International Journal of Electrical and Computer Engineering (IJECE)
Vol. 13, No. 6, December 2023, pp. 6174~6184
ISSN: 2088-8708, DOI: 10.11591/ijece.v13i6.pp6174-6184

Virtual environment for assistant mobile robot

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Article Info

Article history:

Received Apr 12, 2023
Revised May 4, 2023
Accepted Jun 26, 2023

Keywords:

Assistive robot
Convolutional network
Robot navigation
Round-trip time algorithm
Virtual environment
Voice recognition

ABSTRACT

This paper shows the development of a virtual environment for a mobile robotic system with the ability to recognize basic voice commands, which are oriented to the recognition of a valid command of bring or take an object from a specific destination in residential spaces. The recognition of the voice command and the objects with which the robot will assist the user, is performed by a machine vision system based on the capture of the scene, where the robot is located. In relation to each captured image, a convolutional network based on regions is used with transfer learning, to identify the objects of interest. For human-robot interaction through voice, a convolutional neural network (CNN) of 6 convolution layers is used, oriented to recognize the commands to carry and bring specific objects inside the residential virtual environment. The use of convolutional networks allowed the adequate recognition of words and objects, which by means of the associated robot kinematics give rise to the execution of carry/bring commands, obtaining a navigation algorithm that operates successfully, where the manipulation of the objects exceeded 90%. Allowing the robot to move in the virtual environment even with the obstruction of objects in the navigation path.

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1. INTRODUCTION

Assistive robotics began its development in the medical field with great success and permanent progress according to new technologies [1], [2]. Many of them are fixed robots with multiple degrees of freedom [3], but there are also robots oriented to social interaction [4], supervision and assistance of elderly people [5] even in residential environments [6].

An important aspect of an assistive robot is the ability to move in a medical-surgical [7] or industrial [8] environment. Where the relevance of artificial vision systems for robotic navigation is appreciated [9] which gives rise to many application tasks [10], [11]. Highlighting the integration of control algorithms with machine vision system for robust navigation [12] as well as deep learning-based pattern recognition algorithms [13] and specifically convolutional neural networks (CNN) [14].

Convolutional networks have strong applications in pattern recognition in two or multi-dimensional information, for example, with electrocardiogram (ECG) signals [15] or in images [16]. In the case of an assistive robot, a signal such as voice allows the user to interact with the robot in a natural way. Convolutional networks have been widely used in voice recognition with applications in emotion recognition [17], [18] or voice assistants [19].

Likewise, convolutional network architectures such as visual geometry group 16 (VGG16) [20], have been used in the field of industry 4.0 [21] and agriculture [22] for object detention by regions. Aspect required in a machine vision system that interacts with the environment. Thus, nesting the benefits of convolutional networks and assistive robotic systems, the development of a virtual environment for the evaluation of mobile assistive robotics algorithms is presented, where convolutional networks are used so that the user naturally commands a robotic action command and can navigate in a residential environment to accomplish the task.

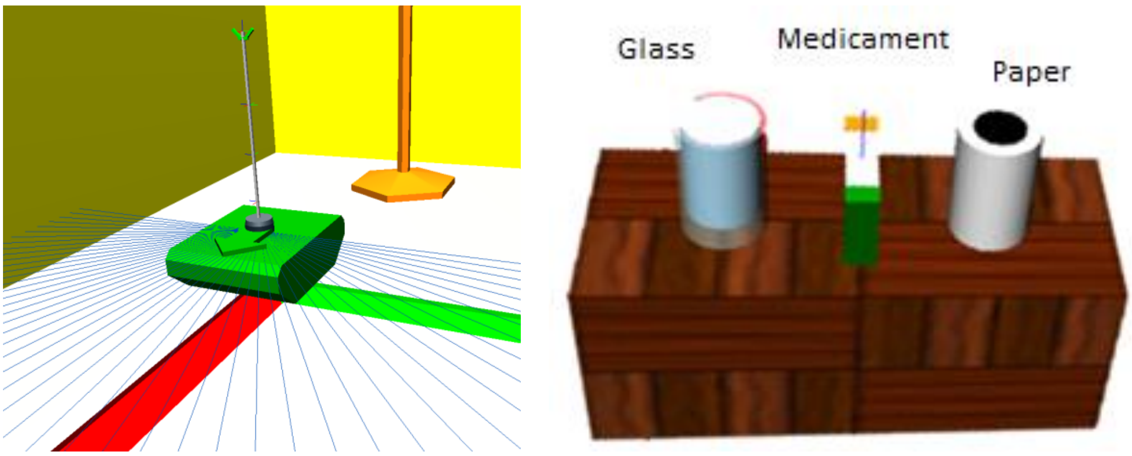
The past coronavirus disease 2019 (COVID-19) pandemic highlighted the need to generate solutions for people living in isolation or living alone, to provide support systems and/or care in their own homes. In the state of the art, although in [6] a robot for elderly care in a residential environment is presented, the exploration by autonomous navigation and interaction by voice commands is still under investigation, from which deep learning techniques are provided here to achieve the interaction of the user with the robot and of the robot with the environment.

