SEMFIRE

Segurança, Exploração e Manutenção de Florestas com Integração de Robótica Ecológica

E4.1b: Multi-Robot Exploration, Patrolling and Localization System

Cofinanciado por:

CENTRO 2020 PORTUGAL 2020 UNIÃO EUROPEIA Fundo Europeu de Desenvolvimento Regional

Document Identification

Title	**SEMFIRE: Segurança, Exploração e Manutenção de Florestas com Integração de Robótica Ecológica**
Reference	CENTRO-01-0247-FEDER-032691
Duration	2018-10-01 - 2021-09-30
Head of Consortium (*Chefe do Consórcio*)	Ingeniarius, Lda. (Ingeniarius)
Copromoters (*Copromotores*)	Instituto de Sistemas e Robótica da Universidade de Coimbra (ISR-UC), SFera Ultimate, Lda. (SFera)
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Work Package/Deliverable

Work Package (*Atividade*)	**A4. Multi-Robot Coordination in the Forestry Environment** (*Análise de requisitos e especificação funcional*)
Deliverable (*Entregável*)	**E4.1b**: Multi-Robot Exploration, Patrolling and Localization System (*Exploração, Patrulhamento Multi-Robô e Sistema de Localização*)
Lead Copromoter	University of Coimbra
Due Date (*Mês*)	2020-01-31 (*M4*)

Change Record

Version	Date	Author	Summary of Changes
v0.1	2020-02-06	David Portugal	Deliverable structure and initial content in all sections
v0.2	2020-04-13	Micael Couceiro	Added some objectives descriptions.
v0.3	2020-04-14	André Araújo	Added SOM method descriptions.
v0.4	2020-04-17	J.F. Ferreira & R. Rocha	Overall revision.
v0.5	2020-04-17	A. Araújo & M. Couceiro	Release final version.
v0.6	2021-11-11	Afonso Eloy	Modified Section 4.3 (3D navigation technique).
v0.7	2021-11-16	M. Couceiro & D. Datcenko	Added SOMAR contributions.
v1.0	2021-11-17	J.F. Ferreira	Final revision

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1 Introduction

The SEMFIRE project contemplates several challenges within the field of forestry robotics and field robotics. This deliverable identifies some of these challenges in the context of the activity 4 of the project: Multi-Robot Coordination in the Forestry Environment. Mainly, we focus on the pervasive **localization** system of the members of the team of forestry robots – the Ranger and the Scouts – developed in the previous months, and on two main multi-robot tasks to fulfill the use case defined in deliverable E1.1 [4]; namely multi-robot **exploration** for cooperative reconnaissance and multi-robot **patrolling** for forestry clearing and cooperative progress monitoring.

We divide this deliverable in three sections, one for each topic: localization, exploration and patrolling. Each of these sections starts with a brief overview of the literature, the work in progress on the topic within the SEMFIRE project, and a discussion of the results achieved thus far. Lastly, we finalize the deliverable with Section 6, presenting the conclusions of the document and the main lines of future work.

2 Multimodal Localization System

2.1 Brief Literature Review

2.1.1 Global and Local Localization

Localization of robotic systems is an active area of research [5], and most outdoor localization applications rely on global navigation satellite systems (GNSS). However, GNSS by itself is not recommended for sensitive and precise tasks. For instance, GPS accuracy, in the best-case scenario, is at the level of tens of centimeters, when coupled with Real-Time Kinematics (RTK), which uses a fixed base station to enhance the precision of incoming GNSS positional data [6]. Moreover, GPS-based tracking does not provide a full 6D pose estimation $(x, y, z, \theta, \phi, \psi)$, which is essential for precision applications, e.g. 3D mapping [7] or automated forestry operations [8], lacking body orientation information (θ, ϕ, ψ), and the estimation of height (z) is generally much less precise than x and y, due to the satellites' geometry that favors perpendicular planes in the triangulation process [9].

Many outdoor localization systems have been proposed over the years, based on different technology, like radio-frequency (RF) receiver-based approaches [10], visual feature matching using cameras [11], RSSI measurements of wireless sensor networks [12], RFID technology [13], and Simultaneous Localization and Mapping (SLAM) [14] with LIDARs and cameras, with varying degrees of success. Some of these techniques such as feature matching and SLAM use purely local information, accumulating error over time, which can only be solved with the explicit integration of complex loop closure techniques [15] to identify places that have been visited in the past, instead of considering them as new observations. On the other hand, global localization techniques, such as GPS, use a global reference system, and can recover more easily from poor estimates. Yet, they suffer from lack of precision and incomplete information at local level.

To overcome the limited accuracy of existing systems, SEMFIRE is based on the premise that local and global localization techniques should be integrated in a common framework to capitalize on the benefits of different approaches. Based on the research group solid experience [16, 17], a multimodal sensor fusion estimation approach is proposed to support and fuse an arbitrary number of distinct tracking input sources to provide accurate 6D localization estimation for field robotic agents.

Given that **global** localization approaches mostly rely on mature technology, such as the acquisition and integration of sensing inputs like GPS [18], GPS-RTK [6] or Ultra Wideband (UWB) triangulation technology [19], in the following paragraphs we overview recent advances in **local** tracking approaches, focusing specially on Simultaneous Localization And Mapping (SLAM), and sensor fusion in outdoor challenging environments.

2.1.2 Simultaneous Localization and Mapping

One of the key works that broke away from 2D SLAM in flat indoor environments in 2D to provide a full 3D SLAM system in less structured outdoor environments was proposed by Cole and Newman [20]. The authors use a 2D scanner continually oscillating about a horizontal axis, thus consecutively building 3D scans, using a simple segmentation algorithm and by executing a "stop-acquire-move" cycle. A scan-matching classification technique is used for inter-scan registrations, which also involves an integrity check step. As a result, the authors were able to successfully perform 3D probabilistic SLAM in an outdoor non-flat terrain, and in a related work [21], the system was augmented with a forward-facing camera to improve loop closure detection using an appearance-based retrieval approach. Detecting loop closure with vision in outdoor environments would be further explored in upcoming works, such as [22, 23, 24].

At around the same time, Thrun and Montemerlo proposed the recognized GraphSLAM offline algorithm [25]. GraphSLAM extracts a set of soft constraints from the dataset, which are represented by a sparse graph. The map and robot path are then acquired by linearising these constraints, and solving a least squares problem using standard optimisation techniques. The approach was tested outdoors in large-scale urban structures, using a two-directional scanning laser and featuring optional GPS measurements integration, achieving valid 3D map representations. Another seminal work on 3D SLAM was proposed in Nüchter et al. [26]. The approach, which makes use of a robot that is equipped with a tiltable SICK LRF in a natural outdoor environment, is based on 6D ICP scan matching, combined with a heuristic for closed loop detection and a global relaxation method, leading to valid mapping of the environment, displaying precise correspondence with an aerial ground truth photo.

Based on the early work of Singh and Kelly on elevation maps for navigating an all-terrain vehicle [27], Pfaff et al. proposed an efficient approach to solve the 3D SLAM problem is proposed [28]. The approach classifies individual cells of an elevation map into four classes representing parts of the terrain seen from above, vertical objects, overhanging objects (e.g. branches of trees or bridges), and traversable areas. This information is then taken into account by the ICP registration algorithm, and a consistent constraint-based robot pose estimation technique is developed. The authors employed a Pioneer II AT robot, equipped with a SICK LMS range scanner on top of a pan/tilt device. Results showed that the techniques lead to significantly increased correspondences and alignments in the generated map.

An interesting review of the literature in SLAM for outdoor environments up to 2009 is provided in [29]. The authors analyse mapping and localisation separately, by comparing firstly different occupancy grid mapping approaches, and then analysing different methods for localisation within the map. This is done by classifying approaches into three categories: visual SLAM (using monocular cameras and stereovison), LIDAR SLAM (scan matching and maximum likelihood estimation approaches with LIDARs) and sensor fusion SLAM (techniques using fusion of any kind of sensors, such as cameras, LRFs, radar and/or others).

2.1.3 Visual Feature Matching for Local Tracking

Stereo vision has also been heavily used for studies in outdoor perception in the last decades [30, 31]. In [32], a hierarchical (topological/metric) approach is proposed for a vehicle in large-scale outdoor urban environments using a low-cost, wide-angle stereo camera, and integrating GPS measurements in low-level visual landmarks metric mapping for improving vehicle positioning. At the high-level, a topological graph-like map consisting of vertices (topological places represented by local metric submaps) and edges (transformation matrices and uncertainties describing the relationship between vertices) is used to reduce global errors and keeping real-time constraints. The authors successfully tested the approach in an autonomous car, covering a 3.17 km long path keeping a small degradation with GPS unavailability, by comparing the results of the estimated path against the ground truth provided by a professional RTK-GPS receiver module mounted on the vehicle. In two related works [33, 34], submap matching for stereo-vision outdoor SLAM is used. However, unlike in [32], a flat terrain is not assumed for matching the 3D local metric maps, and GPS-denied environments are considered. The authors propose a novel method for submap matching based on robust keypoints that are derived from local obstacle classification. By describing discriminative geometrical 3D features, invariance to changing viewpoints and varying light conditions is achieved using only an IMU and a pair of cameras mounted on an outdoor robotic platform.

Visual odometry, together with visual SLAM, has been the object of a substantial amount of research for several decades now [35, 36, 37, 38], and there has been a recent interest in applying these techniques to the more challenging natural outdoor scenarios [39]. An account of research conducted during the last ten years on natural outdoor environments would include work by Konolige et al. [40, 41], Otsu et al. [42] and Daftry et al. [43] and a very interesting biologically-inspired Bayesian approach using convolution neural networks that uses inference of sun direction to reduce drift, by Peretroukhin et al. [44].

