Mechatronics 100 (2024) 103184

Contents lists available at ScienceDirect

Mechatronics

journal homepage: www.elsevier.com/locate/mechatronics

Vision-based collaborative robots for exploration in uneven terrains ☆

Christyan Cruz Ulloa *, Javier Álvarez, Jaime del Cerro, Antonio Barrientos

Centro de Automática y Robótica (UPM-CSIC), Universidad Politécnica de Madrid-Consejo Superior de Investigaciones Científicas, 28006, Madrid, Spain

ARTICLE INFO

Keywords:
Artificial vision
Collaborative robots
Mechatronics
Perception
Robotics exploration

ABSTRACT

Exploring tasks in unknown environments has become a relevant search and rescue robotics approach. Ground robots are a better alternative to rescuers for first exploration. However, exploration progress is often limited by uneven terrains that exceed the kinematic capabilities of robots, including those with complex locomotion systems. This work proposes an innovative solution based on collaborative behaviours to overcome even terrains. A method employing two collaborative robots designed to operate in a marsupial configuration to surmount uneven terrains has been implemented. These robots, denoted as R1 (enhanced with a mobile ramp) and R2 (serving as an explorer), interact synergistically to expand the explored area autonomously. A state machine has been implemented to manage the progression of the mission, based on a perception (RGB-D) system, for both decision-making and autonomous execution of the process. In the initial stage, the terrain and ascent zones to be explored are characterized using point clouds and unsupervised learning. Subsequently, the second stage manages the interaction between the robots by controlling the R2 ascent through the R1 ramp using artificial vision algorithms and beacons. Outdoor tests have been performed to validate the method. The main results show an effectiveness of 95% in automatically identifying access zones.

1. Introduction

As a result of natural events such as earthquakes, hurricanes, or attacks, post-disaster scenarios generate completely devastated areas or cities, with totally or partially collapsed buildings, people dead or trapped, etc. The resulting complex scenarios represent a high risk to first responders and front-line equipment during search and rescue missions. Hence, a robot team is a good alternative for a first exploration.

Several global events, such as the Attack on the Twin Towers (USA-2001) [1], Fukushima nuclear accident (Japan - 2011) [2], Earthquake (Italy-2016) [3], Earthquake (Mexico-2017) [4] have set a precedent, in which there has already been an intervention of the search and rescue robots. Technological development and advances in robotics, communication and sensory systems have made it possible to develop specialized robots with custom instrumentation to develop primary explorations and assist first responders in Search and Rescue (SAR) missions.

In the SAR context, collaborative robotics is important since it addresses larger areas, increasing the efficiency and precision in early detection [5]. Among the main developments in this area are focused on data collection [6,7], reaching areas of risk or difficult access [8], inspection of areas devastated by a natural disaster [9] and victims identification [10–12]. Collaborative robots have a great advantage in accessing complicated areas (variable height, craters, etc.), as shown in [5]. There are robots with complex mechanical adaptations for exploration in these environments; however, their exploration is limited to zones with obstacles that do not exceed their characteristic geometry [13].

Environment exploration is currently one of the most significant challenges in Search and Rescue (SAR) robotics. This is because post-disaster conditions often result in disorganized terrains, limiting robotic exploration due to the presence of uneven terrains. Consequently, a series of technological challenges arise, including environment characterization, autonomy in exploration, and communication management; challenges that are difficult to address by a single robot—despite the sophisticated locomotion mechanisms currently developed—or by drones due to their battery limitations.

This work's main contribution presents a method to increase the explored area in uneven terrains. The method uses a team of two collaborative robots (R1 and R2) and multisensory processing to carry out the autonomous ascent to uneven zones. For this, the robots have been mechanically and sensorial equipped. R1 (Dr Robot Jaguar) has been equipped with a 2DoF ramp capable of generating a bridge between the

☆ This paper was recommended for publication by Associate Editor Yangmin Li.

* Corresponding author.
E-mail address: christyan.cruz.ulloa@upm.es (C. Cruz Ulloa).
URL: https://www.researchgate.net/profile/Christyan-Cruz (C. Cruz Ulloa).

https://doi.org/10.1016/j.mechatronics.2024.103184
Received 19 October 2023; Received in revised form 7 February 2024; Accepted 25 March 2024
Available online 6 April 2024

ground and the elevated area, allowing R2 to climb. Additionally, R1 has visual beacons and ToF sensors to assist R2 in ascent and descent autonomous. On the other hand, R2 is instrumented with an RGB-D sensor for data acquisition.

Vision-based algorithms and multisensory processing have been implemented to carry out the autonomous collaborative ascent, which consists of two stages. The first focuses on identifying the environment and defining the best area for the ascent. The algorithm uses point cloud processing, unsupervised learning techniques and a relationship proposed by the authors that involves the characterized parameters. On the other hand, the second stage involves an autonomous collaborative ascent. The proposed method has been tested in real environments, increasing the exploration coverage area as the main result.

This work has been developed as part of the TASAR (Team of Advanced Search and Rescue Robots) project, which is motivated by the use of terrestrial robots (UGV) to develop collaborative strategies for exploration in search and rescue missions [14], and is structured as follows. Section 2 shows the most relevant works related; Section 3 details the materials and methods. Section 4 shows the experiments and results. Finally, Section 5 presents the main findings.