Robot navigation is performed using the round-trip time (RTT) algorithm, which, compared to classical and heuristic techniques, stands out for its fast convergence and few tuning parameters [23]. A mobile robot that moves through a residential environment must be able to avoid obstacles, although low-cost schemes such as laser sensors have good performance [24], for this development we use an ultrasonic sensor that, given the virtual residential environment, presents a performance of easier reading and even lower cost, simplifying the overall algorithm and reducing execution times.

This article is divided into four sections, the present introduction addressing the state of the art and contribution to it. The methodology section deals with the environment recognition method used and the robotic interaction method. The result analysis section evaluates the integration of the algorithms used and finally the conclusions reached.

2. METHOD

The proposed robotic system consists of a mobile capable of recognizing basic voice commands, oriented to perform an action, and received by the user. Based on the recognition of a valid command that implies the action of bringing or carrying an object and the destination place, the robot will move through the environment, Figure 1 shows this concept. Figure 1(a) shows the mobile robot and its actuator, the interaction point depends to the object desire from a glass, medicament or paper Figure 1(b). Next, the algorithms used for the recognition by the robot and its interaction with the environment are explained.



(a) (b)

Figure 1. Interaction base elements for assistive robotic, (a) mobile robot and interaction arm and (b) objects of interest

2.1. Robot recognition

The recognition by the robot is given in two aspects: the recognition of the voice command and the recognition of the objects with which it will assist the user. This is done through a machine vision system based on the red green blue (RGB) capture of the scene where the robot is located. In relation to each captured image, a VGG16 transfer learning network is used to identify the objects of interest, in the case of towel, glass, paper and medicine.

For human-robot interaction by voice, a neural network of 6 convolution layers is used, each with a filter ratio and number of filters of 7/32, 5/32, 3/64, 3/64, 2/128 and 3/128, oriented to recognize the commands to bring and take, as well as locations in the residential environment kitchen, bathroom, bedroom and living room. For both cases a 2.30 GHz Intel Core i7 computer with NVIDA GeForce RTX 3070 graphics unit is used.

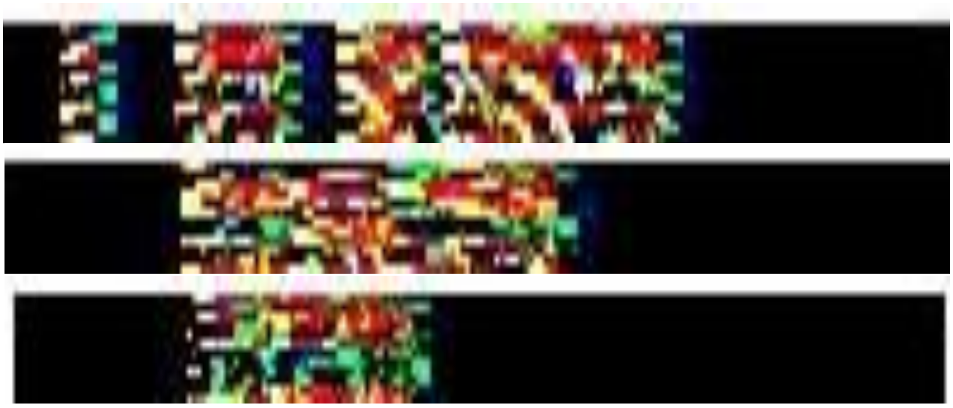
The voice commands guide the action and displacement of the robot, for the case are of the type “robot bring glass to the kitchen”, “robot bring toilet paper”. So, the input to the neural network recognition system corresponds to the processing of the voice input by extracting the MEL frequencies and their derivatives according to (1) to (3) [25]. Figure 2 illustrates the type of network input Figure 2(a) and its training result Figure 2(b) and Figure 3 shows flowchart voice command identification system.

$$Cc'_n = \left(1 + \frac{L}{2}\sin\left(\frac{\pi n}{L}\right)\right) Cc_n, \qquad n = 0, \dots, C \tag{1}$$