2.1.4 Scientific and Technological Challenges and Recent Advances in Localization

Also important for this kind of applications would be work considering 2D camera fusion with 3D-based devices [45, 46, 47, 48], with others more focused on SLAM in forest environments [49]. Also relevant is recent work in visual odometry and navigation for unmanned aerial vehicles (UAVs) in forest applications and other related topics [50, 51, 52, 53, 54, 55, 56].

Besides the technological advances in sensors for 3D perception [57, 58], and increased computation power and storage/memory availability [59, 60], recent significant contributions have also been proposed to improve existing solutions. These include enhanced ICP-based scan matching and data registration approaches [61], more efficient 3D data representation [62, 63], hierarchical/multiresolution mapping approaches [64], improved calibration methods [65], novel probabilistic techniques [66, 67], semantic mapping and terrain modelling [68, 69, 70].

In fact, recent years have shown the possibility of obtaining precise pose and localisation estimation using single cameras, by employing advanced SLAM methods such as RatSLAM [71, 72, 73], a biologically-inspired SLAM system, or ORB SLAM [74, 75], a feature-based monocular SLAM approach. Furthermore, it has been shown that individual SLAM approaches can be extended to decentralized teams of multiple robots, in particular graphSLAM approaches, which can be leveraged to both optimise the map as well as the 6D pose estimation for all participating robots, as shown in [76].

In the light of the points mentioned above, studies on outdoor perception and mapping for forest harvesters and precision agriculture have started to emerge [77, 78, 79, 80]. For instance, in [81], a feature-based method that combines 2D laser localisation and mapping with GPS information to form global tree maps is proposed. The authors study different scan correlation and data association methods to produce simple 2D tree maps of the forest. In [82], an Extended Information Filter (EIF) SLAM implementation is used in an olive grove for precision agriculture mapping based on the detection of stems for a monocular vision system that is coupled with a laser range sensor, and in [83], the localisation of an outdoor robot for applications on steep slope vineyard monitoring tasks is assisted by agricultural wireless sensors, using the Received Signal Strength Indication (RSSI) of iBeacons (Bluetooth based sensors) for distance estimation, allowing to improve unstable localisation accuracy of GPS.

Despite all the reported advances, however, looking at this body of work the conclusions drawn by [39] in terms of the many open scientific and technological challenges for visual odometry and SLAM when considering natural outdoor environments still hold today, in particular those resulting from the difficulties imposed by visual sensor limitations. For instance, forestry environments are unstructured, look-alike and often subject to windy conditions, which can lead to corner cases in feature matching and loop closure techniques. Additionally, high vibration and other motion bias [84] have a significant effect on proprioceptive sensors and their calibration, resulting in motion blur, hindering optical flow techniques and leading to high variance of image scale, as well as rolling shutter effects on vision sensors. In the case of LIDARs and IMUs, motion while acquiring data and lack of stabilization increases the noise of collected sensing data inevitably. The cost factor of outdoor-resistant and compliant solutions are also a challenge, as most cheap and common sensors used in Robotics are not appropriate for rainy, foggy/smoky, and windy conditions. Another challenge identified in Mohammad et al. [85] points towards the high computational cost to process images that is still required nowadays for Visual Odometry and Visual SLAM solutions.

2.2 Work in Progress in SEMFIRE

As seen before, numerous pose estimation approaches use only local information, suffering from error accumulation over time. Inversely, global methods are based on a fixed reference system, and can recover more easily from mislocalizations, as they do not rely necessarily on previous instances to compute the solution in the current estimation step. Yet, they suffer from lack of precision and incomplete information at local level. SEMFIRE builds on the belief that local and global localization methods should be integrated in a common framework to capitalize on the benefits of both types of techniques. To do so, a multimodal sensor fusion estimation approach is proposed, supporting and fusing any number of different local and global tracking inputs, leveraging nonlinear filtering techniques, such as Extended Kalman Filters and Graph-based SLAM to provide improved centimeter-level 6D full pose estimation and detailed 3D map representations as output.

A decoupled system architecture with emphasis on the a priori definition of the communication between components, allows the integration of sensor data acquisition and processing, artificial perception algorithms, and distinct computational approaches for pose estimation, which are implemented, analyzed and tested as inputs for the sensor fusion system. Data fusion from distinct localization sensing sources will explicitly incorporate input measurement uncertainty to allow increased robustness in all situations. These include sensor failures, e.g. neglecting estimates from faulty sources; and overcoming challenging situations that affect specific robotic components, e.g. lack of features for visual tracking, inexistent optical reflection from opaque surfaces corrupting LIDAR data or magnetic interference which degrades inertial measurement units' readings, thus enabling activation or removal of inputs during run-time. The system will also provide trajectory smoothing, as consecutive local measurements are introduced, stabilizing tracking behavior, and reducing discretization "jumps" from global localization approaches.

The solution has been designed in ROS as an integrated hardware and software module: the localization toolbox for SEMFIRE, enabling extendibility beyond field robotic applications. Figure 1 presents the proposed localization approach for SEMFIRE.

Sensory integration in SEMFIRE aimed, in the first instance, to provide a robust, multimodal and hierarchical localization estimation for the Ranger robot. For this purpose, an extended global Kalman filter (EKF) was used, which contemplates the fusion of multiple components of local and global pose estimation, as described in Figure 1.

Firstly, the system locally calculates a continuous 6D pose estimation $(x, y, z, \theta, \phi, \psi)$ using visual odometry fusion based on the Intel RGBD camera, consecutive scan of the point clouds provided by the two 3D LeiShen C16 LIDARs integrated in the robot, as well as 3D accelerometer, gyroscopic and magnetometer orientation data provided by the integrated UM7 inertial measurement unit (IMU). Locally, the system uses a robust Graph-SLAM technique [86] to provide with these inputs an estimate of local and continuous localization, which feeds the global EKF filter.

In addition to this estimate, the EKF filter is also powered by high-precision georeferenced measurements through a GPS-RTK, which allows correcting any accumulation of

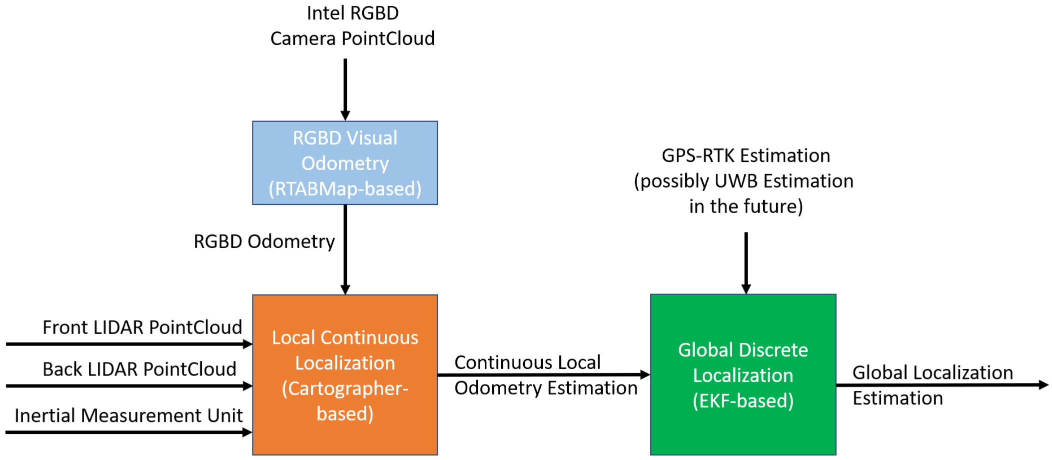


Figure 1: Proposed local and global fusion approach for 6D full pose localization estimation in SEMFIRE.

local errors that come from the local pose estimation system, thus providing an estimation of global pose with precision.

The global pose estimation provided allows the system to map the environment in detail through probabilistic mapping libraries, such as OctoMap [87], which is based on an efficient mechanism to represent 3D information (octrees), relieving the computational weight and storage of classic 3D mapping techniques. Figure 2 presents the 3D mapping approach based on Octomaps, currently in use for SEMFIRE.

Figure 2: Proposed 3D mapping approach currently in use in SEMFIRE.

Note that the use of probabilistic filters such as the EKF allows the estimation constraints to be obtained during run-time, e.g. number of satellites available for GPS, matched features in visual tracking, co-variances of ego-motion estimation, etc. These are leveraged as fundamental inputs for sensor fusion estimation, accounting for the degree of uncertainty of each measurement, and serving as important biases during the fusion process to overcome the corner cases that different techniques tend to have. This way, the system is robust to sensor failures, neglecting estimates from faulty sources, and allowing for activation or removal of tracking inputs during run-time.

2.3 Results, Discussion and Expectations

Accurate localization is a mandatory requirement for field operations, such as ground and aerial robotic navigation or large-scale mapping and perception, thus SEMFIRE aims at improving the maturity of full 6D robotic pose estimation, especially in outdoor areas that are highly dynamic and unstructured, encompassing hard challenges for perception such as GPS dropouts, undistinctive visual features in forestry scenes and high perturbation in motion due to rough terrain traversability.

The localization approach is centered on ROS software components, such as sensor-based perception, pose estimation methods and multimodal fusion estimation; as well as hardware components, including ROS drivers and low-level data acquisition. Figure 3 displays a 3D map obtained in a real-world experimental trial using the Ranger robot, which is localized precisely at all times in 6D with the previously described multimodal sensor fusion hierarchical localization approach.

