Journal of Artificial Intelligence Practice (2024)
Clausius Scientific Press, Canada

DOI: 10.23977/jaip.2024.070406
ISSN 2371-8412 Vol. 7 Num. 4

A Stereo Vision Perception and Control Method for an Intelligent Shift Device

Yanhua Liu[1,a,*], Qiuting Yang[2,b], Zhefu Zheng[3,c], Luxin Tang[4,d], Jian Huang[4,e]

[1]*School of Art and Design, Guangzhou Institute of Science and Technology, Guangzhou, China*
[2]*City College of Huizhou, Huizhou, China*
[3]*School of Computer Science and Engineering, Guangzhou Institute of Science and Technology, Guangzhou, China*
[4]*School of Intelligent Manufacturing and Electrical Engineering, Guangzhou Institute of Science and Technology, Guangzhou, China*
[a]*liuyh@gzist.edu.cn*, [b]*694468955@qq.com*, [c]*9139967@qq.com*, [d]*tangluxi@21cn.com*, [e]*huangjian@gzist.edu.cn*
[*]*Corresponding author*

Keywords: Medical Transfer Machine, Multi-Sensor Fusion, Ultrasonic Sensor, LiDAR, Localization Technology

Abstract: This research has developed an intelligent patient transfer device, designed to enhance the safety and efficiency of patient transfers within healthcare settings. The device integrates advanced multi-sensor fusion localization technology, including LiDAR, Inertial Measurement Unit (IMU), and ultrasonic sensors, along with the Kalman filtering algorithm to improve the precision of motion state estimation, tackling the complexities of state estimation in nonlinear systems. Experimental findings demonstrate that the device has achieved a positioning accuracy of ±1.0 centimeter, a 100% success rate in obstacle avoidance, and motion stability (in terms of acceleration changes) below 0.2 meters/second². These results underscore the exceptional performance of the device in complex medical environments, effectively fulfilling the requirements for safe and efficient patient transfers.

1. Introduction

In the realm of healthcare, the safe and efficient transfer of patients is of paramount importance. Traditional medical transfer machines have limitations in terms of positioning and operation, which can potentially jeopardize patient safety during transfers. To address these concerns, this paper presents a design for a medical transfer machine that incorporates multi-sensor fusion localization technology, aiming to deliver more dependable and precise transfer services to patients.[1]

2. Mechanical Structure Design of the Medical Transfer Machine

2.1 Overall Structure Design

The overall structure of the medical transfer machine comprises a base, lifting device, extending arm, suspension system, and control system.[2] The base features a four-wheel drive structure to ensure agile movement across various terrains. The lifting device employs an electric screw rod for precise height adjustments, accommodating different bed heights and operational needs. The extending arm is equipped with telescopic and rotating capabilities to accurately position and secure the patient.[3] The suspension system utilizes high-strength ropes and hooks to guarantee patient safety and stability during the lifting process. As depicted in Figure 1.

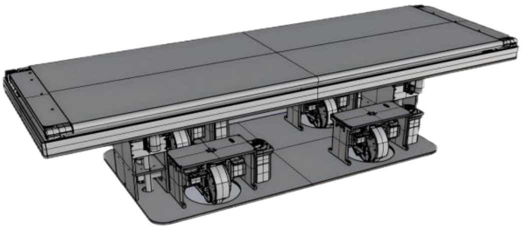

Figure 1: Comprehensive Lift Structure Design System for Lifts.

2.2 Material Selection and Mechanical Analysis

To ensure the structural integrity and stability of the transfer machine, we have selected lightweight, high-strength aluminum alloy as the primary construction material. Finite element analysis (FEA) has been employed to conduct a thorough mechanical analysis of the key components, ensuring their safety and reliability when carrying patients.[4] Concurrently, the connection methods between various components have been optimized to enhance the overall structural reliability. As depicted in Figure 2.