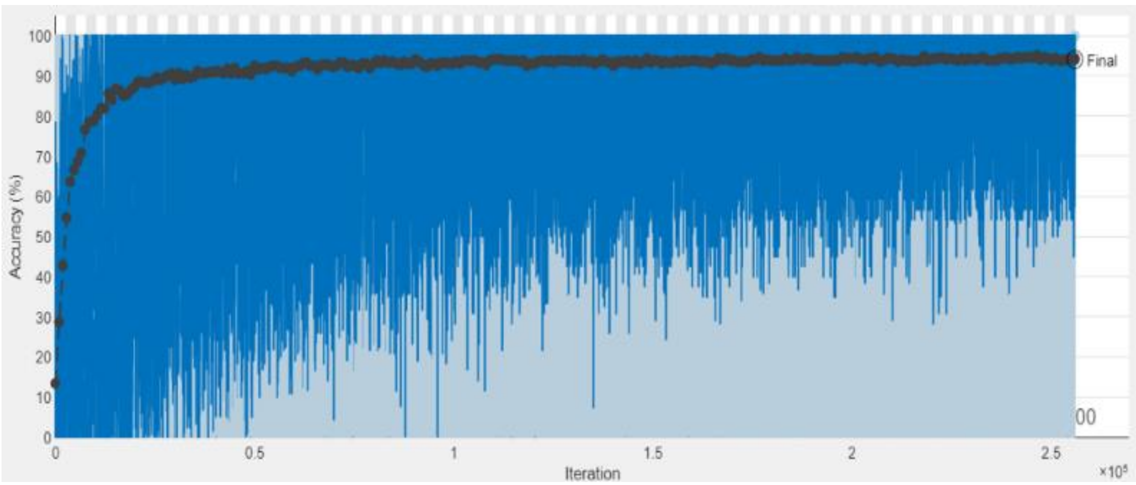
$$\Delta Cc' = \frac{\sum_{n=1}^{N} n(Cc'_{t+n} - Cc'_{t-n})}{2\sum_{n=1}^{N} n^2}, \qquad t = 1, \dots, N_f \tag{2}$$

$$\Delta\Delta Cc' = \frac{\sum_{n=1}^{N} n(\Delta Cc'_{t+n} - \Delta Cc'_{t-n})}{2\sum_{n=1}^{N} n^2}, \qquad t = 1, \dots, N_f \tag{3}$$

By means of VGG16 the robot manages to distinguish the base objects of the actions to be executed, the training is performed with 400 images of the 4 different desired classes paper, towel, glass, medicine. The training is performed using an ADAM optimizer at 25 epochs and a learning rate of 1 to 5. Figure 4 illustrates the final learning and some of its activation filters, for examples of toilet paper and a cup.



(a)



(b)

Figure 2. Voice command identification network input and training (a) example network input and (b) network training