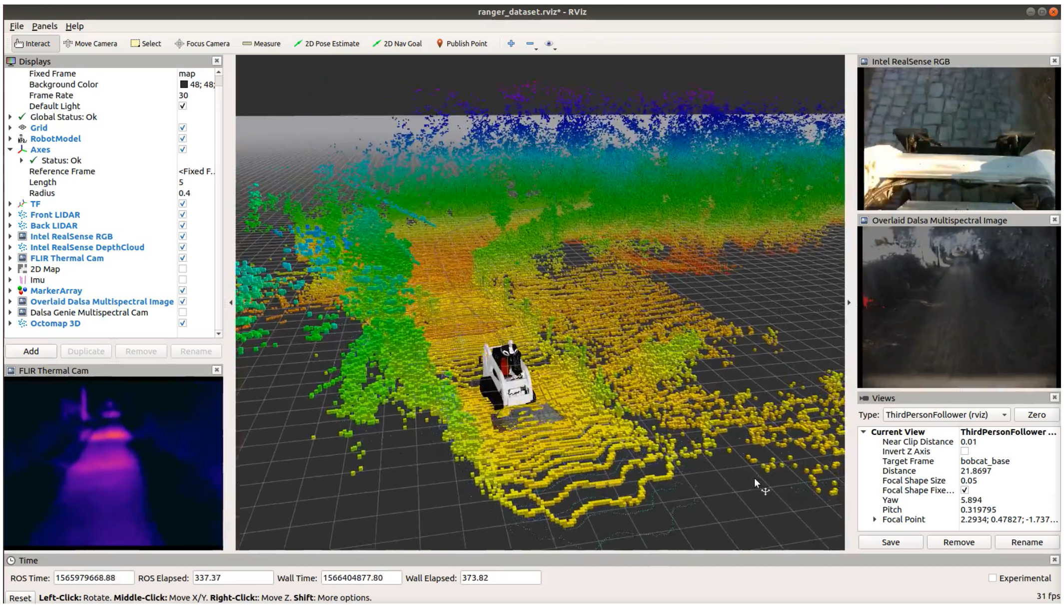


Figure 3: Results of initial tests with a 3D map of a challenging outdoor environment using the proposed localization and mapping approaches.

Results show that the approach proposed for the Ranger localization is extremely precise, reliable and robust. Yet, it is a work in progress that we are constantly aiming to improve. For instance, the Graph-based SLAM approach that we are using does not provide an output when one of the inputs (front LIDAR, back LIDAR, IMU or Visual Odometry) is missing. This is something that we would like to change in the future, i.e. for the approach to be robust to missing inputs over time. Moreover, we would also like to intensively test more parametric combinations and other inputs for the EKF filter used, e.g. testing the integration of the IMU at global localization level to further improve the results. Additionally, the EKF used for localization has the flexibility to also be fed by other sources of localization. As seen in Figure 1, we aim to explore the integration of Ultra Wideband (UWB) technology as a source for global localization in situations where GPS dropouts do not allow the system to maintain a georeferenced system.

Finally, we have been working to extend the localization method in the Ranger ground robot to the team of Scouts aerial robots. For this, we will follow a similar strategy for the Scouts, albeit with different sensing inputs due to the differences in hardware. Alternatively, we would like to look into the possibility of assisted Scouts' localization using the Ranger as a precise reference.

3 Multi-Robot Exploration for Cooperative Reconnaissance

3.1 Brief Literature Review

3.1.1 Autonomous Exploration Fundamentals

Yamauchi defined *exploration* as the “act of moving through an unknown environment while building a map that can be used for subsequent navigation” [88]. Exploration is a key to understand the features of a particular environment perceiving the surroundings for possible danger, obstacles, rough terrain, passage conditions, etc.

The purpose of 3D exploration is to autonomously build a fully detailed 3D map of the unknown environment to represent the explored area [89]. This results from data acquired through the sensing system of the robot during the exploration task. To plan a trajectory of the robot across the environment, the exploration strategy used must take into account the area already explored, using a map that is incrementally maintained, and the area that is still unexplored.

Robotic exploration strategies in the literature are typically frontier-based [90], [88], such as Frontier-Void-based [91], or Receding Horizon [92] strategies. Both of these methods are developed for 3D exploration and use a “next-best-view” planning to select the “best” next step to be performed by the robot in the environment. Next-Best-View (NBV) strategies for exploration focus on the problem of a viewpoint selection and, in this case, path planning for a mobile robotic platform used for 3D reconstruction [93]. NBV is often used to detect objects from different viewpoints around the object to extract maximum information about it, while incorporating the robot's kinematics constraints. In the context of mobile robotics, the NBV planner consists in determining the most favorable viewpoint of sensing action to be performed by the robot, moving the robotic platform to a desired location and acquiring data with the purpose to obtain as much of new information about the environment as possible [94].

The main issue in autonomous exploration is how the robot will get to know the world and wander within it, in such a way to obtain as much of new information as possible about the environment. Developed originally to be performed in a 2D environment, the Frontier-based exploration approach [88] aims to obtain as much new information from an area as possible, by moving the robot to the boundary between open space and uncharted territory, denoted as *frontier*. This early approach chooses the best frontier where it can obtain the maximum information, i.e. the region with more unexplored area. Applying the Frontier-based paradigm to 3D exploration, requires a search in 6 degrees of freedom (DOF) space, combining the frontiers in 3D with the concept of *voids*. Voids are unexplored volumes automatically generated from 3D sensor observations that are occluded or enclosed by obstacles. For an adequate sensor viewpoint for observations of the interior of those voids, the extracted voids are combined with nearby frontiers. By intersecting all the vectors, it is possible to determine a location from which many of the void spaces can be observable, in which for a larger scenario could be more than one location. After extracting those locations, the robot sequentially visits them until the whole area is explored. As the environment is explored, the representation of the area is stored in a volumetric map, e.g. an octomap (see previous section). This tessellates 3D spaces into cells organized in a hierarchical 3D grid structure for more efficient computation, in which finer-grained resolution, i.e. smaller cells, are used only in more complex regions of the environment where smaller geometrical details have to be represented.

Summing up, this approach works in an iterative procedure executing the same steps at each cycle, as following:

1. Capturing a 3D point cloud from the environment using a sensing system.

2. Registering the point cloud and align with previous scans.

3. Integrating the cloud into an hierarchical octomap structure.

4. Extracting the frontiers and the void cells.

5. Determining the NBV locations.

6. Planning and executing a trajectory to that location.

Despite being commonly used, the aforementioned approach may not be the most interesting to perform exploration when the variable of time intends to be reduced. When combining frontiers and voids, this approach has to explore much of the environment and then go through all the voids sequentially. Even when using more than one robot to do it, it is not always a practical approach for 3D exploration, especially in large environments.

An alternative approach to frontier-based strategies employs a sampling-based receding horizon path planning [92], intended to generate a path that covers a "generous" volume of information yet unexplored. A sensing system, capable of acquiring information from the surroundings of the robot, is used to combine that information along with the localization of the robot and then, create a 3D map of the already explored area. This map takes into account collision-free navigation and determination of the exploration progress in order to compute the best path to go through. To compute it, a finite iteration of a random tree is grown using the rapidly-exploring random trees (RRT) algorithm [95], [96] where each branch is evaluated for the amount of unexplored space that can be mapped. The first node of the best branch is executed, while the whole process is then repeated.

With this approach, executing only the first node of the RRT finite branch is enough to explore the area until the robot reaches the edge. While the robot is moving to the edge, it is simultaneously mapping the area around it. Therefore, when it arrives to the edge, the area ahead of it is already mapped and probably there is no need for additional exploration. Another edge is calculated, redirecting the robot to another unexplored area. Summing up, no long paths are needed to explore an environment.

3.1.2 Multi-Robot Coordination for Exploration

Most of the mobile robots used in autonomous exploration missions are limited to 2D or 2.5D[1] environment representations, which are sufficient for several applications [97]. In this case, the robot must be able to estimate its ego-motion to proceed on a regular environment, perceiving the distance to obstacles and even perceiving some objects.

In a 3D environment, there is more space to explore, as it is not just free space and obstacles at a certain height, defined by the sensor system constraints. In these more challenging and complex scenarios, the robot must have the perception of what surrounds it, such as 3D objects, terrain conditions, empty areas, etc.

In 2D and 3D exploration, robots must be capable not only of navigating and mapping their surroundings but also combining navigation and mapping. Moreover, having a team of robots working cooperatively increases the potential to accomplish a single task faster than with a single robot [98]. To cover larger spaces, a team of robots may be employed [99], in SEMFIRE we integrate not only unmanned ground vehicles (UGVs) but also unmanned aerial vehicles (UAVs) covering aerial space, i.e. an heterogeneous multi-robot system. Besides this, using more robots introduces redundancy so we can expect increased fault-tolerant over a single robot solution [99]. Another advantage of using a team of robots is the merging of overlapping information, helping to compensate some sensor uncertainty. This is specially important when using robots with different sensor capabilities [100]. On the other hand, an adequate number of robots must be employed in the environment, in order to minimize interference among members of the team.

[1]2.5D environment representation - 2D map that represents the correspondent elevation of the environment.

Coordinating a team of robots during an exploration mission implies an efficient strategy to keep robots on track on which areas are not yet explored, currently being explored and already explored. For this strategy, robots must communicate among them, sharing their position and map of the area explored. When exchanging messages, it is necessary to share details of the area explored by the robot. For this, robots must be capable of building maps online while moving in the field using SLAM approaches (see Section 2.1.2). While mapping the environment, a robot has to deal with possible errors in localization and range measurements. This imposes some problems when determining the location of a robot relatively to its map.