2. Related work

Multi-robot systems present great advantages within the execution of missions, such as reducing exploration time, increasing explored areas, etc [7,15–17]. Depending on the type of robots, collaborative interactions between them can be generated to complement exploration tasks [18–20]. Other sophisticated alternatives have been extensively explored in the field of navigation in unstructured environments, such as robots with hybrid locomotion mechanisms (wheel-legged), as demonstrated in works by Chen et al. [21,22], proposing a method based on flexible gait transition to overcome unstructured terrains and obstacle avoidance. Additionally, the complementary design of lifting and transport platforms [23,24] can maximize robot capabilities, enabling the execution of complementary tasks such as transferring between environmental points.

Collaborative robots such as the marsupial [25,26] have a main robot or container, which takes one or smaller robots (passengers) to different places that are difficult for them to access, using an inclined platform on which these small robots climb robots are mostly autonomous. In contrast, the main robot is tele-operated. One of the applications of this collaborative robot is rescue, inspection, and environmental recognition [5,27].

Tracked robots are used mainly in raising or lowering uniform, non-irregular steps. This type of locomotion system in robots is widely used in search and rescue applications [28]. Some works focus on studying how adversarial teams of robots can be guided to a disadvantageous location and devising counter strategies to make team functioning more successful and secure [29].

The "Asguard" robot was developed for rough, flat terrain and stairs. It uses additional tilt feedback to make the controller versatile for flat terrain, steep slopes, and stairs. Asguard consists of twenty compatible legs mounted around four hip axes, which rotate individually, using an abstract model of quadruped locomotion [30].

Although the state-of-the-art presents initial approaches to joint alternatives for exploring unstructured terrains, most works focus on overcoming obstacles and terrains using complex locomotion systems, primarily integrating mechanisms such as wheel-leg and tracked-leg. While effective for obstacles and small elevations on the order of 10 centimetres, their applicability diminishes for outdoor terrains with significant disarray that exceeds these robots' kinematic capabilities. In the literature, no similar contribution has been identified to the approach presented in this work, which integrates collaborative and adaptive interaction among robots to explore uneven terrains.

Table 1
Elements used in the implemented method.

Amount	Component	Description
1	R1: Dr Jaguar	Tracked robot
1	HP camera (R1)	RGB camera
2	ToF sensor (R1)	Distance sensor
5	ArUco mark (R1)	Visual beacon
1	Lineal actuator (R1)	Inclination actuator
1	DC motor (R1)	Extension actuator
1	R2: Wall-e	Tracked robot
1	Real-Sense (R2)	RGB-D sensor
1	Nvidia Jetson Xavier-Nx (R2)	Embedded system

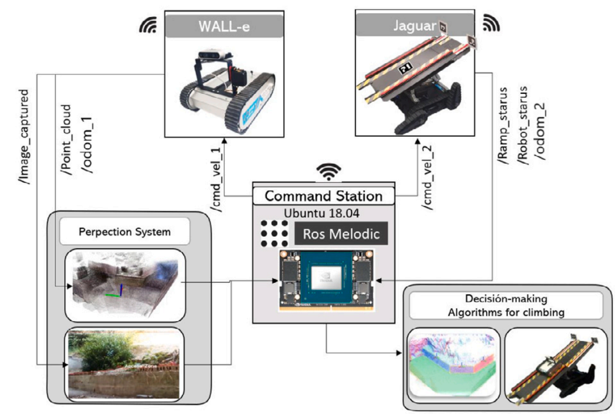

Fig. 1. Systems connection scheme and information flow.

3. Materials and methods

3.1. Hardware–software system architecture

The proposed implementation to address this problem focuses on a centralized multi-robot system based on ROS, a command post with a high-capacity computer and two mobile robots mechanically adapted and instrumented to carry out this task. The materials used are detailed in Table 1.

The robotic team consists of (R1) Dr. Robot Jaguar robot and Wall-e, a smaller tracked robot (R2). R1 is instrumented with a mobile ramp capable of regulating its extension and inclination to generate a bridge between the ground and the uneven exploration area. This ramp has four visual beacons on its top. The second robot is equipped with instrumentation for exploration (RGB-D sensor).

Fig. 1 shows the interconnection scheme of the systems, as well as the information flow of the most relevant sensors. The management of communications between computers, robots, and sensory and actuation information has been wholly developed through ROS due to its great potential to integrate multiple devices simultaneously, information management through topics and nodes.

3.2. Collaborative ascent - Robotic design

The collaborative ascent between the robots is essential to increase exploration. On the other hand, this task is also the most critical of the process since it is a task that carries a high risk of collisions, derailment and falls. This section is dedicated to systematizing the intelligence algorithms and analysing the sensory systems that perform this autonomously.