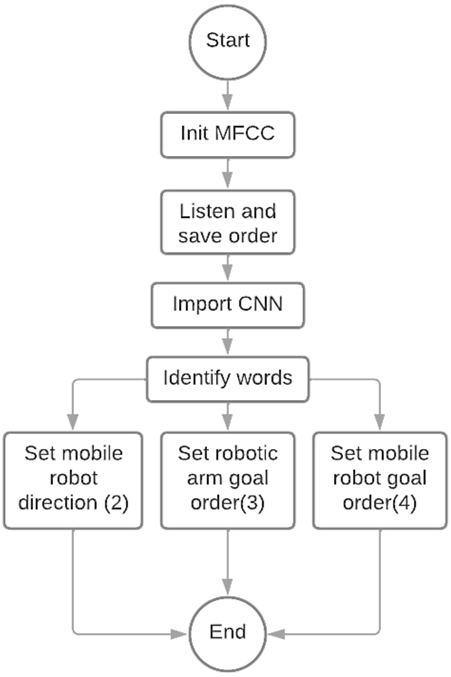


Figure 3. Flowchart voice command identification network

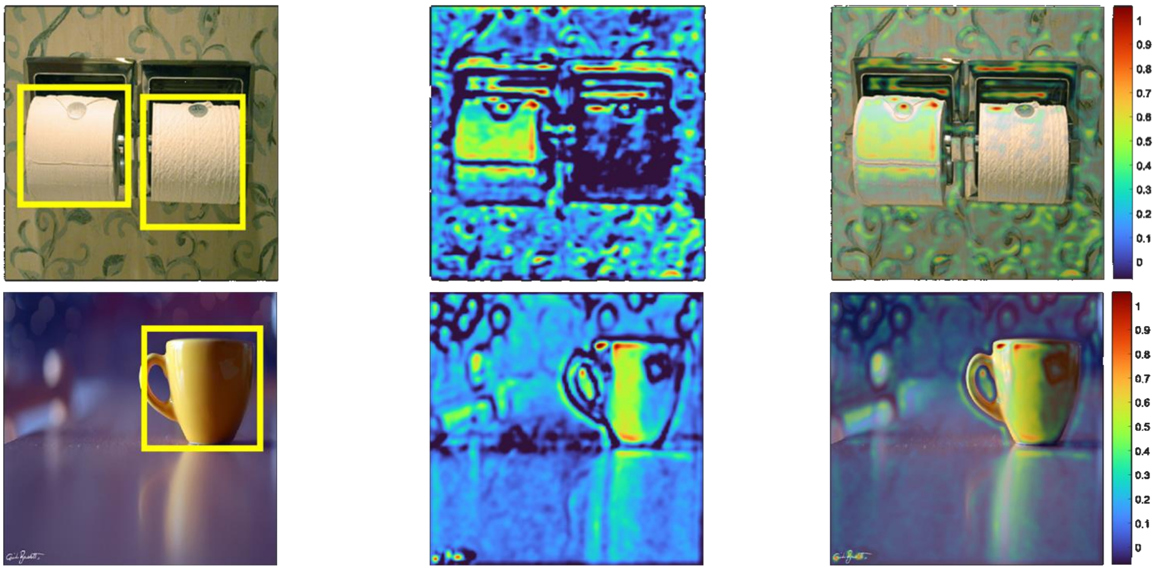


Figure 4. Identification of objects using the VGG16 network and activations

2.2. Robotic interaction

Once the action to be performed by the robot has been identified and where, it should proceed to navigate to the destination and operate the robotic arm to drop off or pick up any of the objects, Figure 5 shows the simulation environment used for testing. Figure 6 shows the kinematics of the robotic arm, and Table 1 the Denavid-Hartemberg parameters that allow to manipulate it to the location of the object. Where the centroid of the bounding box that generates the identification by VGG16, is used to locate the robot end-effector.

Once the action to be performed by the robot has been identified and the robot must navigate to the destination using the rapidly-exploring random tree (RRT*) algorithm [26], the robot dimensions Figure 7 are required to ensure collision-free travel with the edges (walls or objects). The process illustrated in Figure 8 involves stopping the mobile robot over a radius of 2 cm around the target and staying 4 cm away from the edges. The aim is to avoid unintentionally deflecting the mobile robot near the end point to adjust the most appropriate orientation of the mobile robot towards the target (platform with objects) and finally adjust the configuration of the robotic arm in order to pick up the object indicated in the voice command by inverse kinematics. Navigation flowchart and navigation path final can be seen in Figure 8(a) and (b).

Figure 5. Residential environment and interaction environments

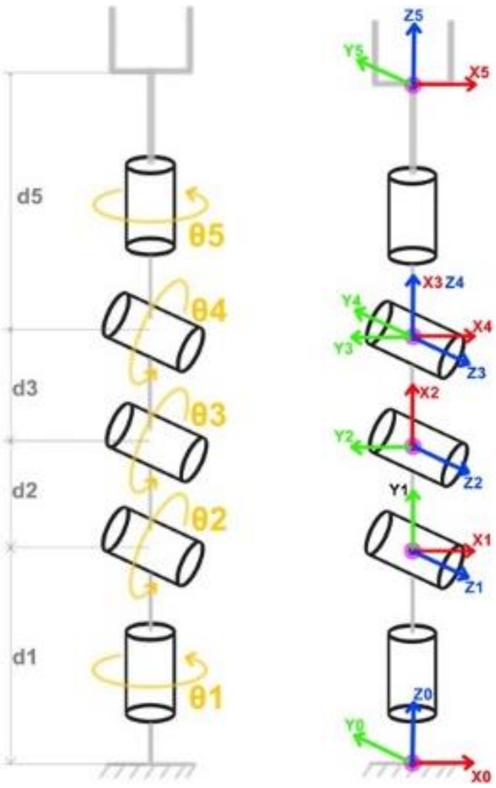


Figure 6. Robotic arm kinematics

Table 1. Denavid-Hartemberg

Articulation	θ	d	a	α
1	θ1*	d1	0	90°
2	θ2*+90°	0	d2	0
3	θ3*	0	d3	0
4	θ4*-90°	0	0	-90°
5	θ5*	D5	0	0