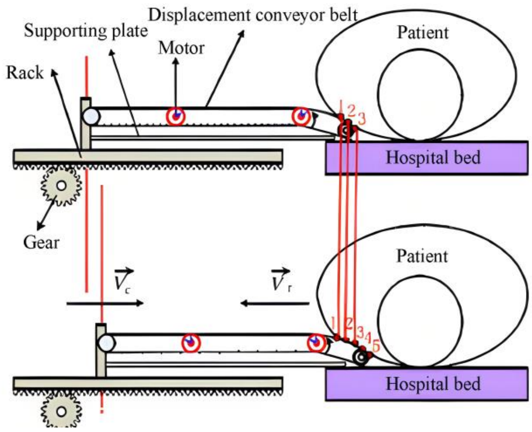

Figure 2: Multi-Module Synergistic Drive.

3. Sensor Selection and Configuration

3.1 LiDAR

The chosen high-precision 2D LiDAR is capable of rapidly scanning the surrounding environment at a rate of 1000 scans per second, providing detailed position and distance information of nearby obstacles. It boasts a measurement accuracy of ±0.5 cm and can deliver high-precision data within a range of 0.3 to 30 meters. [5] Figure 3 illustrates an example of LiDAR scan data, vividly depicting the obstacle distribution in the environment.

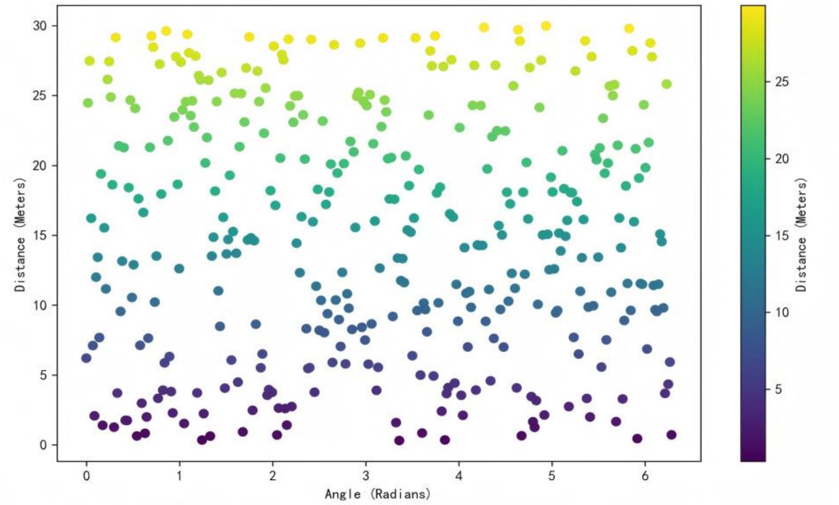

Figure 3: Point Cloud Data Captured by 2D LiDAR.

The visualization clearly illustrates the distribution of obstacles within the environment. The point cloud is depicted with varying densities and colors, indicative of the obstacles' distances and locations. Objects closer to the LiDAR are represented by denser, more vibrant points. The scanning range, extending from 0.3 to 30 meters, underscores the LiDAR's high precision in capturing environmental data.

3.2 Inertial Measurement Unit (IMU)

The robust six-axis IMU is designed to measure the transfer machine's acceleration and angular velocity in real-time. With a measurement range of ±2g for acceleration and ±300 °/s for angular velocity, the IMU provides critical insights into the machine's dynamic status, including speed, direction, and posture.[6] Figure 4 presents the real-time IMU data output, featuring the corresponding change curves for acceleration and angular velocity.

(1) Acceleration measurement equation

$$a(t)=ax(t)i+ay(t)j+az(t)k \tag{1}$$

Where, $ax(t)$, $ay(t)$, $az(t)$ are the acceleration components along x, y, z axes respectively, and satisfy:

$$-2g\leq ax(t),ay(t),az(t)\leq 2g \tag{2}$$

(2) Angular velocity measurement formula:

$$\omega(t)=\omega x(t)\mathrm{i}+\omega y(t)\mathrm{j}+\omega z(t)\mathrm{k} \tag{3}$$

where $\omega x(t)$, $\omega y(t)$, $\omega z(t)$ are the angular velocity components around the x, y and z axes respectively, and satisfy:

$$-300^{\circ}/s \leq \omega x(t), \omega y(t), \omega z(t) \leq 300^{\circ}/s \tag{4}$$