Burgard et al. [99] presented a centralized system capable of coordinating a team of robots following a decision-theoretic approach, primarily presented by M. Moors in his PhD thesis [101]. It presents a solution to the problem of how to assign exploration tasks to individual robots where multiple robots are involved without them moving to the same location. The proposal determines target locations for individual robots. This determination simultaneously considers the cost of reaching a frontier cell and the utility of that cell. The cost of reaching a frontier cell is proportional to the distance from the robot to that cell. The utility of a frontier cell depends on the number of robots that are moving to that cell or close to it. Robot's limited communication is considered. To perform the exploration and coordinate their actions, each robot starts with a blank grid map. The system relies on the assumption that robots must begin their operation in nearby locations that their scans show substantial overlap. Another assumption is that the system must know the approximate relative initial pose of the robots, allowing minor errors in orientation.

Finally, to achieve coordination, the team must be able to communicate and transmit the individual maps during mission. This is done by sending messages from a robot to all teammates within a correspondent cluster. To prevent overlap of information, each robot stores a log of sensor measurements for each other robot perceived by this robot. The robot only transfers those measures that has not been sent to that corresponding robot. If a robot has already those measures from another robot, they are discarded, thus avoiding overlapping.

Another strategy to coordinate a team of robots is presented by Freda et al. based on two-level agents [1]: an exploration and a planner agent. A schematic representation of this strategy is shown in Figure 4. This strategy is based on a distributed coordination system. The exploration agent fits into topological level by planning and adding a new view node on its exploration tree. Here the cooperation is achieved once the planning of the new node is driven by shared information gain. Its continuous monitoring and negotiation of possible entry of conflicting nodes helps to maintain cooperativeness. The planner agent fits into metric conflict by computing the safest path from the current position of the robot to the goal position using the individual map. Applying a multi-robot traversability function guarantees metric coordination by inducing a prioritized path planning, where robots negotiate metric conflicts, preventing the intersection of planned paths. Both agents cooperate, as it is the explorer who assigns the desired goals to the path planner, where he continuously responds with feedback, informing the other of its status and computations.

This approach allows to reduce interference and manage possible deadlocks. While the exploration agent focuses on the most important exploration aspects, the path planner takes care of possible incoming metric conflicts. Furthermore, where the path planner agent may fail in arbitrating challenging conflicts, the exploration agent intervenes and reassign tasks to distribute the robots over the environment.

Bircher et al. [92] presented a benchmark study between Receding Horizon and Frontier-based approaches, demonstrating a better performance for the Receding Horizon planner. Simulations were performed using a hexacopter MAV, able to explore any surface from any viewpoint, reducing kinematics constraints. For the implemented tests, two significantly different exploration scenarios for simulation were created: an apartment and a bridge. The apartment scenario used was a very simple indoor scenario composed only with a few walls

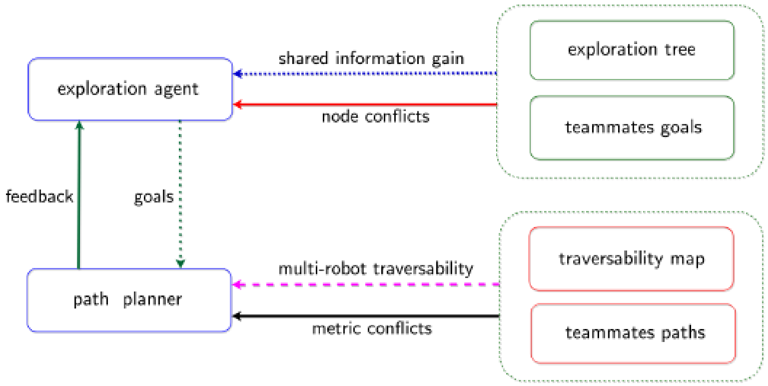


Figure 4: Two-Level strategy for each robot [1].

and with an area of 20×30 m and with 3 m of height. The Frontier-based strategy led to a reduced average exploration time of the whole area but the unmapped area is a higher comparing to the Receding Horizon. Moreover, the average computation time of Receding Horizon is significantly reduced, allowing a seamless integration into robot's control and path planning loops.

In the bridge scenario, with an area of 54×26m and 14 m of height, as opposed to the Receding Horizon approach, the Frontier-based approach was not able to complete the exploration task, took long in terms of computational time, as well as to re-plan a path to proceed with the exploration of the environment. These results showed that Frontier-based approach may not be suitable to explore complex environments.

The Two-Level strategy from Freda et al. [1] employs two agents, they help to reduce interference of information and prevent conflicts between teammates. The fact that the robots must begin the mission in nearby locations while maintaining a continuous communication results in a collective behavior such that they will not move far from each other and will directly affect the objective of reducing significantly the time of the exploration task, moving as a group.

Leader-follower approaches appeared as an efficient approach for multi-robot exploration, being currently adopted by many authors to solve specific MRS applications. In 2004, Takahashi et al. [102] proposed a centralized algorithm to control robots without taking into account their initial deployment. However, real robots were unable to completely avoid obstacles, which is expected under centralized approaches requiring a high level of data exchange between agents that cannot be guaranteed in real-world scenarios. Alternative approaches were proposed to tackle this and other issues, combining leader–follower with consensus-based estimation approaches, as presented by Ren et al. [103]. The proposed distributed formation control architecture accommodated an arbitrary number of group leaders and arbitrary information flow among agents, namely about the neighbours position. Approaches with multiple group leaders and an efficient inter-robot coupling are less prone to failures in the presence of limited information exchange within the formation, though consensus might be hard to achieve [104].

These and other approaches have been proposed over the years, but it was only in the last decade that a new breed of adaptive formation maintenance methods started to emerged. Some authors, such as Cheng et al. [105], proposed decentralized adaptive control approaches to solve the consensus problem of MRS. The authors explored the benefits of adaptive neural network schemes to overcome the effect of some environment disturbances. Yet, most of these works disregarded collision avoidance and other dynamic uncertainties. This was not the case for Alonso et al. [106, 107, 108], who proposed several decentralized approaches to deal with static and dynamic obstacles environments in 3D workspaces. The authors adopted a sequential convex optimization approach to compute a convex region in free position-time space and on non-convex optimization methods to compute the configuration of the team of robots with obstacle avoidance constraints [109]. The authors concluded, however, that deadlocks may still arise due to disagreements occurring when each robot computes an independent global path [108].

Artificial neural network (ANN), such as the self-organising map (SOM), have also been considered to address robotic formation maintenance. For example, Zhu et al. [110] used SOM to plan tasks for multi-AUV systems and develop a velocity synthesis method for path planning according to the assigned tasks. In Zhu et al. [111], the authors incorporated a biologically inspired neural network into the task-allocation algorithm to address the dynamics constraints of the robot when generating the path. More recently, the same authors presented a new study [112, 3], this time considering the orientation and the kinematics of the AUVs. Bucknall et al. [113] expanded the use of SOM by integrating a potential field approach to achieve improved collision avoidance. Despite these accomplishments, the methods were evaluated under ideal, or near ideal, conditions without considering real-world constraints, including dynamic uncertainties and obstacles.

3.2 Work in Progress in SEMFIRE

Within SEMFIRE, multi-robot exploration is a very important task, which enables the team of aerial Scouts to cooperatively proceed with the Reconnaissance mission in the forestry environment. In brief, this phase of the mission consists on having Scouts collectively exploring and mapping the target area with the goal of finding the regions of interest (ROIs) within this area that contain combustible material, e.g. fuel accumulation such as flammable debris, that should be mulched. The result of this phase is a semantic map that results from the collective exploration of the operational theater, containing information on the location of regions that need intervention and of regions that should be preserved, among other elements.

We have been working on multi-robot exploration by proposing an innovative cooperative perception architecture and distributed situational awareness in teams of mobile land and air robots in forestry environments using a common global framework, covering the following aspects:

1. Techniques for efficient information sharing and resilient operation in case of communication failures;
2. Distributed consensus and situational recognition mechanisms;
3. Optimization of the positioning of sensors during activities, enabling effective mechanisms of collective attention and reduction of uncertainty;
4. Detection of flammable material, tree types, people, animals, objects, situations and events relevant to missions carried out in a forest environment;
5. Tests, adjustments and improvements to the architecture developed in a real environment.

The cooperative perception architecture carefully delineated in Deliverable E3.1 [114], provides the groundwork for the development of the multi-robot exploration strategy within the Reconnaissance mission performed by the Scouts aerial robots. This is represented in the cooperative exploration feature within the multi-robot coordination module of the Scout robots, as illustrated in the Figure.

When the reconnaissance mission starts, Scouts need to perform an exploration mission while maintaining a given formation, be it for distributed and collaborative perception, as well as to maintain the connectivity of the network [115]. On an early stage of the project, this will be achieved by combining two state-of-the-art approaches:

- A Rapidly-Exploring Random Tree (RRT) based approach for multi-robot map exploration [116];
- An extension of the the self-organizing map (SOM) neural network method for solving the autonomous robot formation maintenance problem [110].

The RRT exploration strategy has been extensively evaluated on single robot planar applications and limited multi-robot applications [116, 117]. SEMFIRE will generalize the RRT algorithm, already made available to the ROS community[2], with the objective on tackling challenging collaborative 6DoF robotic applications. RRT will be used to find frontier regions in 3D map representations, which will subsequently feed the SOM method as key (target) positions of the expected formation shape. After that point, focus will be given in endowing SOM with obstacle-free navigation, required when operating under realistic environments. The proposed approach is based on obstacle-free convex region local navigator proposed by Alonso-Mora et al. [108], which allows robots to adjust the parameters of the SOM-based formation, while avoiding collisions with static and moving obstacles when progressing towards their goal.