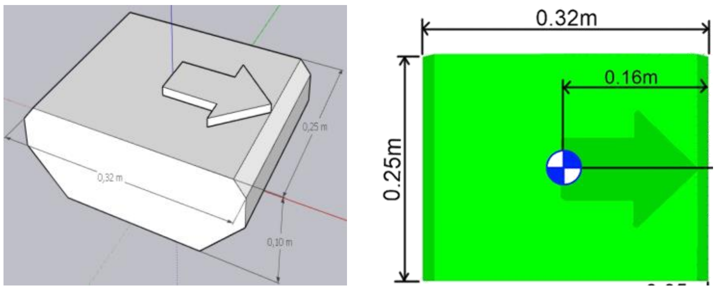
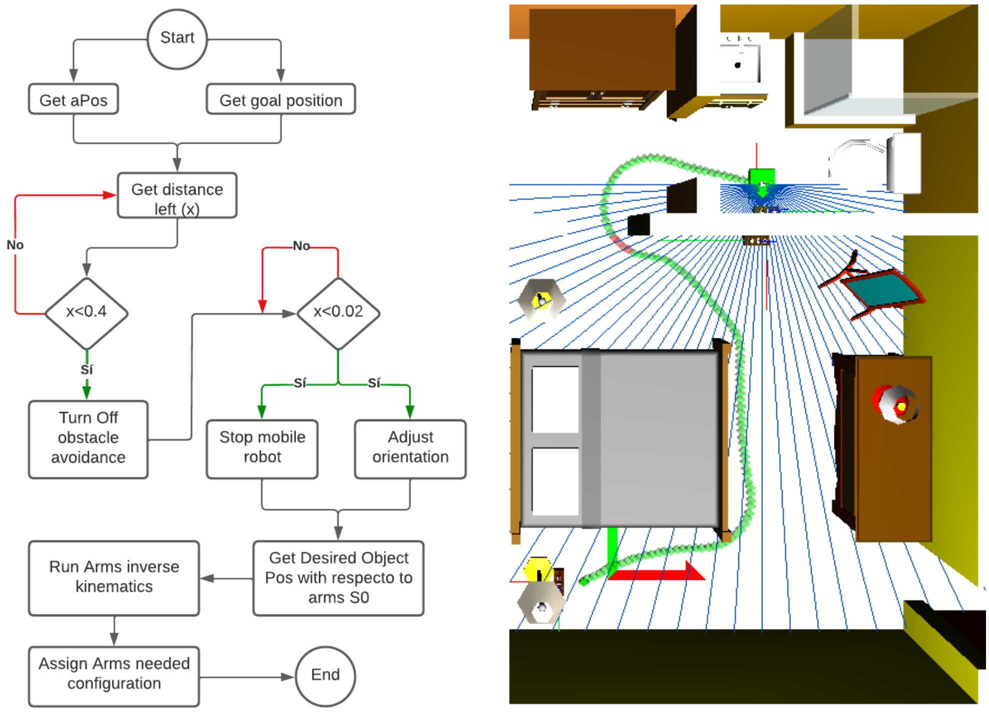


Figure 7. Overall dimensions of the robot



(a) (b)

Figure 8. Navigation method (a) navigation flowchart and (b) navigation path final

Difficulties were evidenced in generating smooth trajectories with obstacle avoidance, which led the robot to make 360-degree turns to solve this a proportional integral derivative (PID) control algorithm was implemented. The tuning of the controller parameters was obtained from the motor characterization of each axis, so that a critically damped response to directional changes was achieved.

3. RESULTS AND DISCUSSION

Once the robot operation parameters are established, using the flowchart illustrated in Figure 8, functionality tests are performed to identify individually the components of the voice commands directed to the robot (place, object, and action), as well as to validate the generation of a valid global trajectory to guide the mobile robot to or from a given destination. It is also required to establish the obstacle avoidance performance in the course of the global trajectory tracking and the assignment of a valid pose to the robotic arm in order to guide the end effector towards a given object.

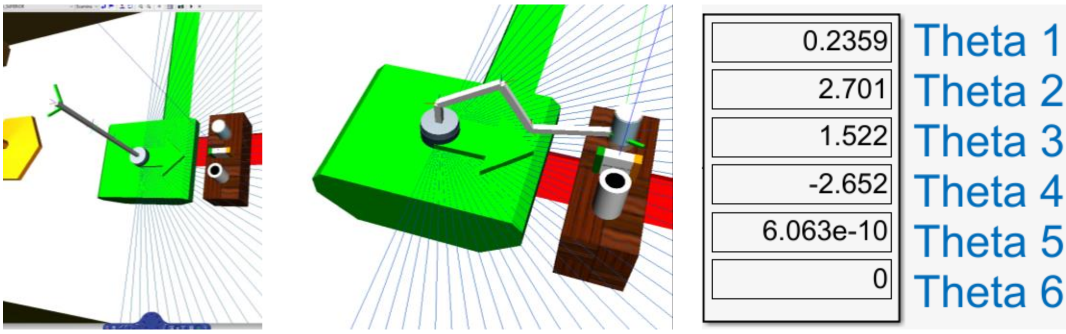
Figures 9 and 10 allow establishing a framework of the testing environment, both in the navigation from the initial to the final point within the residential environment Figure 9, as well as the interaction with the environment under the desired action command Figure 10. Based on these tests, the ability of the assistive robot to identify the target location, of the action commands in carry and bring operations and finally with respect to the global navigation is then analyzed.

