Received 13 June 2023, accepted 7 July 2023, date of publication 17 July 2023, date of current version 27 July 2023.

Digital Object Identifier 10.1109/ACCESS.2023.3296066

RESEARCH ARTICLE

Design of Blind Guiding Robot Based on Speed Adaptation and Visual Recognition

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This work was supported in part by the National Natural Science Foundation of China under Grant 51205463, and in part by the Natural Science Foundation of Shandong Province under Grant ZR2020QE182 and Grant ZR2022QE015.

ABSTRACT It has become urgent to address the traffic challenges faced by this group with the continuous increase in the number of visually impaired individuals. A blind guiding robot based on speed adaptation and visual recognition was designed to address this problem. The speed adaptation of the robot and the blind person is achieved through feedback control of the distance and speed in this paper. Traffic signals are identified using optimized visual recognition method based on YOLOv5 transfer learning, and man-machine interaction is realized by applying multi-module units such as real-time image, speech, and positioning. The experimental results show that the rate of change of the relative distance was controlled within 13.1%, the relative velocity deviation was controlled within 0.3 m/s, the accuracy of identifying traffic signals reached 91.88%. And when the man-machine distance gap is large, the robot can control the man-machine distance to the set distance within 0.7 s in a timely manner, which effectively ensured the travel safety of blind people and provide the groundwork for the practical application of guiding blind robots.

INDEX TERMS Blind guiding robot, deep learning, Kalman filter, YOLOv5.

I. INTRODUCTION

According to the World Health Organization, at least 2.2 billion people around the world have a vision impairment at present [1]. It is imperative to solve the problem of difficult travel for the blind in this context. Nowadays, blind individuals primarily rely on traditional guide sticks and guide dogs for mobility, with only a few complete smart guide devices available. There is an urgent demand for powerful equipment that can help people obtain a better travel experience and provide them with safer, smarter, and more efficient ways to travel.

Currently, Various types of guide equipment with relatively advanced functionalities for the blind have been developed, including smart guide sticks, wearable guide devices, handheld guide instruments, and mobile guide robots. Chang et al. [2] designed a smart guide stick that combined a variety of sensors and a GPS system for an application based on the Android system, thus realizing real-time transmission of location information. Batliwala et al. [3] developed a guide stick that utilizes a buzzer and vibration motor to communicate information about obstacles ahead to the user timely. Suman et al. [4] designed a guide stick that employed a single-shot detection mechanism and a recurrent neural network to recognize and classify objects in front of the user, which could transmit information about objects to the blind. Dernayka et al. [4], [5] proposed an intelligent guide blind stick equipped with laser detectors and infrared sensors, both of which worked independently. Under low-cost conditions, obstacles can still be detected under strong sunlight.

In addition to guide sticks, other innovative devices have been introduced to assist the blind in different environments. Bai et al. [6] designed a type of guide glass that utilized a dynamic sub-object selection strategy to help the blind avoid dynamic obstacles indoors, thus allowing them to walk safely indoors. Hsieh et al. [7] designed a wearable guide device based on deep learning, thereby realizing the functions of detecting objects and indicating safe routes. Rahman et al. [8] designed wearable guide equipment that employed stereo

The associate editor coordinating the review of this manuscript and approving it for publication was Jingang Jiang.

cameras to capture video and applies deep learning algorithms. By integrating this device with web and Android applications, real-time monitoring of the road environment and users can be enabled. Pravin and Sundararajan [9] proposed a handheld guide instrument that used a fixed white LED light as a transmitter and a handheld PIN diode receiver that recorded different frequencies of light to determine the position of the blind.

Inspired by the lane following principle of self-driving cars, Chuang et al. [10] designed a robotic guide dog based on navigation technology and deep convolutional neural network, thus better realizing the function of navigation for the blind. Liu et al. [11] designed a mobile guide robot that employed an improved Dynamic Window Approach (DWA) algorithm to plan the motion path. This reduced the unnecessary steering frequency of the robot, resulting in smoother movements and more timely obstacle avoidance. Du et al. [12] proposed an intelligent blind guiding robot that used the sensor data fusion method based on the D-S evidence theory of the genetic algorithm, which achieved high-precision obstacle recognition and provided essential security for indoor guidance of the blind. Lu et al. [13] proposed an intelligent guide robot that utilized SLAM to estimate the state of the robot and employed the DRL algorithm to predict the best path. It provides navigation information to the users in dynamic environments.