Fig. 2 shows the first phase, which involves CAD-CAM-CAE design and simulations performed in a Gazebo by assembling *xacro* files and ROS control packages to validate the concept and the execution of the ascent. A 2-degree-of-freedom instrumented ramp has been designed and implemented, coupled to the robot R1, serving as a bridge for

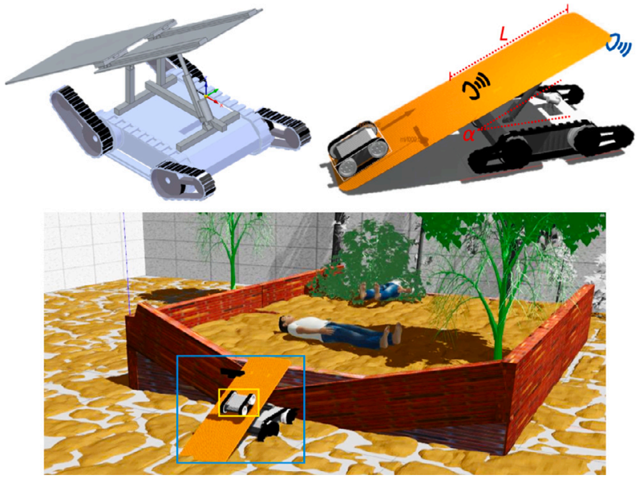

Fig. 2. Conceptualization of the collaborative ascent through simulation in Gazebo.

the ascent of R2. The controlled variables for the ramp are inclination and extension, as described by Eq. (1). Here, H corresponds to the height to be overcome, while A and e represent kinematic constants. This work utilized the ROS Melodic version and the navigation stack packages to manage mobility autonomy. For simulations in Gazebo, environments were recreated with terrain conditions close to reality to facilitate extrapolation, allowing testing of ascent strategies with different conditions in an initial phase. The files used in this work are available in the research group's GitHub repository https://github.com/Robcib-GIT/collaborative-marsupial-robots/tree/main.

$$\alpha_{(H)} = arcsen\left(\frac{H-A}{800-e}\right) \tag{1a}$$

$$d_{(\alpha)} = \frac{A}{sen(\alpha)} \tag{1b}$$

Fig. 2 shows the simulation concept; the 2 DoF of the platform made up of two plates mechanically coupled by rails and screw transmission systems, where α is the angle of inclination of the platform (0–55) [°], which is driven by a **linear actuator** capable of supporting up to 750 N. At the same time, the extension L (0–850) [mm] is controlled by a **DC motor** (with an encoder for position control) joint to a spindle that moves the ramp.

3.3. Automatic detection of the best ascent area

The testing phase was developed in outdoor environments at CAR-UPM facilities (40°26′21.5″N 3°41′18.1″W). The environments have been reconstructed using point clouds for this purpose ($PC_{[xyz]}$) employing the RGB-D sensor of R2 (Fig. 3-left). The method used for mapping is the RTAB-map, which has been widely discussed in the literature [31,32], from which the data related to the positioning of the robots have also been obtained.

Although the point cloud captured from the lower part provides some information from the upper part of the environment, several occluded areas may have relevant data. The second part of the method focuses on the $PC_{[xyz]}$ processing to determine the boarding area for R2, for which a down-sample has been calculated ($PC_{D[xyz]}$) to reduce the initial volume of the cloud and computational processing. Additionally, the noise present as outliers have been eliminated ($PC_{DO[xyz]}$) based on the local density method [33] defined by Eq. (2), which determines the probability that the point is an Outlier, if its value is great [0–1], determining its conservation or elimination based on a threshold:

$$Pro(P_i) = 1 - \frac{1}{k}\sum_{q_j \in K(p_i)} exp(\frac{-dist(P_i,Q_i)}{d_i}) \tag{2}$$

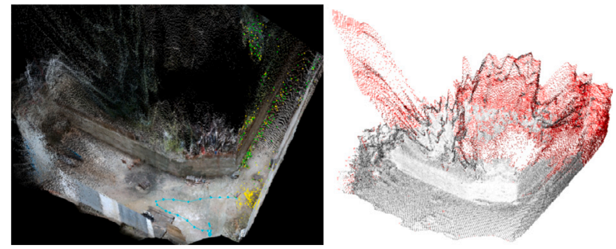

Fig. 3. Environmental analysis and point cloud processing.

P_i is the analysed point and Q_i is the neighbourhood, k is the number of neighbour points. Fig. 3-right shows the removal of outliers (in red); the grey points will be used for processing.

The unsupervised learning method **K-means** was used to determine the clusters. This process is executed cyclically until it detects if there are no changes in the newly assigned groups by minimizing sum of squared error (SSE) criterion is met, given by Eq. (3) [34]:

$$SSE = \sum_{j=1}^{k}\sum_{i=1}^{n_j}\left\|x_i^j - c_j\right\|^2 \tag{3}$$

Pseudocode 1 describes the synthesis followed for the automatic detection of the access zone, its coordinates and trajectory definition for the arrival of R1 and approach of R2.