Figure 10 illustrates the final interaction process of the assistive robot when reaching and detecting the object of interest. From the initial position Figure 10(a) it moves the gripper to the object grasp Figure 10(b), by using the kinematics of the robot arm carrying Figure 10(c) it by using the kinematics of the robotic arm that carries it.

To identify individually the components of the voice commands directed to the robot (place, object, action), a total of 100 tests were performed, 20 for each category Table 2. Excellent performance was obtained when identifying most of the place categories, with most of these exceeding an accuracy of 90%. The overall confidence level reduction is down almost 10% from the CNN network training (~99.42%). Variation is identified due to ambient noise influencing the microphone input, being different in the training database collection and in the tests performed, causing the decrease in the accuracy acquired in these tests.

A total of 100 tests were performed for object identification, 33 for each category Table 3. Excellent performance was obtained when identifying most object categories, all cases exceeding an accuracy of 91%. The overall confidence level reduction is down almost 8.6% with respect to the CNN network training (~99.63%), again due to the noise presented in the command recording.

Figure 9. Navigation tests



(a) (b) (c)

Figure 10. Robotic arm (a) starting position, (b) final position, and (c) kinematic validation

Table 2. Destination identification by voice command

	Order Place				
Place	Bedroom	Bathroom	Study room	Kitchen	Living room
#Successes	20	18	18	19	15
#Tests	20	20	20	20	20
Accuracy	100%	90%	90%	95%	75%

Table 3. Object identification by voice command

	Order Object		
Object	Paper	Glass	Medicine
#Successes	30	31	32
#Tests	33	33	34
Accuracy	91%	94%	94%

A total of 100 tests were performed for action identification, 50 for each type of command (carry or fetch). A total of 100 tests were performed for the identification of the initiating command "robot" Table 4. Excellent performance was obtained when identifying most of the categories, exceeding 92% accuracy in all cases. The background noise generates a 6.58% reduction in the overall confidence level compared to the network training result. No stop command tests were performed on the entire virtual residential environment. However, by performing 10 isolated tests with the pronunciation of this word, it was possible to estimate an accuracy of 100% (10/10) in its recognition.

Table 4. Action identification by voice command

Action	Robot	Carry	Bring
#Successes	95	46	47
#Tests	100	50	50
Accuracy	95%	92%	94%

The generation of a valid global trajectory to guide the mobile robot to or from a given destination was tested by the performance of the RRT* algorithm in finding a valid global trajectory path. Although on some occasions the RRT* algorithm determined more appropriate paths than others, this algorithm was at all times able to find a valid path by which the intention of routing the robot to the requested destination would be fulfilled Table 5. Subsequent to the generation of the global trajectory, and in conjunction with the identified command (carry or bring), tests were performed to check the effectiveness of the obstacle avoidance algorithm in finding its way to the destination, avoiding any possible accident.

Table 5. Global planning using RRT* algorithm

Place	Bedroom	Bathroom	Study room	Kitchen	Living room
#Successes	20	20	20	20	20
#Tests	20	20	20	20	20
Accuracy	100%	100%	100%	100%	100%

The following results were obtained for the algorithm with and without the implementation of the PID to smooth the robot redirection between the obstacle-free path and the global trajectory. At least 1 impact (collision) was considered as a failed test, where without PID the average success rate was 28% Table 6. With the proportional–integral–derivative controller the average success rate was 66% Table 7. The collision cases occurred when the robot was obstructed at close distances that did not allow the algorithm to change trajectory in a timely manner.

Table 6. Obstacle avoidance without PID

	Place	Bedroom	Bathroom	Study room	Kitchen	Living room
Carry	#Successes	2	1	3	0	2
	#Tests	10	10	10	10	10
	Accuracy	20%	10%	30%	0%	20%
Bring	#Successes	8	1	2	6	3
	#Tests	10	10	10	10	10
	Accuracy	80%	10%	20%	60%	30%

Table 7. obstacle avoidance with PID

	Place	Bedroom	Bathroom	Study room	Kitchen	Living room
Carry	#Successes	4	3	3	3	2
	#Tests	5	5	5	5	5
	Accuracy	80%	60%	60%	60%	40%
Bring	#Successes	5	3	3	3	4
	#Tests	5	5	5	5	5
	Accuracy	100%	60%	60%	60%	80%

When the target is reached, a valid pose is assigned to the robotic arm in order to guide the end effector towards the desired object. In this aspect, the effectiveness of the inverse kinematics algorithm in determining an appropriate pose for the manipulator robot was verified, by means of which, starting from the point reached by the mobile robot, the end effector was guided to a sufficient position in which it would specifically reach the previously indicated object.

Table 8 shows that the percentage of success with which the inverse kinematics algorithm found an appropriate pose for the manipulation of the object exceeded 90%, regardless of the previously indicated object. This level of effectiveness is considered formidable considering the variability of the position of the reference system of the robotic arm, which is directly dependent on the path taken by the mobile robot towards the target.