In consideration of the existing shortcomings in blind guidance methods, this study provides a design method of guided robot system for the blind based on speed adaptation and visual recognition. Strive to achieve man-machine speed adaptation and the recognition of traffic signals by integrating technologies such as man-machine interaction, sensors, and audio recognition in this paper, thereby providing more convenience for the blind.

II. THE DESIGN OF A GUIDING ROBOT SYSTEM

This design adopts a self-designed wheeled hexapod robot as the mobile carrying platform, as shown in Figure 1. Combined with a variety of intelligent modules to provide greater independence and autonomy for the blind to travel.

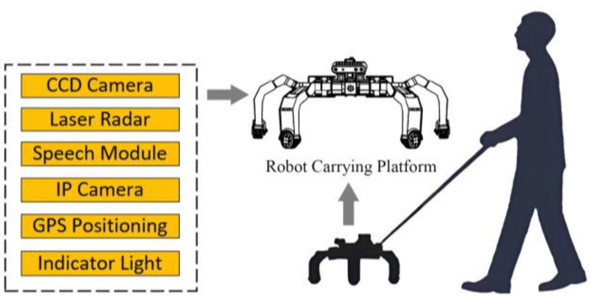

FIGURE 1. System Scheme Composition.

The design of the hexapod robot provides enhanced stability and balance, and can adapt to complex terrain environments. At the same time, the wheel-foot design is added to achieve coordination with the walking speed of the blind under lower cost conditions. The hexapod guiding robot has higher load capacity and better carrying sensors and other equipment. In addition, the hexapod robot can attract the attention of others and provide reliable support for visually impaired individuals because of its unique shape and movement mode.

Inspired by the obstacle avoidance method based on LIDAR by Hutabaratet al. [14], the guiding robot in this design autonomously avoids obstacles by integrating the YDLIDAR X3 Lidar and Hikvision camera. Taking inspiration from Nacir et al. [15] who used YOLOv5 and transfer learning for traffic signal recognition, this study utilizes an optimized YOLOv5 model to recognize traffic signals, thereby improving the safety and independence of visually impaired pedestrians. Referring to the research by An and Lee [16] on robot localization in urban environments, this design combines a GPS module and a network camera to provide positioning and real-time image feedback for blind individuals. At the same time, we add a variety of interactive modules, such as voice control module, indicator light, small speaker, to realize the active control of users and can provide voice and tactile feedback to better convey information to the user. Finally, we also designed a separate control glove for the user, which realized the control of the robot portable.

Therefore, the "Man-Machine-Environment" integrated system is summarized, as shown in Figure 2.

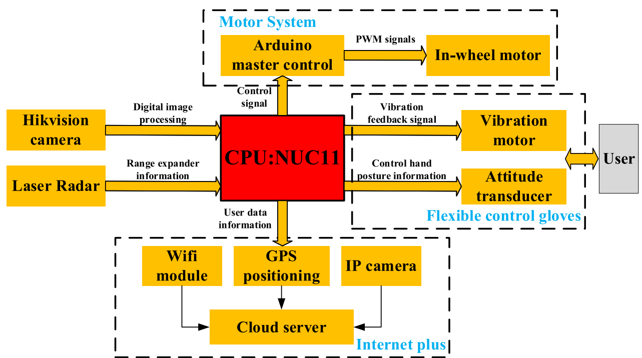

FIGURE 2. "Man-Machine-Environment System" structure composition.

Compared with existing guide robots, this system achieves better man-machine interaction, realizes speed adaptation between the robot and user [17], and can detect and recognize traffic signals.

III. AUTOMATIC SPEED ADAPTATION OF THE MOTOR SYSTEM

Due to variations in walking speed and stride among visually impaired individuals, a fixed guiding speed may be inadequate to meet their needs. Through the implementation of human-robot speed adaptation, a guide robot can automatically adjust its navigation speed according to the user's walking pace, enhancing comfort and safety during the guidance of visually impaired individuals.