Algorithm 1 Best Access Zone Definition

Data:
$PC_{[xyz]} \Leftarrow$ Point Cloud of Environm.
$Im_{[RGB]} \Leftarrow$ Image from R2.
$n \Leftarrow$ Clusters (seed #Random)
$PC\_Clust_{[1...n]} \Leftarrow [init]$
Result:
$v_{R1[l]}, v_{R1[\alpha]} \Leftarrow [0,0]$
$v_{R2[l]}, v_{R2[\alpha]} \Leftarrow [0,0]$
Data Preprocess:
$PC_{D[xyz]} \Leftarrow Downsample(PC_{[xyz]})at75\%$
$PC_{DO[xyz]} \Leftarrow Outliers(PC_{D[xyz]})ratio\_max = 0.1$
$PC_{DON[xyz]} \Leftarrow Normals(PC_{DO[xyz]})$
$PC\_Clust_{[1...n]} \Leftarrow Kmeans(PC_{DON[xyz]})$
while End_Clust is $False$ **do** ▷ Clusterization-Characterization of environment.
  $PC\_Clust\_New_{[1...n]} \Leftarrow [init]$
  $PC\_Clust\_New_{[1...n]} \leftarrow Kmeans(PC\_Clust_{[1...n]})$
  if SSE in $PC\_Clust\_New_{[1...n]}$ is min **then**
    $End\_Clust = True$
  end if
  $PC\_Clust_{[1...n]} = PC\_Clust\_New_{[1...n]}$
end while
for $i = 1$ in $len(PC\_Clust_{[1...n]})$ **do** ▷ Evaluation of Best Access Zone.
  $Area, m, h, l \leftarrow extract\_caract(PC\_Clust_{[1...n]})$
  if Area > min_access **then** and $Continuous\_Zone$ in $Im_{[RGB]}$
    $eval$ **eq.3** $(Fit\_Clust_{[1...n]})$
    $orden\_max\ PC\_Clust_{[1...n]}$
  end if
end for
if Best Zone is Defined **then** ▷ Authonomous Positioning R1-R2.
  $Def\_Path\_R1_{(RRT)} \leftarrow From(Pos\_R1(x,y))$ To $(PC\_Clust\_Max(x,y))$
  $eval\_Path\_R1(current\_pose, goal\_pose)$
  $publish(v_{R1[l]}, v_{R1[\alpha]}, \alpha, l)$
  $Def\_Path\_R2_{(RRT)} \leftarrow From(Pos\_R2(x,y))$ To $(PC\_Clust\_Max(x,y-wR1))$
  $eval\_Path\_R2(current\_pose, goal\_pose)$
  $publish(v_{R2[l]}, v_{R2[\alpha]})$
end if

All clusters are initially characterized to evaluate the optimal climbing zone in terms of dimensions (width w, length h)[mm] and surface inclination [°]. These data are used to feed Eq. (4) proposed by the authors, which allows obtaining the fitness of each zone and evaluates the best alternative for climbing. This equation directly involves the variables in such a way that the inclination negatively penalizes steep surfaces; the height is standardized according to the geometric limitations of the ramp, as is the width.

$$Fit\_Clust_{[1...n]} = |cos(m)| * (\frac{850\ [mm]}{h}) * (w - w_{R1}) \tag{4}$$

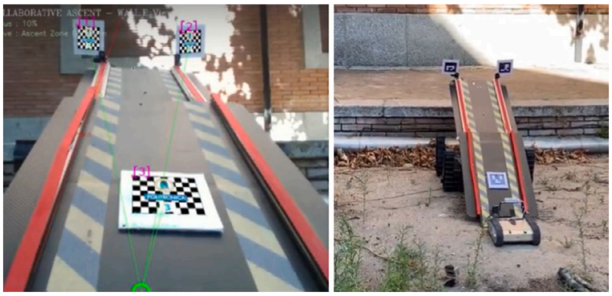

Fig. 4. Beacon detection system and estimation of distances-orientations.

3.4. Vision-based autonomous ascent-descent strategy

Before executing this stage, R1 and R2 must be positioned at the defined ascent point, and the ramp should be deployed towards the ascent zone. The trajectories for each robot are calculated using the ascent zone coordinates and the robot's positions, as indicated in the "Autonomous Positioning R1–R2" in Algorithm 1. R1 is first mobilized towards the next area, and its ramp is deployed; the ToF sensor helps to adjust the R1 position towards the surface. Then, R2 is mobilized towards an area close to the base of the ramp and climb.

The autonomous ascent bases its functionality on a mixed system of combined states, on the one hand, on detecting visual beacons and calculating their approximate distance. The ToF Algorithm gives a True flag in the middle of the ramp. It helps in case of loss of sight of the beacons to continue, guiding it to the end of the platform.

Fig. 4-left shows the ArUcos 1,2,3 detected with the function "Beacon Detection" of Algorithm 2 (with superimposed identifying figures and green lines from its centre to the robot centre). Fig. 4-right shows the external perspective of the approach process for the ascent of R2 on the ramp; the ramp also has safety rails, marked in red to compensate for calculation errors and possible falls.

4. Experiments and results

In this section, the experimental phase and the resulting outcomes are described. A link to the video https://www.youtube.com/watch?app=desktop&v=jYkwVPW-9sY&t about the experimental phase is provided, showcasing in detail the synthesis of this section, commencing with the functionalities and characteristics of each robot, the functioning of perception algorithms, and initial indoor and outdoor testing. Various outdoor scenarios with varying heights are tested to verify the system's functionality and robustness; to enhance versatility, different shots of mission execution are included, both from a first-person perspective (captured by the robot) and lateral and rear perspectives.

4.1. Environment characterization and definition of ascent areas

The method proposed for the autonomous detection of the access site has shown a mean average efficiency of 95% in the characterization of potential access sites. Resulting from the average of the average errors evaluated ($error_w$, $error_h$, $error_m$).