Table 8. Order object

Action	Robot	Carry	Bring
#Successes	30	31	32
#Tests	33	33	34
Accuracy	91%	94%	94%

4. CONCLUSION

The development of an assistive robot using voice commands for human-machine interaction in a residential environment was demonstrated. The convolutional networks allowed the adequate recognition of words and objects, which through the associated kinematics lead to the execution of carry/bring commands. Where the final performance is lower than that obtained in the training stage, due to the inherent noise of the environment that cannot be considered in the same conditions during training. This leads to the fact that the robot should be requested to ask the user to reconfirm the command or repeat it for validation as an external solution to pattern recognition.

The navigation algorithm operates satisfactorily allowing the robot to move adequately in the environment and considering slight changes in the environment (dynamic obstacles), as long as they are given with the necessary anticipation for the convergence of the algorithm. The speed of the robot was kept low for safety purposes with the environment, but given the possibility of collision with people, due to the type of environment.

ACKNOWLEDGEMENTS

The authors are grateful to Universidad Militar Nueva Granada and Universidad de Los Llanos. Special grateful to the Vice-rectory for Research of the Universidad Militar Nueva Granada, for the funding of this project with code IMP-ING-3405 (validity 2021-2022) and titled "*Prototipo robótico móvil para tareas asistenciales en entornos residenciales*".

REFERENCES

[1] A. Kakibuchi, F. Ito, T. Kokabu, H. Okimura, O. Takaoka, and T. Mori, "Robot-assisted laparoscopic hysterectomy for early-stage endometrial cancer with massive uterine leiomyomas: A case report," *International Journal of Surgery Case Reports*, vol. 97, Aug. 2022, doi: 10.1016/j.ijscr.2022.107473.

[2] L. Zhu, J. Shen, S. Yang, and A. Song, "Robot-assisted retraction for transoral surgery," *IEEE Robotics and Automation Letters*, vol. 7, no. 4, pp. 12102–12109, Oct. 2022, doi: 10.1109/LRA.2022.3211491.

[3] S. Shrey, S. Patil, N. Pawar, C. Lokhande, A. Dandage, and R. R. Ghorpade, "Forward kinematic analysis of 5-DOF LYNX6 robotic arm used in robot-assisted surgery," *Materials Today: Proceedings*, vol. 72, pp. 858–863, 2023, doi: 10.1016/j.matpr.2022.09.080.

[4] D. Dell'Anna and A. Jamshidnejad, "Evolving fuzzy logic systems for creative personalized socially assistive robots," *Engineering Applications of Artificial Intelligence*, vol. 114, Sep. 2022, doi: 10.1016/j.engappai.2022.105064.

[5] D. Gutman *et al.*, "Evaluating levels of automation with different feedback modes in an assistive robotic table clearing task for eldercare," *Applied Ergonomics*, vol. 106, Jan. 2023, doi: 10.1016/j.apergo.2022.103859.

[6] M. Luperto *et al.*, "User feedback and remote supervision for assisted living with mobile robots: a field study in long-term autonomy," *Robotics and Autonomous Systems*, vol. 155, Sep. 2022, doi: 10.1016/j.robot.2022.104170.

[7] G. Pivazyan, K. D. Cobourn, J.-M. Voyadzis, and F. A. Sandhu, "Use of computer navigation and robotics in adult spinal deformity," *Seminars in Spine Surgery*, vol. 34, no. 4, Dec. 2022, doi: 10.1016/j.semss.2022.100988.

[8] T. Wang, B. Chen, Z. Zhang, H. Li, and M. Zhang, "Applications of machine vision in agricultural robot navigation: a review," *Computers and Electronics in Agriculture*, vol. 198, Jul. 2022, doi: 10.1016/j.compag.2022.107085.

[9] P. Wei, X. Yu, Z. Di, X. Dai, B. Wang, and Y. Zeng, "Design of robot automatic navigation under computer intelligent algorithm and machine vision," *Journal of Industrial Information Integration*, vol. 28, Jul. 2022, doi: 10.1016/j.jii.2022.100366.

[10] R. Möller, A. Furnari, S. Battiato, A. Härmä, and G. M. Farinella, "A survey on human-aware robot navigation," *Robotics and Autonomous Systems*, vol. 145, Nov. 2021, doi: 10.1016/j.robot.2021.103837.

[11] J. A. Dulce-Galindo, M. A. Santos, G. V. Raffo, and P. N. Pena, "Distributed supervisory control for multiple robot autonomous navigation performing single-robot tasks," *Mechatronics*, vol. 86, Oct. 2022, doi: 10.1016/j.mechatronics.2022.102848.