The key technology of the guiding robot is to achieve its speed adaptation to the user. In this design, the YDLIDAR X3 LiDAR mounted on the robot mobile platform was used for distance measurement [18], [19] in order to achieve speed adaptation of the guide robot in response to the user's movements and to track the target. The relative distances x_n and x_{n-1} between the robot and the user were measured at time t_n and time t_{n-1}. By utilizing the uniform velocity model, the relative velocity v_{n} of the user with respect to the robot at time t_n was calculated as follows:

$$v_n = \frac{x_n - x_{n-1}}{t_n - t_{n-1}} \tag{1}$$

The absolute speed v_{an} of the robot at time t_n was measured by the absolute speed sensor of the robot platform, thus calculating the absolute speed v_{bn} of the user at time t_n:

$$v_{bn} = v_{an} + v_n \tag{2}$$

Owing to systematic and random errors in the range measurement of Lidar, the deviation between the measured value and the real value can lead to a decline in following accuracy and an increase in the possibility of accidents.

To eliminate these errors, this study employed the Kalman filter [20] for error elimination. The Kalman filter [21] is a time-varying optimization linear recursive algorithm primarily known for its observational capabilities. By extracting accurate observations from noisy data, it proves to be advantageous for resource-limited devices.

In this study, a discrete equation was introduced to describe the measurement data of the lidar system.

$$X(k) = AX(k-1) + BU(k) + W(k) \tag{3}$$

In the presence of noise, the system measurements are described as:

$$Z(k) = HX(k) + V(k) \tag{4}$$

In Equation (3) and (4), $U(k)$ represents the system input vector at time k, while $X(k)$ refers to the system state vector at time k. $Z(k)$ denotes the measured value at time k, and H represents the parameter matrix of the measurement system. $W(k)$ and $V(k)$ represent the process and measurement noise, respectively, with covariances Q and R.

By combining the relationship between the predicted value and the measured value and performing relevant parameter updates, the following equation can be derived.

$$X(k|k-1) = AX(k-1|k-1) + BU(k) \tag{5}$$

Equation (5) is the updated Equation of system results, where $X(k|k\text{-}1)$ is the predicted result of the previous state, $X(k\text{-}1|k\text{-}1)$ is the optimal result of the previous state, and $U(k)$ is the currently measured value of the lidar.

$$P(k|k-1) = AP(K-1|K-1)A^T + Q \tag{6}$$

In Equation (6), $P(k|k\text{-}1)$ is the covariance corresponding to $X(k|k\text{-}1)$, $P(k\text{-}1|k\text{-}1)$ is the covariance corresponding to $X(k\text{-}1|k\text{-}1)$, X^{T} is the transpose matrix of A, and Q is the covariance of the system process.

$$\begin{aligned} X(k|k) = X(k|k-1) \\ + K_g(k)(Z(k) - HX(k|k-1)) \end{aligned} \tag{7}$$

$$K_g(k) = \frac{P(k|k-1)H^T}{HP(k|k-1)H^T + R} \tag{8}$$

In Equations (7) and (8), $K_g(k)$ is the Kalman gain, and $X(k|k)$ is the optimal estimated value under the current state, which is the true value of the lidar measurement.

$$P(k|k) = (1 - K_g(k)H)P(k|k-1) \tag{9}$$

In Equation (9), $P(k|k)$represents the covariance of the optimal estimated value that serves as a measure of uncertainty in the estimation process.

Using Equations (5) and (6), the estimation of the lidar returned data is completed, and then the estimation is further processed based on Equations (7) and (8) to refine the results. The Kalman filter algorithm is run recursively on a Next Unit of Computing (NUC11) processor. This enables the estimated distance x_n and speed v_n of the Lidar to gradually converge to their true values.

After the true values of distance x_m and speed v_m are measured, cascade Proportional Integral Derivative (PID) control is adopted. For distance and speed control, a PID controller [22] was used respectively. Equation (10) describes the principle of the PID controller.

$$u(t) = K_p[e(t) + \frac{1}{T_i}\int_0^t e(t)dt + T_d\frac{de(t)}{dt}] \tag{10}$$

First, the measured distance x_m was compared with the set distance x_0, and the deviation $e(t)$, representing the error between them, was obtained. The corresponding coefficients K_p, T_i, and Td were set for the proportional, integral, and derivative controllers, respectively. The outputs of the three controllers were combined to calculate the desired velocity v_e. Then, the expected speed v_e was compared with the measured relative speed v_m. The above process is repeated cyclically to calculate the duty ratio of the Pulse Width Modulation (PWM) signal required for motor control. This controls the operation of the wheel motor, enabling the tracking of a given distance and facilitating man-machine speed adaptation.

In comparison to a single-ring PID control approach, the cascade PID control method makes better use of sensor information, resulting in smoother control, extended robot lifespan, and improved comfort and safety when guiding visually impaired individuals.