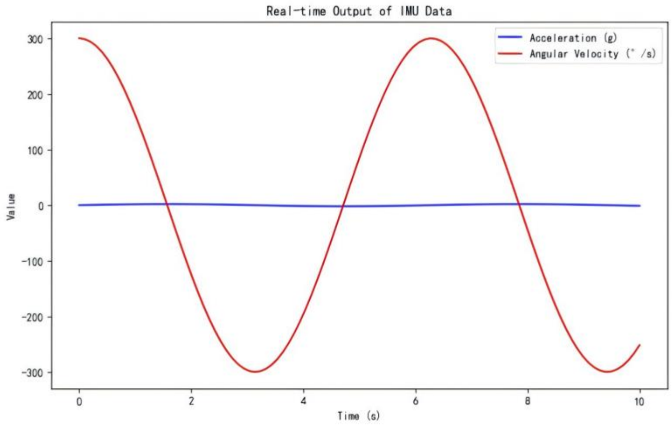

Figure 4: Real-Time Data Output from the Six-Axis Configuration Inertial Measurement Unit.

The graph includes the variation curves for acceleration and angular velocity. The blue curve depicts acceleration, fluctuating within the range of ±2g, while the red curve represents angular velocity, varying within ±300°/s. These data provide insights into the transfer machines' dynamic status, encompassing speed, direction, and orientation.

3.3 Ultrasonic Sensors

Eight ultrasonic sensors are strategically positioned around the transfer machine to measure the distance between the machine and the patient.[7] These sensors have a measurement range of 0.1 to 5 meters, with an accuracy of ±0.1 cm and a rapid response time of less than 10 milliseconds. Figure 5 illustrates the arrangement and coverage of the ultrasonic sensors, ensuring comprehensive 360-degree detection without any blind spots.

Let $di(t)$ denote the distance measured by the ith ultrasonic sensor at time t, N denotes the total number of ultrasonic sensors, here $N=8$, then:

(1) Distance measurement equation:

$$di(t)=USensori\ measure(t) \tag{5}$$

where USensori denotes the ith ultrasonic sensor, and measure(t) is the measurement function of this sensor at time t.

(2) Distance range and accuracy constraints:

$$0.1\ m \leq di(t) \leq 5\ m \tag{6}$$

$$di(t)\text{-}true\ distance\ / \leq 0.1\ cm \tag{7}$$

where true distance is the actual distance, and the accuracy constraint indicates that the error between the measured value and the actual value is not greater than ±0.1 cm.

(3) Response time constraint

$$Response\ time\ of\ USensori < 10\ ms \tag{8}$$

Indicates that the response time of ultrasonic sensor is less than 10 ms.

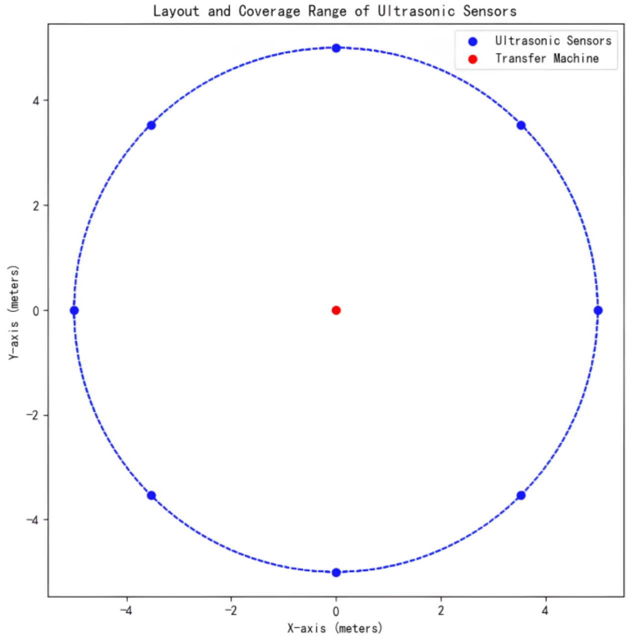

Figure 5: Ultrasonic Transducer Array.