3.3 Discussion and Expectations

Very few state-of-the-art solutions for forestry robotics focus on cooperative teams of field robots, with the notable exceptions of the RHEA [118] and RASBerry projects [119]. These projects make use of teams of robots, sometimes heterogeneous (i.e. involving various kinds of robots), which tend not to be numerous, usually involving less than 10 robots. Heterogeneous teams are of particular interest since, for instance, they are able to combine the actuation abilities of large robots with the perceptive abilities of UAVs, as in SEMFIRE. Swarm robotics, on the other hand, operates on the principle of employing large teams of small, relatively simple and cost-effective robots to perform a certain task. We could not find work exploring the perceptual abilities of large swarms of small robots for field operations, e.g. robust distributed mapping with multiple agents, be it for agricultural or forestry applications, which constitutes an important scientific and technological gap.

Multi-robot coordination is one of the most common and crucial tasks in a MRS [2]. Overall system performance can be directly affected by the quality of coordination and control. Coordination can be rigid or dynamic.

Some of the main areas of research in motion coordination are *formation tracking and control*[3], where the goal is to achieve a desired pattern defined by relative position vectors, *time-varying formation tracking control* [120], where the goal is to track a pre-established trajectory, while the agents maintain a time-varying desired formation.

In spite of the general obvious problems of motion coordination, the main MRS issue is the space sharing between agents; a resource sharing problem which has been studied mainly in relation to multi-robot motion planning, collision free, connectivity maintenance, congestion and deadlock avoidance problems. As further discussed, extensive formation-related studies have been carried out in recent decades around these topics, with formation control being the most actively investigated area. The aim of formation control is to generate appropriate control commands to drive multiple vehicles to achieve the prescribed constraints on their own states[121]. Several scientific groups has focused on consensus-based formation control, which uses the distance between vehicles information to allow the formation to maintain a certain shape while navigating. More recently, the concept of using dynamic formation shapes for collision avoidance purposes has been proposed and studied in a number of different works. However, the focus of these research efforts remains on low-level controllers without the high-level decision-making capability.

[2]http://wiki.ros.org/rrt_exploration

[3]In literature there is no a consensus in the application of the terms *formation control* and *formation tracking*. Through this document it is assumed that both share the same terminology.

In order to overcome these drawback and enable multi-robot formation systems to operate in complex missions, some cooperative motion planning techniques ended out being dominant over the past few years. These techniques take into consideration information, such as the mission start and end goal, as well as the environmental constraints, the aim of cooperative motion planning is to provide optimised trajectories for the formation to benefit the coordination of multiple robots [122]. In addition, MRS planning needs to take into account other constraints beyond the costs that are routinely considered in conventional planning, such as the shortest distance cost. MRS planning also needs to contemplate constraints specifically related to the formation itself, such as the required formation shape, in order to facilitate the formation control [123].

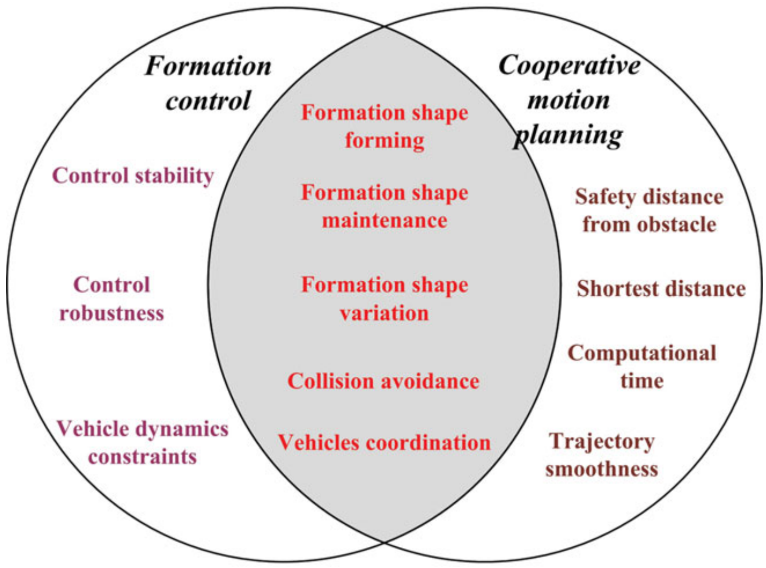


Figure 5: Overlap between formation control and cooperative motion planning, Liu et al.[2]

In Figure 5, we can see the large overlap between formation tracking and cooperative motion planning research topics. It clearly indicates the number of key concepts shared between it, and both topics should contemplate their interaction when being implemented in multi-vehicle formation systems. For instance, when performing cooperative motion planning, the trajectory for each vehicle should be generated with specific formation shape, so that the shape can be reached efficiently. Also, the formation control strategy should be capable of evaluating the features of the computed trajectories and decide how rigorously follow each individual path, or modify them in a way to avoid collisions. In addition, the vehicle dynamic constraints are important when designing the controller [124]; whereas for cooperative motion planning, safety distance from obstacles, total distance cost, computational time and trajectory smoothness are key costs when planning the path [125, 126].

As a preliminary methodology to tackle these described problem, Figure 6 depicts a diagram to easily understand the main components of the overall pipeline and better identify the main contributions.

As the main purpose of this architecture is do deal with multi-robot motion coordination, it is necessary to define the following main components:

- **Global Planner -** the global path will be generated by one of the several global planners available in the literature (section 4.2). We intend to explore different approaches **Rapidly Exploring Random Tree (RRT)**, with improvements of the [116] approach and a new exploration strategy based on the use of multiple RRTs[4];

[4] `http://wiki.ros.org/rrt_exploration`

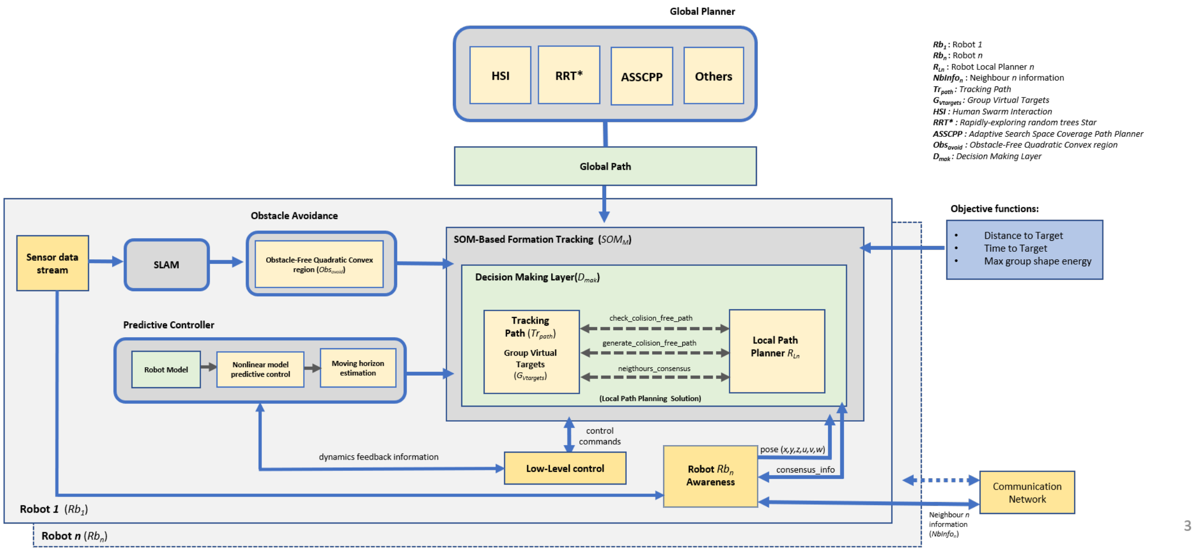


Figure 6: Purposed SOM-based formation tracking system architecture overview.

Adaptative Search Space Coverage Path Planner (ASSCPP) [127][5], proposing improvements over online sweeping for path generation and for polygon decomposition problems, such as coverage alternatives and the interrupted path concept. Besides those, other suitabler planners will be exploited with the intent to provide a global path to be used as reference to the main SOM-based component.

- **Sensor data stream -** as a general component to provide a stream of sensors, such as LiDAR, camera-based, localization sensors, among others;

- **SLAM -** as a general SLAM technique and non-technology dependent to provide information about the agents localization and surrounding map, fed by the sensor data and to provide an output for the Obstacle Avoidance component;

- **Obstacle avoidance -** input for the main SOM-based component by adopting the [106] work to compute the largest collision-free convex polytope in the neighborhood, followed by a constrained optimization via sequential convex programming, as a way to improve the obstacle avoidance capability of the SOM-based method;

- **Predictive Controller -** input for the main SOM-based component by following the [128] approach, designed to obtain an optimal trajectory tracking for agents, using a linear model predictive controller (MPC) in combination with non-linear state feedback. This predictive component depends on the robot model dynamics which exploits the feedback information provided by the low-level of control. The low-level control acts as the hardware abstraction layer for a given platform control, receiving linear and angular velocities.

- **Communication Network -** input for the main SOM-based component by managing inter-robot communication network connectivity and quality [129];

- **Robot Awareness -** input for the main SOM-based component by gathering information from the sensor data stream (implicit communication) and communication network (explicit communication), providing the pose of neighbour robots;

[5] `https://github.com/uenota/cpp_uav`

- **SOM-Based Formation Tracking -** main focus and contributions of this research as a novel an adaptive self-organizing map (SOM) neural network method for distributed robot-agnostic formation control (AUVs, USVs, UGVs or UAVs). This component will control and track the group of autonomous robots, keeping their position in the formation when moving as a whole. The group reaches the desired locations in an expected formation shape along pre-planned trajectories, provided by a given global planner component. The proposed approach is distributed in the sense that the controller of each robot only uses its own information and limited neighboring information, provided by the aforementioned components. The formation control strategy is based on self-organizing competitive calculations carried out with workload balance, without the need to designate the leader and the followers explicitly. All robots are treated equal, both as leader and follower, so that important characteristics, such as adaption and fault tolerance, emerge. A decision-making layer will be integrated within the approach to define component input weights to influence the formulation of the formation tracking. At last, a local planner provides the necessary navigation ability of each individual robot towards their virtual target.