IV. THE DETECTION OF TRAFFIC SIGNALS

The detection and recognition of traffic lights is key to guiding robots to guarantee the travel of blind people. This design uses advanced deep learning technology to detect and identify traffic lights. It has good adaptability and robustness when dealing with complex and changeable environments, and is suitable for real-time monitoring. YOLO (You Only Look Once) is an object recognition and location algorithm based on deep neural network [23] that has a faster running speed and can be used in real-time systems. However, in terms of small target detection, it has a poor effect, and the construction time of the traffic signal data set is long.

This design optimizes the defects of YOLOv5 in detecting small targets and combines the target detection algorithm based on deep learning with the traditional visual recognition algorithm to improve the recognition speed, accuracy, and anti-interference. At the same time, in this study, transfer learning was adopted for model training, which greatly reduced the collection time of data sets.

A. OPTIMIZATION OF YOLOV5

In real traffic conditions, traffic signals may occupy a small number of pixels owing to the large distance or shooting angle. According to the investigation, the down sampling rate of YOLOv5 in convolution is too large, which leads to too few pixels of small targets and fewer target features. Moreover, the first-order SSD algorithm lacks feature fusion, resulting in poor detection for small targets [24].

Based on the target detection algorithm proposed by Google [25], the PANet layer in YOLOv5 was modified to BiFPN (Bi-directional Feature Pyramid Network) in this paper. In addition, this study simplified the backbone feature extraction network, accelerated the feature fusion speed, and effectively reduced the detection time under limited equipment resources. As shown in Figure 3, the red line is the path that transmits semantic information, whereas the green line is the path that transmits location information, thus realizing the two-way integration of top-down and bottom-up deep and shallow features. After fusion, the features are output to the Class and Box networks to detect traffic lights.

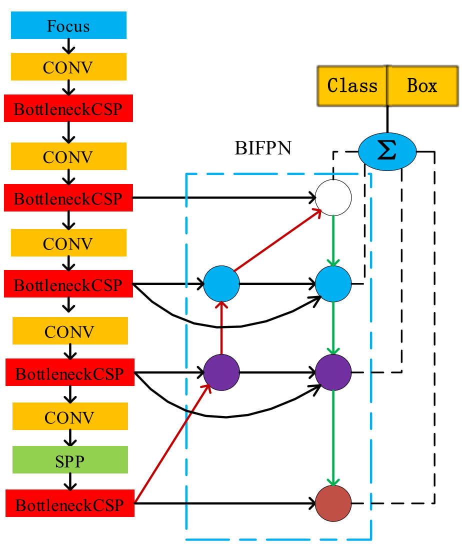

FIGURE 3. YOLOv5 optimization.

B. MODEL TRAINING BASED ON TRANSFER LEARNING

This study uses data sets for model training to train the blind guiding robot. In order to further broaden the data set and diversify the data of the training model, this study independently collected real-time traffic condition pictures from different angles, backgrounds, and lighting conditions as the training set and test set. Part of the image data is as follows:

FIGURE 4. Images of traffic lights.

This study used the transfer learning method. As shown in Figure 5, this study first used labeled data from ImageNet Dataset to conduct preliminary training for the guiding robot. It then uses the homemade data set for secondary training and merges the two data sets to obtain a new data set. Through transfer learning, starting the training model from scratch is avoided, the efficiency of training and learning is greatly improved, the required cost is reduced, and high-quality data sets are obtained. After training the guiding robot several times, it finally realized the recognition of traffic lights.

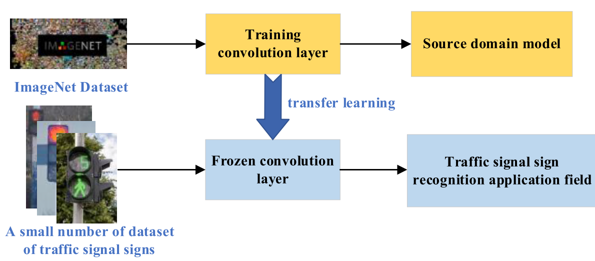

FIGURE 5. Training model of transfer learning.

Finally, the trained model was combined with OpenCV. In the test and real road conditions, the guiding robot can accurately recognize traffic lights, thus providing a safety guarantee for the blind to travel.