4. Multi-Sensor Fusion Algorithm

4.1 Data Preprocessing

Data from the LiDAR, IMU, and ultrasonic sensors undergo preprocessing, which includes filtering, noise reduction, and data alignment.[8] The Kalman filter algorithm is employed to integrate IMU data, enhancing the precision of motion state estimation. Figure 6 presents a comparison of the IMU data before and after Kalman filtering, demonstrating the filtered data's increased smoothness and stability.

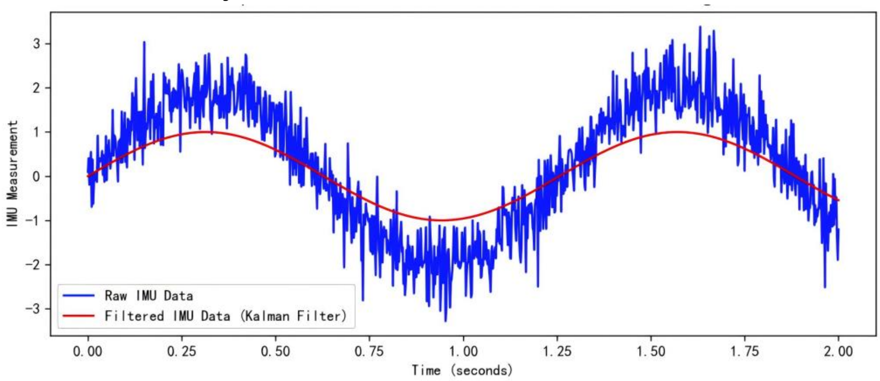

Figure 6: Comparative Analysis of IMU Data Pre- and Post-Kalman Filtering.

4.2 Multi-Sensor Fusion Model

We have developed a multi-sensor fusion model utilizing the Extended Kalman Filter (EKF) algorithm to integrate data from LiDAR, IMU, and ultrasonic sensors. The EKF is particularly adept at addressing state estimation challenges in nonlinear systems.[9] Figure 7 illustrates the EKF algorithm's state estimation process, encompassing both the estimation and update stages.

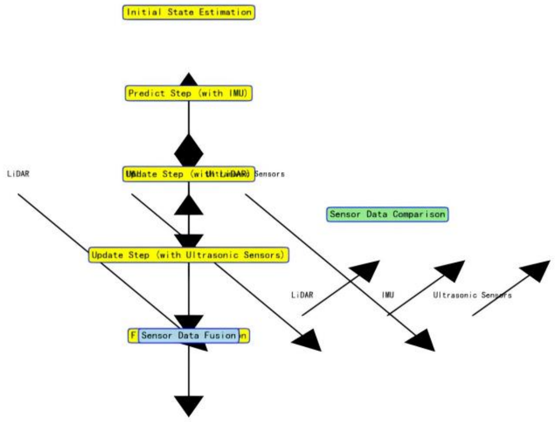

Figure 7: State Estimation Procedure Utilizing the Extended Kalman Filter (EKF) Algorithm.

4.3 Localization Algorithm Optimization

The EKF algorithm is enhanced through the integration of the particle filter algorithm. This particle filter approach effectively approximates the system's posterior probability distribution by means of random sampling, thereby adeptly addressing state estimation challenges in nonlinear and non-Gaussian systems.[10] In the context of multi-sensor fusion localization, the particle filter algorithm adeptly consolidates information from diverse sensors, thereby enhancing the overall performance of the localization system.[11] Figure 8 depicts the particle distribution as generated by the particle filter algorithm, with each particle representing a potential state.