[12] D. K. Mishra, A. Thomas, J. Kuruvilla, P. Kalyanasundaram, K. R. Prasad, and A. Haldorai, "Design of mobile robot navigation controller using neuro-fuzzy logic system," *Computers and Electrical Engineering*, vol. 101, Jul. 2022, doi: 10.1016/j.compeleceng.2022.108044.

[13] J. Sa, Z. Li, Q. Yang, and X. Chen, "Packaging defect detection system based on machine vision and deep learning," in *2020 5th International Conference on Computer and Communication Systems (ICCCS)*, May 2020, pp. 404–408, doi: 10.1109/ICCCS49078.2020.9118413.

[14] Y. Cheng, D. HongGui, and F. YuXin, "Effects of faster region-based convolutional neural network on the detection efficiency of rail defects under machine vision," in *2020 IEEE 5th Information Technology and Mechatronics Engineering Conference (ITOEC)*, Jun. 2020, pp. 1377–1380, doi: 10.1109/ITOEC49072.2020.9141787.

[15] M. Sepahvand and F. Abdali-Mohammadi, "A novel multi-lead ECG personal recognition based on signals functional and structural dependencies using time-frequency representation and evolutionary morphological CNN," *Biomedical Signal Processing and Control*, vol. 68, Jul. 2021, doi: 10.1016/j.bspc.2021.102766.

[16] G. Kaur *et al.*, "Face mask recognition system using CNN model," *Neuroscience Informatics*, vol. 2, no. 3, Sep. 2022, doi: 10.1016/j.neuri.2021.100035.

[17] M. Aslan, "CNN based efficient approach for emotion recognition," *Journal of King Saud University-Computer and Information Sciences*, vol. 34, no. 9, pp. 7335–7346, Oct. 2022, doi: 10.1016/j.jksuci.2021.08.021.

[18] Z. Yao, Z. Wang, W. Liu, Y. Liu, and J. Pan, "Speech emotion recognition using fusion of three multi-task learning-based classifiers: HSF-DNN, MS-CNN and LLD-RNN," *Speech Communication*, vol. 120, pp. 11–19, Jun. 2020, doi: 10.1016/j.specom.2020.03.005.

[19] P. Arun G and P. Annapurani K, "Design of an integrated learning approach to assist real-time deaf application using voice recognition system," *Computers and Electrical Engineering*, vol. 102, Sep. 2022, doi: 10.1016/j.compeleceng.2022.108145.

[20] K. S. Chandrasekar and P. Geetha, "Multiple objects tracking by a highly decisive three-frame differencing-combined-background subtraction method with GMPFM-GMPHD filters and VGG16-LSTM classifier," *Journal of Visual Communication and Image Representation*, vol. 72, Oct. 2020, doi: 10.1016/j.jvcir.2020.102905.

[21] J. Yan and Z. Wang, "YOLO V3+VGG16-based automatic operations monitoring and analysis in a manufacturing workshop under Industry 4.0," *Journal of Manufacturing Systems*, vol. 63, pp. 134–142, Apr. 2022, doi: 10.1016/j.jmsy.2022.02.009.

[22] Z. Song, L. Fu, J. Wu, Z. Liu, R. Li, and Y. Cui, "Kiwifruit detection in field images using Faster R-CNN with VGG16," *IFAC-PapersOnLine*, vol. 52, no. 30, pp. 76–81, 2019, doi: 10.1016/j.ifacol.2019.12.500.

[23] H. S. Hewawasam, M. Y. Ibrahim, and G. K. Appuhamillage, "Past, present and future of path-planning algorithms for mobile robot navigation in dynamic environments," *IEEE Open Journal of the Industrial Electronics Society*, vol. 3, pp. 353–365, 2022, doi: 10.1109/OJIES.2022.3179617.

[24] T. Van Nguyen, M. H. Do, and J. Jo, "MoDeT: a low-cost obstacle tracker for self-driving mobile robot navigation using 2D-laser scan," *Industrial Robot: the international journal of robotics research and application*, vol. 49, no. 6, pp. 1032–1041, Sep. 2022, doi: 10.1108/IR-12-2021-0289.

[25] Y. Qian, M. Bi, T. Tan, and K. Yu, "Very deep convolutional neural networks for noise robust speech recognition," *IEEE/ACM Transactions on Audio, Speech, and Language Processing*, vol. 24, no. 12, pp. 2263–2276, Dec. 2016, doi: 10.1109/TASLP.2016.2602884.

[26] B. B. Maseko, C. E. van Daalen, and J. Treurnicht, "Optimised informed RRTs for mobile robot path planning," *IFAC-PapersOnLine*, vol. 54, no. 21, pp. 157–162, 2021, doi: 10.1016/j.ifacol.2021.12.027.

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