V. RESULTS AND ANALYSIS

A. OPTIMIZATION OF YOLOV5

To verify the processing effect of Kalman filter and the effect of cascade PID control in speed adaptation, this study selected a common pedestrian section as the test section. The sampling time was set at 50 ms, the distance was set at 1 m between the robot and the user, and the guide test was conducted. After Kalman filter processing, the man-machine relative distance control and speed adaptation data are shown in Figure 6 and 7, respectively.

As can be seen from Figure 6, the maximum fluctuation range of the original measured distance x_n is 0.58 m, and the noise is relatively large. These noisy data adversely affect the stability of the robot's control system, increasing the risk of potential loss of control."

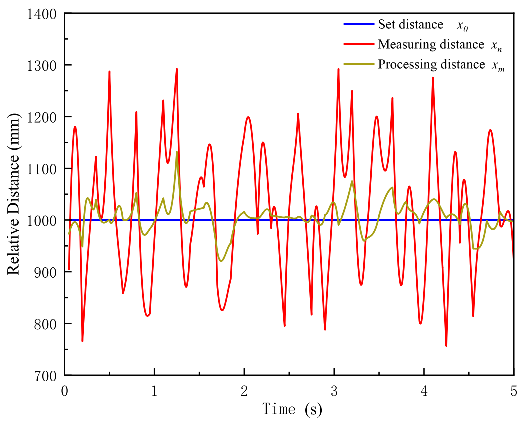

FIGURE 6. Man-machine distance changes with time before and after Kalman filter processing.

After being processed by Kalman filter, the changes in relative man-machine velocity over time are depicted in Figure 7. The average fluctuation range of the original relative velocity v_n is 0.68 m/s. Because the relative velocity v_n is obtained through two different operations of the adjacent distance, the local trend lines of the two groups of data are similar, the overall large fluctuations are obvious, and the noise covariance R is large.

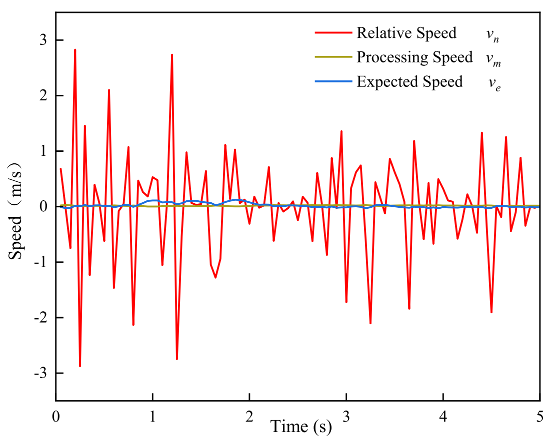

FIGURE 7. Man-machine speed changes with time before and after Kalman filter processing.

From the data processed in Fig. 6 and 7 and Table 1, it is evident that the application of the Kalman filter has significantly improved the results. The average fluctuation range of processing distance x_m drops below 0.06 m, and the average fluctuation range of processing speed v_m drops below 0.19 m/s. The control fluctuated within 13.1% of the set distance x_0, effectively suppressing most of the noise.

TABLE 1. Data characteristics before and after processing.

Data characteristics	Measuring distance x_n(m)	Processing distance x_m(m)	Relative velocity v_n(m/s)	Processing velocity v_m (m/s)
Average fluctuation range	0.17	0.06	0.68	0.19
Standard deviation	0.16	0.04	0.91	0.18

Table 1 shows that after treatment, the standard deviation of relative distance x_m decreases to 0.04 m, and the standard deviation of relative velocity v_m decreases to 0.18 m/s. The speed of the robot controlled by the cascade PID can match the speed of the blind person very well, and the speed of the guiding robot can be truly adaptive.

In practical applications, it is important for the robot to autonomously adapt to the relative distance in order to enter the initial state of the guide mode. When the robot is placed in different initial positions, the autonomous adaptation process of the robot is shown in Figure 8.

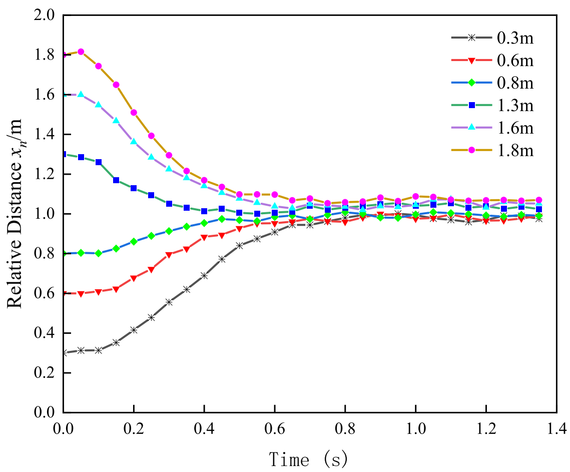

FIGURE 8. Different relative distance autonomous adaptation process.