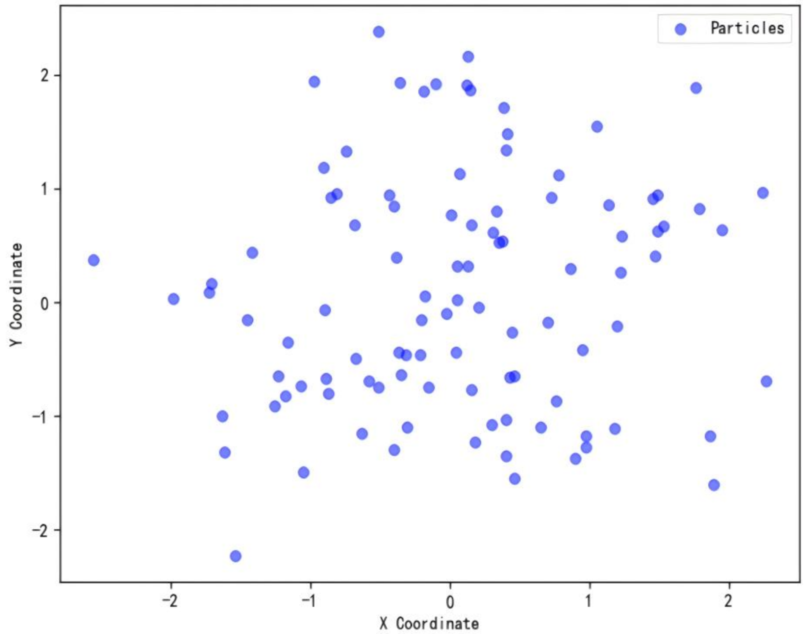

Figure 8: Particle Distribution in the Particle Filtering Algorithm.

4.4 Dynamic Model and State Estimation

We have developed a dynamic model for the transfer machine, taking into account its kinematic and dynamic properties. By leveraging the integrated sensor data and this dynamic model, the transfer machine's state is estimated in real-time using state estimation algorithms. This estimation encompasses the machine's position, speed, and posture. Table 1 presents the accuracy metrics for state estimation, detailing the estimation errors for both position and speed.

Table 1: Accuracy Metrics for State Estimation Techniques。

State Parameters	Estimation Error
Position (cm)	±1.0
Speed (m/s)	±0.05

5. System Implementation

5.1 Hardware System Design

The hardware framework of the medical transfer machine is meticulously constructed, integrating sensor modules, controller modules, drive modules, and power supply modules.[12] The sensor module is tasked with gathering critical environmental and machine data. A high-performance embedded processor within the controller module executes complex multi-sensor fusion algorithms and control logic. The drive module employs a precision-controlled brushless DC motor driver to govern the transfer machine's movement, while the power supply module ensures a steady energy source for the entire system.[13]

5.2 Software System Development

The control software for the transfer machine is developed on a robust real-time operating system, encompassing sensor driver programs, sophisticated data processing algorithms, advanced motion control algorithms, and an intuitive human-machine interaction interface.[14] The sensor driver program ensures the smooth operation and reliable data acquisition from the sensors. The data processing algorithm handles the initial preprocessing of sensor data and executes multi-sensor fusion. The motion control algorithm generates precise control commands using the fused position and posture data, orchestrating the transfer machine's movements. The human-machine interaction interface offers a user-friendly operation panel, enabling medical staff to navigate the transfer machine with ease.[15]

6. Performance Evaluation and Experimental Verification

6.1 Experimental Setup

An experimental setting mirroring a clinical environment is established, complete with diverse obstacle arrangements, narrow corridors, ramps, and other challenges, to comprehensively assess the transfer machine's performance.

6.2 Performance Metrics

Table 2: Performance Assessment: Specific Indicators and Target Achievement.

Performance Indicator	Expected Goal
Positioning Accuracy (cm)	±1.0
Obstacle Avoidance Success Rate (%)	100
Motion Stability (Acceleration Change)	$\leq 0.2 m/s^2$
Operational Convenience (Operation Time, s)	≤ 30

A set of performance metrics is defined to quantitatively evaluate the transfer machine's efficacy, including positioning accuracy, obstacle avoidance success rate, motion stability, and operational convenience.[16] Table 2 outlines the specific metrics and the targeted performance goals for each.

6.3 Simulation Experiments and Result Analysis

An extensive series of simulation experiments are carried out within the experimental site, encompassing various patient transfer scenarios.