The objective functions include minimizing the distance to target, the time to target, and the group shape energy, though other objectives might be considered in the future. In term of constrains, network connectivity, energy autonomy, time, rendezvous problems, and robots model dynamics will be considered.

The dimension of the configuration space is equal to the number of independent variables in the representation of the configuration, also known as the degrees of freedom (DOF). In this case, six degrees of freedom are considered: three to represent the position (Cartesian position) and three to represent the orientation (Euler angles) in its respective 3D axis.

4 Ranger Patrolling for Forest Clearing

4.1 Brief Literature Review

Multi-robot systems (MRS) and related subjects, such as design [130], communication [131], and path-finding [132] gained increased attention during the 80s. Still, early work on inspection robots [133], navigation of patrol robots [134], and robot security guards [135] focused exclusively on single robot solutions. In the end of the 80s and beginning of the 90s, the first physical multi-robot systems have been documented in pioneering research works with small populations of robots by researchers from Japan and the USA [207, 208, 209, 210]. During the 90s, a significant boost in work on MRS has been noticeable, with a growing involvement of European researchers. In this decade, robotics competitions, especially RoboCup [211] played an important role to foster MRS research.

Patrol is generally defined as "the activity of going around or through an area at regular intervals for security purposes" [212]. For MRS, this is a somehow complex mission, requiring an arbitrary number of mobile robots to coordinate their decision-making with the ultimate goal of achieving optimal group performance by visiting all point in the environment, which require surveillance. It also aims at monitoring, protecting and supervising environments, obtaining information, searching for objects and detecting anomalies in order to guard the grounds from intrusion. Hence, a wide range of applications are possible, as exemplified in Table 1.

Employing teams of robots for active surveillance tasks has several advantages over, for instance, a camera-based passive surveillance system [213]. Robots are mobile and have the ability to travel in the field, collect environmental samples, act or trigger remote alarm systems and inspect places that can be hard for static cameras to capture. These capabilities are highly beneficial to safeguard human lives and provide a great amount of flexibility to the deployed system [214].

Table 1: Examples of applications of multi-robot patrol.

Area of Application	**Example**
Rescue Operations	Monitoring trapped or unconscious victims
Military Operations	Mine clearing
Surveillance and Security	Clearing a building
Supervision of Hazardous Environments	Patrolling toxic environments
Safety	Preventive patrol for gas leak detection
Environmental Monitoring	Sensing humidity and temperature levels inside a facility
Planetary Exploration	Collecting samples
Cooperative Cleaning	Household vacuum and pool cleaning
Areas with restricted access	Sewerage inspection
Vehicle Routing	Transportation of elderly people
Industrial Plants	Stock Storage
Computer Systems	War-game simulations

Early work on applications using teams of mobile robots in surveillance contexts addressed essentially cooperative sweeping, coverage, and multi-robot coordination [215, 216, 217, 218, 219]. The MRP as we know it, started to receive more attention following the pioneer work of Machado *et al.* [220], where the environment was abstracted using a topological representation, *i.e.*, a patrol graph, which connected the key points in the area that needed regular visits by agents. The authors proposed and compared several patrolling architectures, using different agent behaviors, different communication assumptions and decision-making methods. Criteria based on the average and maximum idleness of the vertices were proposed to evaluate the performance of each technique using a simplistic JAVA-based patrolling simulator [221]. However, conclusions were solely drawn on two scenarios, and unweighted edges were used, meaning that agents always take the same time to travel from one vertex to another, independently of the distance between them.

Since then, several different MRP strategies with increasingly less relaxed assumptions have been presented, based on a wide variety of concepts, such as: simple reactive architectures [222], game theory [223, 224, 225, 226], task allocation [227, 228], market-based coordination [229, 230, 231, 232], graph theory [233, 234, 235, 236, 237], Gaussian processes theory [238, 239], Markov decision processes [240, 241], evolutionary algorithms [242], artificial forces [243], reinforcement learning [244, 245], swarm intelligence [246, 247, 248], linear programming modeling [249], Bayesian heuristics [250, 251] and others with sub-optimal results, leading to several detailed dissertations and thesis on the subject [252, 253, 254, 255, 256, 257, 258, 259, 260, 261]. Lately, an effort for real world validation of MRP systems has been evident [262, 263, 264, 265].

There are slight variations to the MRP. The idleness concept, *i.e.* the time that a point in the environment spends without being visited by any robot, has been broadly used in the literature as a basic performance metric, while other authors proposed alternatives such as the frequency of visits to important locations [266, 267]. Additionally, different coordination methods for the team of agents have been studied, such as centralized deterministic [268] and distributed probabilistic methods [269].

Important theoretical contributions on the area patrolling problem have also been presented previously [270, 271, 272, 273, 274], and it has been showed that the multi-robot patrolling problem is NP-Hard, and it can also be solved optimally for the single robot situation by finding a TSP tour in the graph that describes the environment to patrol (*cf.* Fig. 7).

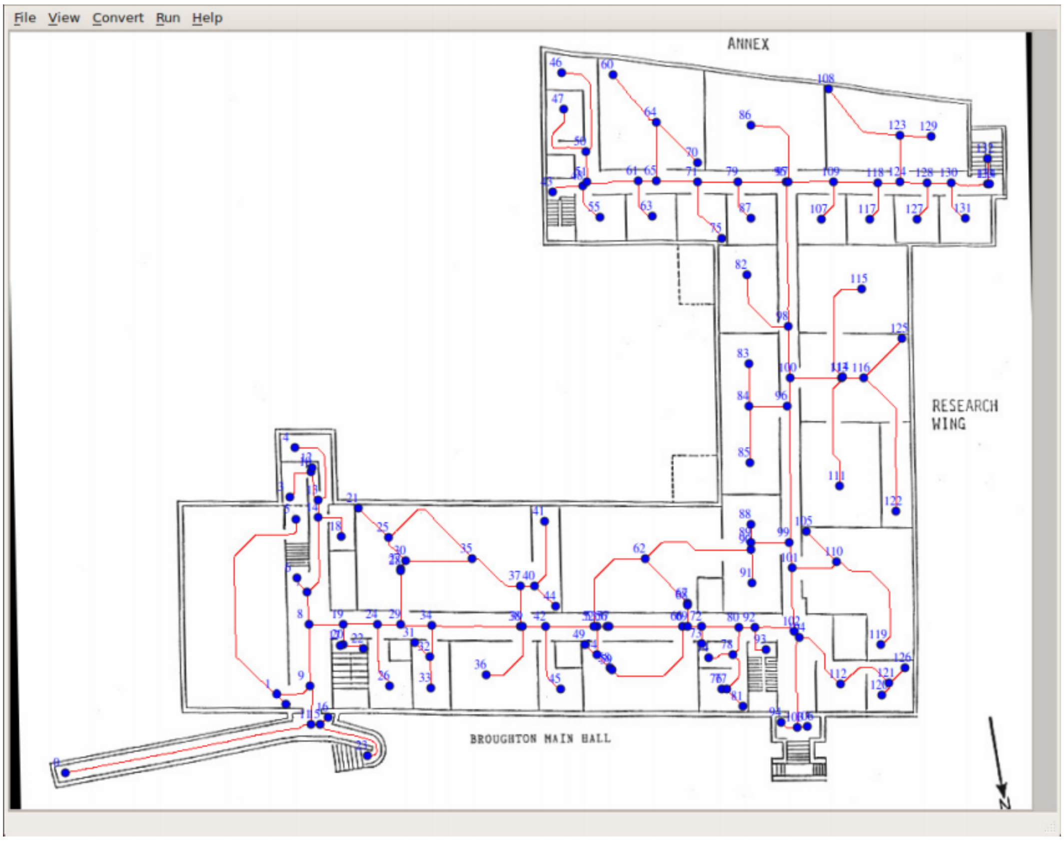


Figure 7: A patrol graph displayed on top of a metric map to be used in multi-robot patrolling tasks. The blue dots represent the vertices of the graph that must be visited, while the red arcs represent the edges that connect pairs of vertices [254].

4.2 Work in Progress in SEMFIRE

After the exploration/reconnaissance task is finished, the Scouts fly to key points that delimit the target area, while maintaining communication, and remain stationary in a controlled formation. The Scouts then monitor the progress of the clearing task, by assessing the fraction of existing debris over their initial state. At this point, the Ranger starts visiting the Regions of Interest (ROIs) previously identified in the reconnaissance stage so as to reduce the accumulation of combustible material by cutting down trees and mowing down ground vegetation (e.g. bushes, shrubs, brush, etc.) in the forestry environment.

The Ranger must plan efficiently the visits to all ROIs. This is done in a similar way to an area patrolling task, while the Scouts cooperatively monitor the mission progress. To do so, the Ranger must be able not only to navigate autonomously in the challenging 3D environment but also make decisions regarding the clearing mission. Therefore, in SEMFIRE we have also been working on these two preconditions for the Ranger patrolling task.