Under different initial relative distances, the machine can stably control the relative distance to 1 m (set distance x_0) within 0.7 s. Moreover, the average relative velocity value was 1.15 m/s, the speed changed smoothly, and the control was more stable. This study verified the stable dynamic adaptive ability of the guiding robot at different initial distances.

B. TEST OF TRAFFIC LIGHT RECOGNITION

Data augmentation is very important for improving the performance of deep learning [26]. Data collected from traffic light samples as shown in Table 2, then expanded the original data set and fused it with the ImageNet data set to build our own data set.

TABLE 2. Fewer sample data sets.

Model	Total	Proportion (%)
Red	250	43.5
Green	260	45.2
Amber	65	11.3

The guiding robot system was equipped with an Intel NUC11PHi7 microcomputer as the core processor, which adopted the optimized YOLOv5 method to detect and recognize real traffic light images. The results are shown in Figure 9, and the processing time can reach 33 ms. As can be seen from the figure, this method can accurately locate and identify the traffic signals in the image.

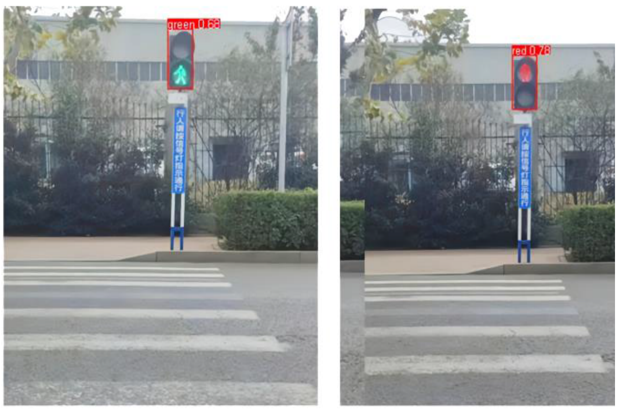

FIGURE 9. Traffic Light Identification Results. (a) green light, (b) red light.

In a real experimental environment, videos of traffic lights in different sections were selected to carry out recognition tests of red, green, and amber lights. Each video contained 120 image frames. The experimental results are listed in Table 3.

TABLE 3. Identification performance of traffic lights.

Target type	Number of Videos	Detection Rate (%)	Recognition Rate (%)
Red	76	97.62	95.43
Green	78	96.95	94.95
Amber	49	95.63	94.32

As can be seen from the experimental results, the detection rate and recognition rate of the guiding robot in a real traffic light environment were more than 94%. The recognition accuracy (detection rate $\times$ recognition rate) of each group was 93.16%, 92.05%, and 90.20%, respectively, all exceeding 90%. The overall recognition accuracy rate was 91.88% and the confirmed confidence probability was 0.95. It can be seen that the confidence intervals are (90.58%, 93.16%), indicating that the system can recognize traffic lights accurately, effectively avoid interference, adapt to complex environment, and meet the guiding robot's recognition of traffic lights.

C. ADVANTAGES OF OUR GUIDING ROBOT SYSTEM IN VARIOUS ASPECTS

To demonstrate the advantages of our proposed design for the blind guidance robot system in the current stage of products, we compared it with existing products [27] in terms of obstacle avoidance technology and visual recognition, as shown in Table 3. It can be observed that our robot exhibits outstanding performance in obstacle avoidance technology, visual recognition capability, and user experience.

TABLE 4. Comparative analysis of research.

	Our study	Bai 's wearable guide device	Li 's wearable guide device	Chuang's intelligent guide dog
Obstacle Avoidance Technology	Double guarantee: LIDAR+ CCD camera	Depth camera + ultrasonic range finder	RGB-D camera and IMU real-time detection	Multiple fisheye cameras+ Jetson TX1
The Degree of Visual Recognitio n	Deep Learning (YOLOv5) Accuracy: 91.88%	Identify indoor obstacles	Only identify indoors	Only support identificati on guide line
Contains Functions	Speed adaptation, Traffic signal recognition	Autonomo us path planning	3D acoustic feedback mechanism	High torque motor support handle tension
Sphere of application	Suitable for indoor and outdoor	Suitable for indoor	Suitable for indoor	Only suitable for tracing
Factor of safety	Excellent	Fair	Fair	Good

