasibility of 3D telemedicine for remote healthcare.
Dinh et al.[55]	AR with depth sensors, HMD	General HMDs	N/A	Showed potential of AR for real-time healthcare feedback and education.
Proposed method	2D pose estimation, HoloLens-based content visualization	HoloLens 2	(Speed) 32.26 ms	Developed a low-bandwidth telemedicine system suitable for challenging communication environments.

bandwidth indicates the need for more efficient systems. The proposed system addresses these challenges by leveraging a 3D pose estimation algorithm integrated with HoloLens 2. Unlike prior systems that depend heavily on high-resolution data transmission, our approach transmits only pose estimation results and utilizes preinstalled content on the HoloLens 2. This design significantly minimizes bandwidth requirements, making the system suitable for disaster zones or military operations with unreliable communication networks. Moreover, the proposed system demonstrates superior real-time capabilities, achieving an average processing speed of 31 FPS (32.26 ms per frame). The total operation time, encompassing both processing and transmission times, was measured to evaluate the system's overall efficiency. While latency is not assessed as an independent metric, the holistic evaluation of operation time confirms that the system performs reliably even in constrained network environments. This performance surpasses many existing systems, such as those by Yu et al.[33] which faced latency issues in low-bandwidth environments. The proposed system ensures seamless real-time interaction, enabling accurate and timely interventions, particularly in emergency medical scenarios. Its ability to visualize 3D medical content for real-time instructions supports healthcare providers in delivering precise care, expanding its applicability to diverse situations, including military operations and disaster relief. Compared to existing systems, our approach eliminates the need for additional hardware, such as external webcams or other devices, as seen in studies, such as those by Garcia et al.[50] and Lo et al.[54] This simplification reduces overall system complexity and enhances practicality. Furthermore, by optimizing the system for low-bandwidth environments, we ensure consistent performance, positioning it as a cost-effective and scalable solution for remote medical consultations. The comparison presented in Table 7 emphasizes the unique contributions and complementary strengths of various MR-based remote medical systems rather than attempting a direct one-to-one comparison. These features make the system an effective tool for real-time interaction and emergency medical support, significantly expanding the practical applications of MR technology while addressing key challenges faced by earlier systems.

CONCLUSION

This article proposes a remote medical consultation system utilizing MR devices, with a particular focus on the HoloLens 2 as the cornerstone for constructing a telemedicine system. Recently, there have been numerous attempts to leverage MR devices in the context of remote medical care. In this article, we suggest technologies for building a remote consultation system using MR devices. The proposed system architecture includes essential communication and object recognition technologies necessary for establishing a remote consultation system. Specifically, the system employs a pose estimation method to mark joint positions based on images acquired through the HoloLens 2 and a depth-based object matching technique for 3D mapping. This setup allows the system to transmit the acquired biometric data of patients to medical control rooms via high-speed wireless communication.

In the control room, medical professionals can assess the patient's condition in real time based on these data and provide specific medical instructions to emergency responders. The algorithms developed in this study are optimized for fast data processing and transmission, with a focus on designing a system that facilitates real-time remote medical consultations. To evaluate the system's performance, we used both public datasets and a proprietary dataset constructed for testing purposes. This system shows significant potential, especially in emergency situations where access is limited or onsite support is challenging.

Ultimately, this article explores the object recognition system based on the MR device HoloLens 2 and its applicability, aiming particularly to carve out new domains in telemedicine. Such research plays a crucial role in advancing innovative developments in the medical field and improving the quality of patient care.

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