Fig. 5 shows the result of characterized environments and the definition of the best access zones carried out with the Algorithm 1. The soil has been marked with green, the best access zone in blue and the subsequent ones with random colours. The environment point cloud's main surfaces (ground and access areas) have been marked with colours and delimited their edges.

This environment had heights greater than 700 mm; three potential ascent zones have been identified, defined in blue, purple and red. The placed point (in coordinates XYZ) references the climbing goal.

Algorithm 2 Automatic access based on multisensorial processing.

Data:
$Im_{[RGB]} \Leftarrow$ Image from R2.
$ID\_Beacon_{[1...5]} \Leftarrow$ Init Dictionary 4x4
$ToF_{dist} \Leftarrow$ Sensor read.
Result:
$v_{R2[l]}, v_{R2[\alpha]} \Leftarrow [0, 0]$
Data Preprocess:
$Im_{[RGB]} \Leftarrow$ Morphological Conditioning $(Im_{[RGB]})$
function DETECT_BEACON($Im_{[RGB]}$) ▷ Beacon Detection.
  return[$IDs, Poses, Angles$]
end function
while $Climb$ is not $Finished$ **do** ▷ Ascent.
  $IDs, Poses, Angles \leftarrow$ eval $DETECT\_BEACON\ Im_{[RGB]}$
  $v_{R2[l]}, v_{R2[\alpha]} \leftarrow$ eval_controller ($error\_dist$ & $error\_ang$) in $IDs[1, 2, 3]$
  if $Ramp\_Strategy$ is $requiered$ **then**
    $wait$ for $ToF_{dist} < 5\ cm$
    $Ramp\ Down$
  end if
  if $ToF_{dist} < 5\ cm$ **then**
    $Flag\_middle = True$
  end if
  if $ToF_{dist} > 80\ cm$ and $Flag\_middle$ **then**
    $Climb = Finished$
  end if
  $publish(v_{R2[l]}, v_{R2[\alpha]})$
end while
while $Down$ is not $Finished$ **do** ▷ Descent.
  $IDs \leftarrow$ eval $DETECT\_BEACON\ Im_{[RGB]}$
  $v_{R2[l]}, v_{R2[\alpha]} \leftarrow$ eval_controller ($error\_dist$ & $error\_ang$) in $IDs[4, 5]$
  if $Ramp\_Strategy$ is $requiered$ **then**
    $wait$ for $ToF_{dist} < 5\ cm$
    $Raise\ Ramp$
  end if
  if $ToF_{dist} < 5\ cm$ **then**
    $Flag\_middle = True$
    $Counter \leftarrow start$
    $v_{R2[l]} \leftarrow 0.2[m/s]$
    if $Counter > 5\ s$ **then**
      $Down = Finished$
    end if
  end if
  $publish(v_{R2[l]}, v_{R2[\alpha]})$
end while

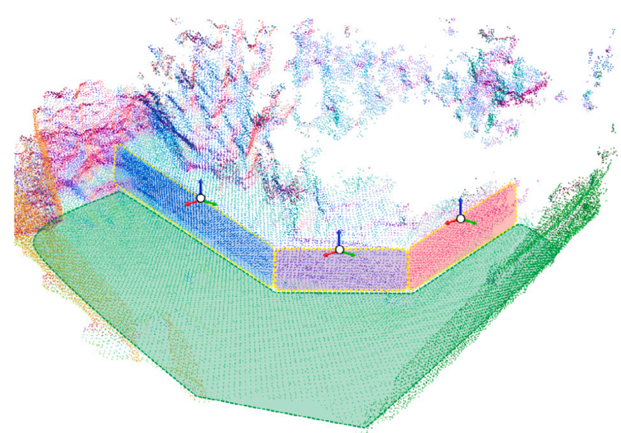

Fig. 5. Detection of ascent zones in the environment defined by Fig. 3.

4.2. Collaborative ascent development

A total of ten repetitions were performed to test the method in this environment. Fig. 6-left shows the ascent of R2 from the ground towards the area with a height of 760 mm. R2 is shown in different positions along the bridge generated by R1's ramp, and in blue is the descriptive trajectory generated during the process. Similarly, Fig. 6-right shows the descent process. The trajectory described is shown in red.

Fig. 7 shows the temporal evolution of the sensory system, the stage where its reading began, and the estimated distances during the ascent process. The ascent process described using the temporal sensory evolution in Fig. 7 starts with detecting one of the beacons. In this case,

Fig. 6. Ascending and descending for environment exploration using collaborative robots in environment defined by Fig. 3.

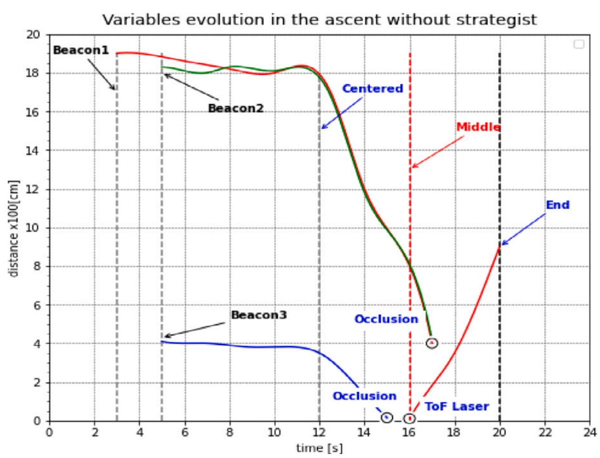

Fig. 7. Temporal evolution of the measurements of the sensory systems directly involved in the ascent process.

the detected beacon corresponds to the indicator [1]. Subsequently, it begins the sequential process of turns to detect beacons [2,3] until R1 is wholly centred in front of the ramp to start the ascent. From this, the estimated distances to the beacons decrease, and the first beacon is to lose visual contact due to occlusion [3].