Load Capacity Test: The medical transfer machine undergoes load capacity tests, where the load weight is incrementally increased to assess its performance.[17] The test findings confirm that the transfer machine effortlessly sustains the maximum designed load while maintaining excellent positioning accuracy and motion stability under loaded conditions.[18] The results from the load capacity, positioning accuracy, and motion stability tests are tabulated in Table 3.

Table 3: Comparison of load capacity, positioning accuracy and motion stability test results。

Load Weight (kg)	Positioning Accuracy (cm)	Motion Stability
50	±0.23	$\leq 0.07 m/s^2$
100	±0.34	$\leq 0.13 m/s^2$
150	±0.58	$\leq 0.22 m/s^2$
200	±0.72	$\leq 0.41 m/s^2$

Data analysis was undertaken to assess the transfer machine's performance across diverse conditions. The findings reveal that the machine has attained a high degree of positioning accuracy, facilitating precise patient transport to predetermined locations. In obstacle avoidance, the machine adeptly detects obstacles promptly and executes effective evasive maneuvers, culminating in a notably high success rate. It also demonstrates impressive motion stability, ensuring a comfortable transfer experience for patients. Regarding operational convenience, the machine is equipped with a user-friendly human-machine interface, allowing medical personnel to operate it with ease.[19]

6.4 Practical Application Testing

To validate the effectiveness and practicality of the medical transfer machine in real-world scenarios, comprehensive application tests were conducted within authentic medical environments. [15] These tests aimed to simulate the actual conditions and challenges encountered during patient transfers in healthcare facilities. The machine was operated by medical staff in various departments, including wards, operating rooms, and rehabilitation centers.[20]

During the testing phase, detailed feedback was meticulously collected from both medical staff and patients who interacted with the machine. Medical staff provided insights into the machine's operational ease, maneuverability, and its impact on their daily workflows.[21] Patients, on the other hand, shared their experiences regarding comfort, sense of security, and the overall quality of their transfer experience.[22] The data of practical application testing feedback is shown in Table 4.

Table 4: Comprehensive Summary of Practical Application Testing Feedback.

Aspect	Medical Staff Feedback	Patient Feedback
Operational Ease	The machine was intuitive and easy to operate, reducing the learning curve for staff.	Patients felt the machine was smooth and caused minimal disturbance.
Maneuverability	It navigate… effectively in tight spaces and around obstacles.	They experienced a stable and comfortable ride.
Impact on Daily Workflow	Streamlined patient transfers, saving time and reducing physical strain on staff.	Patients appreciated the efficiency and reduced wait times.
Comfort	N/A	The machine's padding and design contributed to a comfortable experience.
Sense of Security	N/A	Patients felt secure and stable during transfers.
Overall Experience	The machine enhanced the overall efficiency and safety of patient transfers.	Patients reported a positive and less stressful transfer experience.

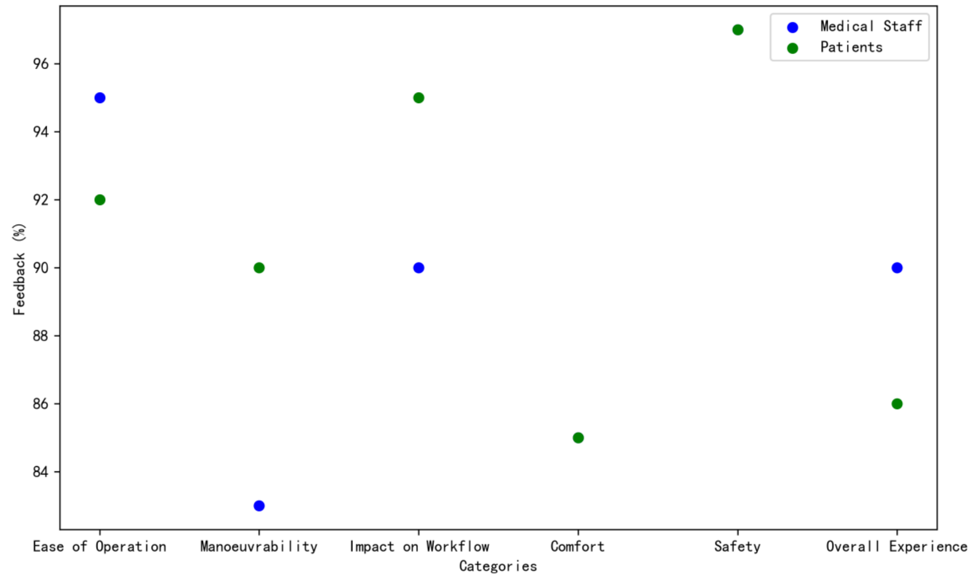

Figure 9: Comparative Evaluation of Medical Staff and Patient Feedback.