In Figure 8, the navigation architecture of the Ranger robot is illustrated. In summary, provided with a precise localization (see Section 2), the Ranger is able to plan 3D navigation goals, using a combination of local information (local planner and local costmap) and global information (global planner and global costmap). The navigation architecture encompasses a hierarchical safe design by automatically detecting traversable areas to navigate, considering all the entities that are present in the environment (people, animal, trees, etc.), recovery mechanisms for situations where the robot may feel trapped, and at the higher level a navigation emergency stop mechanism that can be triggered by the human operator in charge

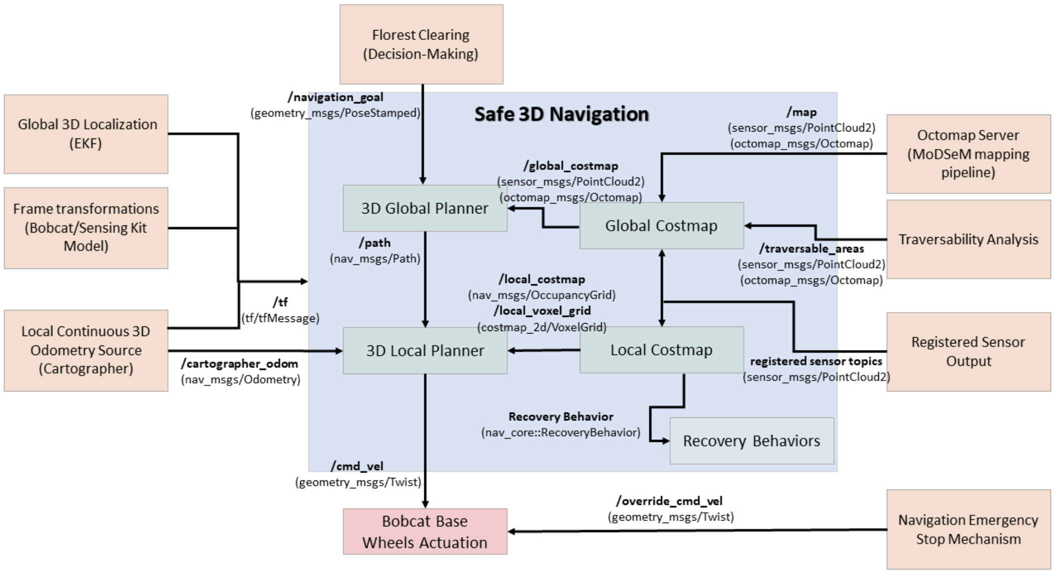


Figure 8: Ranger's Safe 3D Navigation Architecture.

at any point of the mission to override the autonomous navigation commands generated by the ranger robot.

The navigation allows the robot to plan traversable paths through the 3D environment to reach a specific region of interest which is sent to the robot by the Forest Clearing Decision-Making module, illustrated in Figure 9.

This module represents the most decisive action-coupling component of the SEMFIRE project. Assuming proper sensor registration, localization and mapping, as well as safe navigation and an advanced artificial attention system, given all ROIs previously identified, the forestry decision making module will perform the patrolling mission by planning all ROI visits and send navigation goals to the Ranger. Moreover, when reaching a ROI, this module is also responsible to safely move the arm of the robot and start mulching the flammable material, while assessing the clearing and robot state during the mulching procedure. Similarly to the navigation architecture, the Forest Clearing decision making framework also provides safety at the arm and mulching tool level. Firstly, autonomous mulching will only be triggered if the robot is fully confident that it and/or the entities around the robot do not incur in safety danger. Secondly, at the higher level an arm and a mulching emergency stop mechanism can be triggered by the human operator in charge at any point of the mission to override the autonomous decisions of the ranger robot.

For the Ranger forestry clearing, the robot will make use of a patrolling strategy. The research team has plenty of experience in this matter, as several patrolling strategies have already been implemented on ROS, and can be re-used for this purpose[6]. For the SEMFIRE project, we envisage to make use of the Concurrent Bayesian Learning Strategy (CBLS) for area patrolling proposed by Portugal and Rocha [264]. This is a probabilistic strategy, where the agent adapt its moves to the state of the system at the time, using Bayesian decision rules and distributed intelligence. The robot evaluates the context and adopts a reward-based learning technique that influences future moves to different regions of interest. Extensive results have shown the potential of the approach in terms of effectiveness, presenting superior results to several state of the art patrolling strategies. Moreover, we also made use of the proposed multi-robot patrolling approach in the recently finished P2020 R&D projecto

[6]See `http://wiki.ros.org/patrolling_sim`

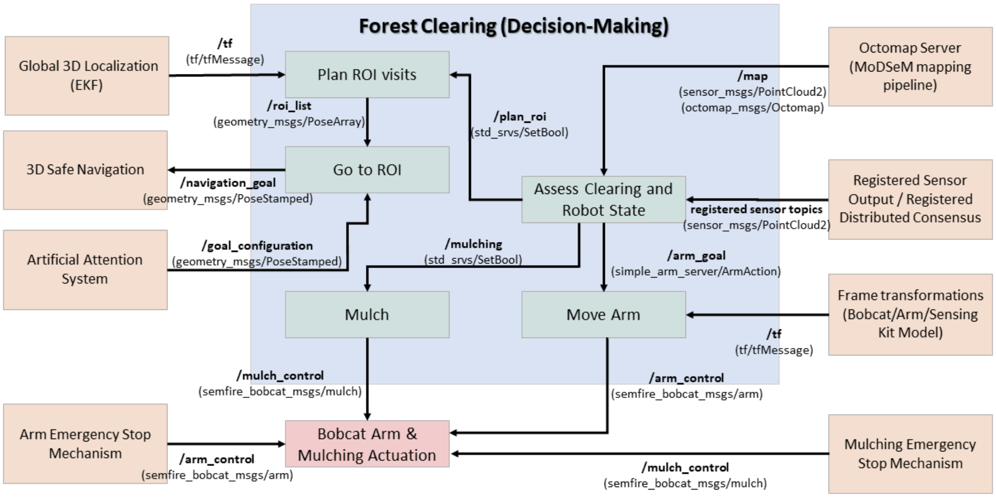


Figure 9: Ranger's Decision-Making Process for Forestry Clearing.

STOP[7] for cooperative security in large indoor environments.

Like for reconnaissance, Scouts formation will be managed by the extended SOM approach. Nonetheless, unlike before, wherein the RRT exploration algorithm was used to find frontier regions as target positions of the expected formation shape, the SOM method now relies on the Ranger's pose over time. This allows to establish the target configuration that Scouts should maintain to better estimate the position of the Ranger using UWB and to keep track on the progress of the mission. In ideal scenarios (i.e., obstacle-free scenarios), the Scouts should remain equidistant to each other, forming a geometry centred in the Ranger (x_R, y_R) planar position. Put it differently, for a fixed number of 4 Scouts, the optimal shape will be a square. However, one expects inter-Scout distances to change over time so they may adapt to the changes in the environment.

The clearing mission of SEMFIRE ends when the volume of combustible material in the target area falls below a predefined threshold, ideally zero.

4.3 Discussion and Expectations

As mentioned before, the CBLS patrolling strategy will be employed in the Ranger robot for forestry clearing. For this to become a reality, we have been working on the implementation of the Ranger navigation architecture. We currently have a navigation implementation for the Ranger robot based on [275], and we are extending the 2D navigation and path planning approach to 3D, by testing and improving the baseline approach in the SEMFIRE simulator, as illustrated in Figure 10.

Namely, we are currently working in extracting the 3D gradient of the terrain in relation to the robot, so as to distinguish traversable ramps and slopes from non-traversable ones (i.e. slopes that exceed the angular limits of the robot). By following the process illustrated in Figure 11, we are incorporating the gradient of the occupancy points contained in the *a priori* 3D point cloud map of the environment – or the map that results from the used SLAM technique – as an observation source to the navigation framework, then thresholding along the gradient (we consider that the robot does not climb slopes with more than 45 degrees of inclination) to understand whether the known terrain is safe to traverse. Moreover, we

[7] `http://stop.ingeniarius.pt`

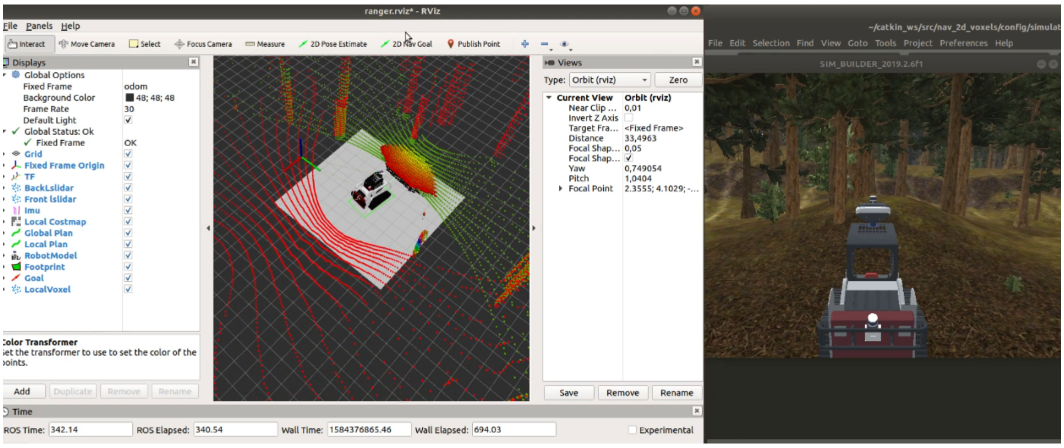


Figure 10: Ongoing Ranger Navigation simulation tests.

perform a statistical analysis on the perceived environment in order to concurrently detect and register obstacles, fusing the data from the two above steps into a single costmap. This not only allows the robot to avoid obstacles and select valid pathways, but to also select the most efficient paths available based on the described traversability cost estimation. After intensive testing of the proposed planning approach, which is still work in progress, we aim to test the 3D planning approach in the real Ranger with the existing low-level track actuation controller (see next paragraph), and check whether we need to modify the higher-level software that inspects the costmaps to reach a navigation goal by sending adequate velocity commands to the mobile robot base[8].