When the R1 reaches the centre of the ramp, the distance sensor (ToF) changes its measurement to a minimum value (20 [mm]) that indicates the current position of the robot to the system status. As it advances, its distance increases and beacons [1,2] are occluded. However, if there is a momentary loss of visibility of the beacons, the system is designed to maintain the measurement for a while before evaluating that it is occluded.

Although it does not have the reading of any beacon at second 17, R1 continues with the ascent, being assisted by the ToF sensor. The ascent is finished when the ToF reading exceeds 85 cm. In this case, the ramp angle remains constant all the time.

Once up, R1 goes into a tele-operated mode to continue exploring the environment. The subsequent descent phase is executed autonomously, and the operator takes the robot towards an area close to the ramp. The reason for executing the autonomous descent is the system's reliability; since the operator is remote, there is latency and possible loss of communication, thus ensuring that the robot descends without possible falls.

4.3. Influence of proposed method

The total number of points of the reconstructed point cloud environment before ($PC_{Before[xyz]}$) and after ($PC_{After[xyz]}$) the R2 ascent towards the uneven terrain has been analysed to evaluate the relative percentage variation in the explored environment (Rel_Exp_Var); considering the first exploration ($PC_{Before[xyz]}$ before R2 going up) as 100% relative which points increase will be measured with the new exploration in height ($PC_{After[xyz]}$), using Eq. (5).

$$Rel\_Exp\_Var = \frac{PC_{After[xyz]} - PC_{Before[xyz]}}{PC_{Before[xyz]}} \quad (5)$$

The relative percentage between before and after the exploration in height increases by approximately 36% in the purposed terrains. This method has shown its effectiveness and has allowed us to verify the hypothesis.

Fig. 8 shows the percentage of areas explored before and after implementing the collaborative method for the outdoor environments of Terrain 1 and in Scenario 2, where ramp strategy was applied for a height of 500 mm.

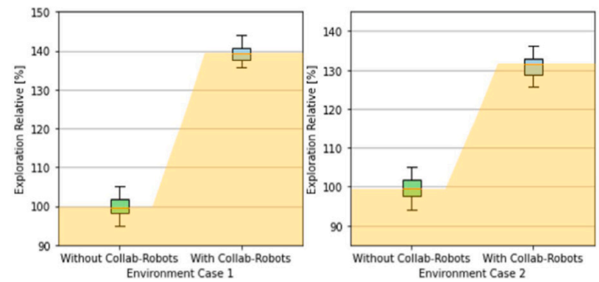

Fig. 8. Analysis of the relative percentage of the environment explored with and without the purposed collaborative method.

4.4. Discussion

In this study, a comprehensive exploration of navigation in unstructured environments was undertaken, addressing challenges such as terrain characterization and collaborative ascent. Initially, the experimental phase was meticulously detailed, showcasing the functionalities and characteristics of each robot through indoor and outdoor testing, including various scenarios with differing heights.

Key to the study was the development of an autonomous method for detecting access sites, demonstrating an impressive 95% efficiency in characterizing potential access points. Collaborative ascent development involved multiple repetitions, illustrating successful ascents and descents of robots in the environment, supported by real-time sensory system feedback.

Crucially, the proposed method significantly increased the percentage of explored areas in the terrain, validating its effectiveness in enhancing exploration capabilities. By integrating collaborative and adaptive interaction among robots, the study offers a promising solution to the challenges of navigating uneven terrains, opening new avenues for exploration and discovery in challenging environments.

5. Conclusions

This article presented a novel method to address the problem of exploring uneven terrains with collaborative robots (a mobile ramp robot and an explorer), showing an exploration zone increase.

Collaborative robots have proven to be a viable alternative for increasing exploration in uneven areas by generating an adaptative mobile bridge connecting two zones at different levels to allow a second robot to climb to the new unexplored zone.

The method proposed for identifying ascent zones based on point cloud processing has shown high efficiency (mean of 95%) for characterizing zones, allowing continued exploration through the ascent through the zone determined by the algorithm.

The sensory integration of sources from the ramp and the system based on vision and AruCos has allowed a robust method to autonomously execute the mobile ramp robot positioning and the ascent and descent of the explorer robot.

Regarding future work, one of the lines to continue this research is using immersive systems and exteroceptive perception for monitoring the process, providing relevant information about the environment and the state of the process that helps the user in the control and monitoring.

CRediT authorship contribution statement

Christyan Cruz Ulloa: Conceptualization, Data curation, Formal analysis, Investigation, Methodology, Project administration, Resources, Software, Validation, Visualization, Writing – original draft, Writing – review & editing. **Javier Álvarez:** Conceptualization, Data curation, Formal analysis, Investigation, Methodology, Software, Validation, Writing – original draft. **Jaime del Cerro:** Conceptualization, Funding acquisition, Investigation, Project administration, Resources, Supervision, Validation, Writing – review & editing. **Antonio Barrientos:** Conceptualization, Formal analysis, Funding acquisition, Project administration, Supervision, Visualization, Writing – review & editing.