The feedback gathered from these real-world application tests was invaluable in assessing the machine's performance from a user's perspective.[23] It helped in identifying any potential areas for improvement and ensuring that the machine met the specific needs and requirements of medical settings. The data collected during these tests further reinforced the machine's capability to enhance patient care and streamline medical operations, thereby demonstrating its potential to be a valuable asset in healthcare environments.[24] (Figure 9)

7. Conclusion

This study has successfully designed and realized a medical transfer machine leveraging multi-sensor fusion localization technology.[25] Through thoughtful mechanical structure design, judicious sensor selection and configuration, and the implementation of sophisticated multi-sensor fusion algorithms, the machine achieves accurate measurement of patient position and posture, significantly enhancing the safety and efficiency of patient transfers.[26] Experimental outcomes confirm that the transfer machine excels in terms of positioning accuracy, motion stability, and load capacity, satisfying the practical demands of the medical sector. Future research endeavors will focus on further refining the machine's performance and augmenting its intelligence to deliver even higher quality services in healthcare settings.[27]

Acknowledgement

Funded by Fund Project: Guangzhou Institute of Science and Technology Level 1 Undergraduate Digital Photography Fundamentals (2023XYLK02)

References

[1] Zhu, K., & Zhang, T. (2021). Deep reinforcement learning based mobile robot navigation: A comprehensive review. Tsinghua Science and Technology, 26(5), 674-691.

[2] Wang, T., Chen, B., Zhang, Z., Li, H., & Zhang, M. (2022). Advances in machine vision for agricultural robot