VI. CONCLUSION

In this paper, a hexapod wheel-foot robot based on independent design is proposed as mobile carrier platform. THE cascade PID control based on Kalman filter processing is used to realize human-machine speed adaptation. And the method of combining the optimized YOLOv5 with transfer learning is used to realize the recognition of traffic lights. The main conclusions are as follows:

(1) The Kalman filter algorithm and cascade PID speed control algorithm are used to achieve autonomous control of the speed of the guiding robot autonomously, and realize the relative distance deviation between the man and machine control within 13.1% and man-machine relative speed deviation control within 0.3 m/s. When the man-machine distance gap is large, the robot can timely control the man-machine distance to the set distance within 0.7 s.

(2) The system realizes the detection and recognition of traffic lights by optimizing YOLOv5 visual recognition algorithm and transfer learning method. The recognition accuracy of each signal lamp is more than 90% and the overall recognition rate reached 91.88% in the real scenario.

In addition, we innovatively apply these methods to the field of guiding robots for individuals with visual impairment, improving the synergy and interaction between guiding robots and users. The incorporation of multiple intelligent modules, such as voice interaction, GPS positioning, and posture control, greatly enhances the capabilities of the guidance robot in assisting individuals with visual impairments. thereby laying a theoretical foundation for the practical application of the guiding robot.

REFERENCES

[1] World Health Organization. (2021). World Vision Report. [Online]. Available: https://www.who.int/zh/news-room/fact-sheets/detail/blindness-and-visual-impairment

[2] Y.-H. Chang, N. Sahoo, and H.-W. Lin, "An intelligent walking stick for the visually challenged people," in *Proc. IEEE Int. Conf. Appl. Syst. Invention (ICASI)*, Chiba, Japan, Apr. 2018, pp. 113–116.

[3] J. Batliwala, S. Chauhan, K. Dedge, and P. R. Patil, "Smart blind stick for the visually impaired," *Int. J. Sci. Advance Res. Technol. (IJSART)*, vol. 6, 2020.

[4] S. Suman, S. Mishra, K. S. Sahoo, and A. Nayyar, "Vision navigator: A smart and intelligent obstacle recognition model for visually impaired users," *Mobile Inf. Syst.*, vol. 2022, pp. 1–15, Mar. 2022.

[5] A. Dernayka, M.-A. Amorim, R. Leroux, L. Bogaert, and R. Farcy, "Tom Pouce III, an electronic white cane for blind people: Ability to detect obstacles and mobility performances," *Sensors*, vol. 21, no. 20, p. 6854, Oct. 2021.

[6] J. Bai, S. Lian, Z. Liu, K. Wang, and D. Liu, "Virtual-blind-road following-based wearable navigation device for blind people," *IEEE Trans. Consum. Electron.*, vol. 64, no. 1, pp. 136–143, Feb. 2018.

[7] Y.-Z. Hsieh, S.-S. Lin, and F.-X. Xu, "Development of a wearable guide device based on convolutional neural network for blind or visually impaired persons," *Multimedia Tools Appl.*, vol. 79, nos. 39–40, pp. 29473–29491, Oct. 2020.

[8] M. A. Rahman, S. Siddika, M. A. Al-Baky, and M. J. Mia, "An automated navigation system for blind people," *Bull. Electr. Eng. Inform.*, vol. 11, no. 1, pp. 201–212, Feb. 2022.

[9] M. Pravin and T. V. P. Sundararajan, "VLC based indoor blind navigation system," in *Proc. 9th Int. Conf. Comput., Commun. Netw. Technol. (ICCCNT)*, Bengaluru, India, Jul. 2018, pp. 1–6.

[10] T.-K. Chuang, N.-C. Lin, J.-S. Chen, C.-H. Hung, Y.-W. Huang, C. Teng, H. Huang, L.-F. Yu, L. Giarré, and H.-C. Wang, "Deep trail-following robotic guide dog in pedestrian environments for people who are blind and visually impaired—Learning from virtual and real worlds," in *Proc. IEEE Int. Conf. Robot. Autom. (ICRA)*, Brisbane, QLD, Australia, May 2018, pp. 5849–5855.

[11] L. Tianyu, Y. Ruixin, W. Guangrui, and S. Lei, "Local path planning algorithm for blind-guiding robot based on improved DWA algorithm," in *Proc. Chin. Control Decis. Conf. (CCDC)*, Nanchang, China, Jun. 2019, pp. 6169–6173.