Declaration of competing interest

The authors declare the following financial interests/personal relationships which may be considered as potential competing interests: Antonio Barrientos reports financial support was provided by Polytechnic University of Madrid. Antonio Barrientos reports a relationship with Polytechnic University of Madrid that includes: employment. If there are other authors, they declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

Data links in the article.

Acknowledgements

This research has been possible thanks to the financing of RoboCity2030-DIH-CM, Madrid Robotics Digital Innovation Hub, S2018/NMT-4331, funded by “Programas de Actividades I + D en la Comunidad Madrid” and cofunded by Structural Funds of the EU; TASAR (Team of Advanced Search And Rescue Robots), funded by “Proyectos de I + D + i del Ministerio de Ciencia, Innovacion y Universidades” (PID2019-105808RB-I00) and Proyecto “CollaborativE Search And Rescue robots (CESAR)” (PID2022-142129OB-I00) founded by MCIN/AEI/10.13039/501100011033 and “ERDF A way of making Europe”.

Appendix A. Supplementary data

Supplementary material related to this article can be found online at https://doi.org/10.1016/j.mechatronics.2024.103184.

References

[1] Blackburn MR, Everett HR, Laird RT. After action report to the jointprogram office: center for the robotic assisted search and rescue (CRASAR) related efforts at the world trade center. Space and Naval Warfare Systems Center San Diego CA; 2002.

[2] Times NY. Six years after fukushima, robots finally find reactors melted uranium fuel - the new york times. 2023, Available from: URL https://www.nytimes.com/2017/11/19/science/japan-fukushima-nuclear-meltdown-fuel.html.

[3] Kruijff I, Freda L, Gianni M, Ntouskos V, Hlavac V, Kubelka V, Zimmermann E, Surmann H, Dulic K, Rottner W, Gissi E. Deployment of ground and aerial robots in earthquake-struck amatrice in Italy (brief report). In: 2016 IEEE international symposium on safety, security, and rescue robotics. SSRR, 2016, p. 278–9. http://dx.doi.org/10.1109/SSRR.2016.7784314.

[4] Whitman J, Zevallos N, Travers M, Choset H. Snake robot urban search after the 2017 Mexico city earthquake. In: 2018 IEEE international symposium on safety, security, and rescue robotics. SSRR, 2018, p. 1–6. http://dx.doi.org/10.1109/SSRR.2018.8468633.

[5] Murphy RR. Marsupial and shape-shifting robots for urban search and rescue. IEEE Intell Syst Appl 2000;15(2):14–9.

[6] Wang L. Collaborative robot monitoring and control for enhanced sustainability. Int J Adv Manuf Technol 2015;81:1433–45.

[7] Pillai BM, Suthakorn J. Challenges for novice developers in rough terrain rescue robots: A survey on motion control systems. J Control Sci Eng 2019;2019.

[8] Halder S, Afsari K. Robots in inspection and monitoring of buildings and infrastructure: A systematic review. Appl Sci 2023;13(4). http://dx.doi.org/10.3390/app13042304, Available from: URL https://www.mdpi.com/2076-3417/13/4/2304.

[9] Lee W, Hirai M, Hirose S. Gunryu III: reconfigurable magnetic wall-climbing robot for decommissioning of nuclear reactor. Adv Robot 2013;27(14):1099–111.

[10] Cruz C, Garrido L, del Cerro J, Barrientos A. Autonomous victim detection system based on deep learning and multispectral imagery. Mach Learn: Sci Technol 2023;4(1):015018, Available from: http://dx.doi.org/10.1088/2632-2153/acb6cf.

[11] Cruz Ulloa C, Prieto Sánchez G, Barrientos A, Del Cerro J. Autonomous thermal vision robotic system for victims recognition in search and rescue missions. Sensors 2021;21(21). http://dx.doi.org/10.3390/s21217346, Available from: URL https://www.mdpi.com/1424-8220/21/21/7346.

[12] Cruz Ulloa C, Garcia M, del Cerro J, Barrientos A. Deep learning for victims detection from virtual and real search and rescue environments. In: Tardioli D, Matellán V, Heredia G, Silva MF, Marques L, editors. ROBOT2022: fifth iberian robotics conference. Cham: Springer International Publishing; 2023, p. 3–13.

[13] Bouman A, Ginting MF, Alatur N, Palieri M, Fan DD, Touma T, Pailevanian T, Kim SK, Otsu K, Burdick J, a. Agha-Mohammadi A. Autonomous spot: Long-range autonomous exploration of extreme environments with legged locomotion. In: 2020 IEEE/RSJ international conference on intelligent robots and systems. IROS, 2020, p. 2518–25. http://dx.doi.org/10.1109/IROS45743.2020.9341361.

[14] TASAR. Team of Advanced Search And Rescue Robot. 2021, Available from: URL https://www.car.upm-csic.es/?portfolio=tasar.

[15] Lee J, Hwangbo J, Wellhausen L, Koltun V, Hutter M. Learning quadrupedal locomotion over challenging terrain. Sci Robot 2020;5(47):eabc5986.