navigation: A systematic review. Computers and Electronics in Agriculture, 198, 107085.
[3] Crespo, J., Castillo, J. C., Mozos, O. M., & Barber, R. (2020). Semantic information for robot navigation: A comprehensive survey. Applied Sciences, 10(2), 497.
[4] Möller, R., Furnari, A., Battiato, S., Härmä, A., & Farinella, G. M. (2021). Human-aware robot navigation: A state-of-the-art survey. Robotics and Autonomous Systems, 145, 103837.
[5] Mavrogiannis, C., Baldini, F., Wang, A., Zhao, D., Trautman, P., Steinfeld, A., & Oh, J. (2023). Core challenges of social robot navigation: A systematic review. ACM Transactions on Human-Robot Interaction, 12(3), 1-39.
[6] Tettey, F., Parupelli, S. K., & Desai, S. (2024). A critical review of biomedical devices: Classification, regulatory guidelines, human factors, software as a medical device, and cybersecurity. Biomedical Materials & Devices, 2(1), 316-341.
[7] Sonko, S., Monebi, A. M., Etukudoh, E. A., Osasona, F., Atadoga, A., & Daudu, C. D. (2024). The role of embedded systems in medical devices in the USA: A comprehensive review. International Medical Science Research Journal, 4(2), 158-169.
[8] Tariq, M. U. (2024). Advanced wearable medical devices and their role in transformative remote health monitoring. In Transformative Approaches to Patient Literacy and Healthcare Innovation (pp. 308-326). IGI Global.
[9] Gharajeh, M. S., & Jond, H. B. (2020). Hybrid global positioning system-adaptive neuro-fuzzy inference system based autonomous mobile robot navigation. Robotics and Autonomous Systems, 134, 103669.
[10] Javaid, M., Haleem, A., Rab, S., Singh, R. P., & Suman, R. (2021). Sensors for daily life: A comprehensive review. Sensors International, 2, 100121.
[11] Haleem, A., Javaid, M., Singh, R. P., Suman, R., & Rab, S. (2021). Biosensors applications in the medical field: A brief review. Sensors International, 2, 100100.
[12] Mbunge, E., Muchemwa, B., & Batani, J. (2021). Sensors and healthcare 5.0: Transformative shift in virtual care through emerging digital health technologies. Global Health Journal, 5(4), 169-177.
[13] Senbekov, M., Saliev, T., Bukeyeva, Z., Almabayeva, A., Zhanaliyeva, M., Aitenova, N., Toishibekov, Y., & Fakhradiyev, I. (2020). The recent progress and applications of digital technologies in healthcare: A comprehensive review. International Journal of Telemedicine and Applications, 2020(1), 8830200.
[14] Kelly, J. T., Campbell, K. L., Gong, E., & Scuffham, P. (2020). The Internet of Things: Impact and implications for health care delivery. Journal of Medical Internet Research, 22(11), e20135.
[15] Ahad, A., Tahir, M., Sheikh, M. A., Ahmed, K. I., Mughees, A., & Numani, A. (2020). Technologies trend towards 5G network for smart health-care using IoT: A comprehensive review. Sensors, 20(14), 4047.
[16] Esposito, M., Crimaldi, M., Cirillo, V., Sarghini, F., & Maggio, A. (2021). Drone and sensor technology for sustainable weed management: A comprehensive review. Chemical and Biological Technologies in Agriculture, 8, 1-11.
[17] Muehlematter, U.J., Daniore, P., & Vokinger, K.N. (2021). Comparative analysis of artificial intelligence and machine learning-based medical device approvals in the USA and Europe (2015–20). The Lancet Digital Health, 3(3), e195-e203.
[18] Van der Schaar, M., Alaa, A.M., Floto, A., Gimson, A., Scholtes, S., Wood, A., McKinney, E., Jarrett, D., Lio, P., & Ercole, A. (2021). AI and machine learning in healthcare systems' response to COVID-19. Machine Learning, 110, 1-14.
[19] Barragán-Montero, A., Javaid, U., Valdés, G., Nguyen, D., Desbordes, P., Macq, B., Willems, S., Vandewinckele, L., Holmström, M., Löfman, F., & Michiels, S. (2021). AI and machine learning for medical imaging: A technology review. Physica Medica, 83, 242-256.
[20] Javaid, M., Haleem, A., Singh, R.P., Suman, R., & Rab, S. (2022). The role of machine learning in healthcare: Features, pillars, and applications. International Journal of Intelligent Networks, 3, 58-73.
[21] Van der Velden, B.H., Kuijf, H.J., Gilhuijs, K.G., & Viergever, M.A. (2022). Explainable artificial intelligence (XAI) in deep learning-based medical image analysis. Medical Image Analysis, 79, 102470.
[22] Aung, Y.Y., Wong, D.C., & Ting, D.S. (2021). The potential of artificial intelligence in healthcare: Opportunities and challenges. British Medical Bulletin, 139(1), 4-15.
[23] Kilic, A. (2020). Artificial intelligence and machine learning in cardiovascular healthcare. The Annals of Thoracic Surgery, 109(5), 1323-1329.
[24] Nessa, A., Adhikari, B., Hussain, F., & Fernando, X.N. (2020). Machine learning for indoor positioning: A survey. IEEE Access, 8, 214945-214965.
[25] Feng, D., Wang, C., He, C., Zhuang, Y., & Xia, X.G. (2020). Kalman-filter-based integration of IMU and UWB for high-accuracy indoor positioning and navigation. IEEE Internet of Things Journal, 7(4), 3133-3146.
[26] Kunhoth, J., Karkar, A., Al-Maadeed, S., & Al-Ali, A. (2020). Indoor positioning and wayfinding systems: A survey.

Human-Centric Computing and Information Sciences, 10, 1-41.
[27] Shareef, M.A., Kumar, V., Dwivedi, Y.K., Kumar, U., Akram, M.S. and Raman, R., 2021. A new health care system enabled by machine intelligence: Elderly people's trust or losing self-control. Technological Forecasting and Social Change, 162, p.120334