[12] D. Du, J. Xu, and Y. Wang, "Obstacle recognition of indoor blind guide robot based on improved D-S evidence theory," *J. Phys., Conf. Ser.*, vol. 1820, no. 1, Mar. 2021, Art. no. 012053.

[13] C.-L. Lu, Z.-Y. Liu, J.-T. Huang, C.-I. Huang, B.-H. Wang, Y. Chen, N.-H. Wu, H.-C. Wang, L. Giarré, and P.-Y. Kuo, "Assistive navigation using deep reinforcement learning guiding robot with UWB/voice beacons and semantic feedbacks for blind and visually impaired people," *Frontiers Robot. AI*, vol. 8, Jun. 2021, Art. no. 654132.

[14] D. Hutabarat, M. Rivai, D. Purwanto, and H. Hutomo, "LiDAR-based obstacle avoidance for the autonomous mobile robot," in *Proc. 12th Int. Conf. Inf. Commun. Technol. Syst. (ICTS)*, Surabaya, Indonesia, Jul. 2019, pp. 197–202.

[15] O. Nacir, M. Amna, W. Imen, and B. Hamdi, "YOLO v5 for traffic sign recognition and detection using transfer learning," in *Proc. IEEE Int. Conf. Electr. Sci. Technol. Maghreb (CISTEM)*, vol. 4, Tunis, Tunisia, Oct. 2022, pp. 1–4.

[16] J. An and J. Lee, "Robust positioning and navigation of a mobile robot in an urban environment using a motion estimator," *Robotica*, vol. 37, no. 8, pp. 1320–1331, Aug. 2019.

[17] S. N. Al-Bargothi, G. Qaryouti, and Q. M. Jaber, "Speed control of DC motor using conventional and adaptive PID controllers," *Indonesian J. Electr. Eng. Comput. Sci.*, vol. 16, no. 3, pp. 1221–1228, 2019.

[18] R. Neuville, J. S. Bates, and F. Jonard, "Estimating forest structure from UAV-mounted LiDAR point cloud using machine learning," *Remote Sens.*, vol. 13, no. 3, p. 352, Jan. 2021.

[19] S. Muro, Y. Matsui, M. Hashimoto, and K. Takahashi, "Moving-object tracking with LiDAR mounted on two-wheeled vehicle," in *Proc. 16th Int. Conf. Informat. Control, Autom. Robot.*, 2019, pp. 453–459.

[20] R. Kunjumon and G. S. Sangeetha Gopan, "Sensor fusion of camera and LiDAR using Kalman filter," in *Proc. Intell. Syst. (SCIS)*. Singapore: Springer, 2021, pp. 327–343.

[21] R. E. Kalman, "A new approach to linear filtering and prediction problems," *ASME J. Basic Eng.*, vol. 82, no. 1, pp. 35–45, Mar. 1960.

[22] M. A. Siddiqui, M. N. Anwar, S. H. Laskar, and M. R. Mahboob, "Closed-loop tuning of cascade controllers based on set-point experiment," *J. Eng. Res.*, vol. 8, no. 4, pp. 117–138, Nov. 2020.

[23] J. Redmon, S. Divvala, R. Girshick, and A. Farhadi, "You only look once: Unified, real-time object detection," in *Proc. IEEE Conf. Comput. Vis. Pattern Recognit.*, Jun. 2016, pp. 779–788.

[24] A. N. Gorban, E. M. Mirkes, and I. Y. Tyukin, "How deep should be the depth of convolutional neural networks: A backyard dog case study," *Cogn. Comput.*, vol. 12, no. 2, pp. 388–397, Mar. 2020.

[25] M. Tan, R. Pang, and Q. V. Le, "EfficientDet: Scalable and efficient object detection," in *Proc. IEEE/CVF Conf. Comput. Vis. Pattern Recognit. (CVPR)*, Seattle, WA, USA, Jun. 2020, pp. 10778–10787.

[26] C. Shorten and T. M. Khoshgoftaar, "A survey on image data augmentation for deep learning," *J. Big Data*, vol. 6, no. 1, pp. 1–48, Dec. 2019.

[27] Z. Li, F. Song, B. C. Clark, D. R. Grooms, and C. Liu, "A wearable device for indoor imminent danger detection and avoidance with region-based ground segmentation," *IEEE Access*, vol. 8, pp. 184808–184821, 2020.

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