[16] Roldan-Gomez J, de Leon Rivas J, Garcia-Aunon P, Barrientos A. A review on multi-robot systems: current challenges for operators and new developments of interfaces. Rev Iberoam Autom Inform Ind 2020;17(3):294–305.

[17] Hebert P, Bajracharya M, Ma J, Hudson N, Aydemir A, Reid J, Bergh C, Borders J, Frost M, Hagman M, Leichty J, Backes P, Kennedy B, Karplus P, Satzinger B, Byl K, Shankar K, Burdick J. Mobile manipulation and mobility as manipulation—Design and algorithms of RoboSimian. J Field Robotics 2015;32(2):255–74. http://dx.doi.org/10.1002/rob.21566, Available from: URL https://onlinelibrary.wiley.com/doi/abs/10.1002/rob.21566.

[18] Dang T, Tranzatto M, Khattak S, Mascarich F, Alexis K, Hutter M. Graph-based subterranean exploration path planning using aerial and legged robots. J Field Robotics 2020;37(8):1363–88. http://dx.doi.org/10.1002/rob.21993, Available from: URL https://onlinelibrary.wiley.com/doi/abs/10.1002/rob.21993.

[19] Asadi K, Kalkunte Suresh A, Ender A, Gotad S, Maniyar S, Anand S, Noghabaei M, Han K, Lobaton E, Wu T. An integrated UGV-UAV system for construction site data collection. Autom Constr 2020;112:103068. http://dx.doi.org/10.1016/j.autcon.2019.103068, Available from: URL https://www.sciencedirect.com/science/article/pii/S0926580519306545.

[20] Chen X, Qi Y, Yin Y, Chen Y, Liu L, Chen H. A multi-stage deep reinforcement learning with search-based optimization for air–ground unmanned system navigation. Appl Sci 2023;13(4):2244.

[21] Chen Z, Li J, Wang S, Wang J, Ma L. Flexible gait transition for six wheel-legged robot with unstructured terrains. Robot Auton Syst 2022;150:103989. http://dx.doi.org/10.1016/j.robot.2021.103989, Available from: URL https://www.sciencedirect.com/science/article/pii/S0921889021002499.

[22] Chen Z, Li J, Wang J, Wang S, Zhao J, Li J. Towards hybrid gait obstacle avoidance for a six wheel-legged robot with payload transportation. J Intell Robot Syst 2021;102(3):60.

[23] Chen Z, Zhou L, Huang J, Tu Z, Liu Q, Li J. Multi-link mechanism-inspired palletizing manipulator: Design, optimization and experimental results. Proc Inst Mech Eng C 09544062231181811, Available from: URL https://doi.org/10.1177/09544062231181811.

[24] Gonzalez DJ, Asada HH. Design and analysis of 6-DOF triple scissor extender robots with applications in aircraft assembly. IEEE Robot Autom Lett 2017;2(3):1420–7. http://dx.doi.org/10.1109/LRA.2017.2671366.

[25] Petris PD, Khattak S, Dharmadhikari M, Waibel G, Nguyen H, Montenegro M, Khedekar N, Alexis K, Hutter M. Marsupial walking-and-flying robotic deployment for collaborative exploration of unknown environments. 2022.

[26] Hourani H, Wolters P, Hauck E, Jeschke S. A marsupial relationship in robotics: A survey. In: International conference on intelligent robotics and applications. Springer; 2011, p. 335–45.
[27] Mashrik T, Baized A, Iftekhar L, Ahmed N. Urban search and rescue mission: The use of marsupial robots. J Mod Sci Technol 2016;4(1).
[28] Dong P, Wang X, Xing H, Liu Y, Zhang M. Design and control of a tracked robot for search and rescue in nuclear power plant. In: 2016 international conference on advanced robotics and mechatronics. ICARM, IEEE; 2016, p. 330–5.
[29] Pettinati MJ, Arkin RC. Push and pull: Shepherding multi-agent robot teams in adversarial situations. In: 2019 IEEE international conference on advanced robotics and its social impacts. ARSO, 2019, p. 407–14. http://dx.doi.org/10.1109/ARSO46408.2019.8948797.
[30] Eich M, Grimminger F, Kirchner F. A versatile stair-climbing robot for search and rescue applications. In: 2008 IEEE international workshop on safety, security and rescue robotics. IEEE; 2008, p. 35–40.
[31] Labbé M, Michaud F. RTAB-map as an open-source lidar and visual simultaneous localization and mapping library for large-scale and long-term online operation. J Field Robotics 2019;36(2):416–46. http://dx.doi.org/10.1002/rob.21831, Available from: URL https://onlinelibrary.wiley.com/doi/abs/10.1002/rob.21831.
[32] Das S. Simultaneous localization and mapping (SLAM) using RTAB-MAP. 2018, CoRR abs/1809.02989. Available from: URL http://arxiv.org/abs/1809.02989.
[33] Ning X, Li F, Tian G, Wang Y. An efficient outlier removal method for scattered point cloud data. PLoS One 2018;13(8):e0201280.
[34] Guo R, Chen J, Wang L. Hierarchical K-means clustering for registration of multi-view point sets. Comput Electr Eng 2021;94:107321.