The low-level controller of the Ranger intends to be a standard in leading the research into existing heavy-duty autonomous machines, with the integrated Society of Automotive Engineers (SAE) J1939 Controller Area Network (CAN) protocol. Even though this might seem like a hard constraint, the SAE J1939 has become the accepted industry standard for heavy-duty machines in agriculture, forestry and construction. The SEMFIRE consortium successfully conceived a microcontroller bridge, capable of interpreting and generating J1939 messages, thus allowing to seamlessly exchange messages with the central controller of the compact track loader. Currently, ongoing work is being carried out on developing a low-level PID controller to continuously correct the motion of the Ranger based on the difference between the desired velocity, provided by the navigation layer, and the measured velocity, estimated by the localization architecture.

As soon as we have the navigation ready and stable on the Ranger robot, the patrolling node is ready to receive the list of ROIs in order to continuously plan effective visits to mulch and clear the forestry environment in areas where flammable material is accumulated.

Also, driven by application needs, this work will focus in adaptive methods based in neural networks with unsupervised learning. More specifically, the proposed architecture will revolve around the use of Self-Organizing Maps (SOM) for formation tracking with the following key features:

- Distributed decision-making using limited information of the neighbors;
- Adaptive to the environmental constraints (e.g., density of obstacles, limited space, communication constraints, etc.);
- Safe navigation in 3D workspace while avoiding dynamic obstacles;
- Fault-tolerant mechanisms to recover from breakdowns (e.g., robot stopped working);

[8] http://wiki.ros.org/move_base

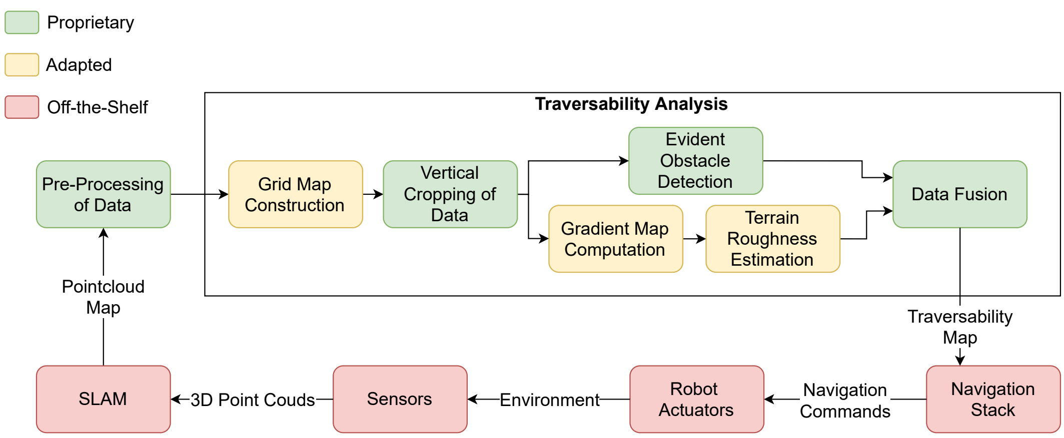


Figure 11: Incorporation of the 3D gradient as a navigation observation source, extending the global planning to 3D.

- Scalable to any number of robots;
- Integrated dynamics uncertainties;

The proposed motion coordination MRS architecture will try to mitigate these problems, going beyond the state-of-the-art in formation tracking and control algorithms. The contributions of this ongoing work revolve around the possibility of combining current formation control methodologies with artificial neural network (ANN) techniques, proposing a novel motion coordination MRS architecture based on *Self-Organizing Map* (SOM). SOM-based methods prove to be suitable when applied to the formation coordination problem, mostly due to their self-organizing characteristics. Nevertheless, the fundamentals around SOM approaches rely in a fault-tolerance premise, where most proposed approaches are so far unable to perform dynamic collision-free formation tracking, as well as handling severe environmental conditions. The herein proposed SOM-based architecture features such as, competitive, adaptive, distributed (fault-tolerance), deterministic and self-organizing characteristics, which are attractive to real-world MRS.

5 Multi-robot formation

The SEMFIRE project contemplates several fields of research, among which the development of a team of aerial and ground platforms for forestry robotics applications. This section presents the preliminary approach for Multi-robot coordination approaches algorithms as well as, the methodology to be followed in terms of communication, signal processing and position estimation in outdoor environment.

5.1 Introduction

In the last decade, significant amount of research efforts in the area of robotics have been made involving multiple robots over single agents. A robot as single-agent system is often designed to deal with a specific task or a sequence of tasks, without efficient multitasking. Such robots are usually equipped with multiple sensors, implying the need for a complex mechanism and an advanced intelligent control system. Although a single-robot system can lead to a relatively strong performance, some tasks may be inherently too complex, or even impossible, for it to perform, such as spatially distributed tasks, as it will be addressed throughout this document.

MRS offer several advantages over single solutions due to their practical potential in various real-world challenging applications, offering a panoply of scientific and technological challenges arising from the necessary level of coordination and control [136, 137]. MRS, as a definition, contains more than one robot, being formed by a group of homogeneous or heterogeneous collaborative robotic agents. Advantages of MRS over a single-robot system have been well-described in the literature, being summarized as:

- Optimal spatial distribution;
- Achieve better overall system performance. The performance metrics could be the total time required to complete a task [138] or the energy consumption of the robots [139];
- Introduces robustness that can benefit from data fusion and information sharing among the robots, and fault tolerance that can benefit from information redundancy. For example, multiple robots can localize themselves more efficiently if they exchange information about their position whenever they sense each other [100, 140, 141];
- Cost effectiveness, as each robotic platform comprising the MRS may be simpler (at a processing and sensing level), cheaper to build than using a single powerful robot that usually are more complex and expensive, to accomplish a task [142];
- Better system reliability, flexibility, scalability and versatility [143]. Robots with diverse abilities can be combined together to deal with complex task, and one or several robots may fail without affecting the task completion.

The field of MRS has grown over the past years since it can be used to effectively assist humans in multiple relevant application domains, such as industrial logistics management [144], precision agriculture [145], search and rescue [146], infrastructure inspection and surveillance [147], environment monitoring [148], transportation [149], forestry operations [150], among others. This is in line with the past work carried out by the candidate, developing robotic systems that were integrated within MRS deployed in different environments, including land [151], underwater[152], and air [153].

While this evident growth is extremely motivating, supporting the development and contribution of new approaches by the community, there are still many open challenges that need to be overcome in order to successfully deploy MRS under real-world scenarios. In particular, multi-robot motion control is considered as a contemporary area with some relevant work presented in the last decade, especially in terms of strategies for coordinating teams of mobile robots. However, many of these studies present unrealistic simplifications, strong limitations or questionable applicability and versatility, as it will be illustrated in section 3. The multi-robot motion coordination problem is very challenging in real-world scenarios, because robots must:

- Navigate autonomously while avoiding dynamic obstacles;
- Coordinate, collaborate and cooperate depending on their tasks;
- Decentralize their decision-making to avoid relying on a central agent;
- Overcome communication constraints;
- Accomplish the expected tasks, regardless of the number of robots and the environment's dimension.

Ensuring all of these requirements will inevitably lead to successful deployment of MRS in real-world scenarios. Moreover, and bearing in mind that, to date, one cannot guarantee that the MRS is endowed with all of these requirements, there is room for an eminent potential growth in this domain that is likely to take place in the next few years.

5.2 Multi-robot coordination

Significant amount of research efforts in the area of robotics have been made involving multiple robots over single agents. One of the key reasons relies on the practical potential of MRS in various applications, as well as theoretical challenges arising in their coordination and control [137]. This field has grown in the last years since it can be used to effectively assist humans in multiple relevant application domains, such as warehouse management, search and rescue, infrastructure inspection, transportation, among others.

The theory behind MRS suggests a task-sharing problem into simpler robots [154, 155], by cooperating with each other to achieve complex behaviors, combining different tasks and the dynamics of the environment [156, 157, 158, 159]. Due to their inherent time and space distribution characteristics, it is necessary that each robot maintains a consistent level of awareness about the task assigned to the team and about its agents, thus allowing the robot to break down complex problems, increasing robustness and reliability, and decreasing cost. These systems should be decentralized, distributed, redundant and fault-tolerant [160]. Therefore, from a cost-effective point of view, it may actually be cheaper and more pragmatic to build a set of less capable and simpler robots that can cooperate, instead of one single robot to perform the entire mission [161, 162, 163]. However, in general, it is unarguable that the development of MRS is scientifically and technologically more challenging than the single-robot counterpart.

The increasing of MRS promote a large research interest in recent decades. This section present a detailed survey to review the main approaches and techniques related to the application of MRS in distinct domains, including ground, aerial and aquatic applications, with the specific attention centred on formation control.

5.2.1 Common Methods and Recent Studies

Recent developments in the field of MRS Formation Control have led to a renewed interest in topics within the realm of multi-agent systems, which generally aim to drive multiple agents to achieve prescribed constraints on their states. Depending on the sensing capability and the interaction topology of agents, a variety of formation control problems have been studied in the literature over the past two decades [164, 165, 166, 104, 167, 168, 159, 169, 170, 171, 172, 173, 121, 174, 175, 176].

Based on the aforementioned set of state-of-the-art studies, it is possible to assess and categorize the main relevant variables for formation control as depicted in table 2.

The combination of these controlled variables gave rise to several formation control approaches. In the early beginnings of the 21^{th} century, the first approaches focused mainly in potential fields with attractive and repulsive behaviours, as presented in Koren et al.[177] and Balch et al.[178] works. This initial trend got popular due to the obstacle avoidance capabilities of the methods (typically modelled as repulsive forces). In 2001, Yamaguchi et al. [179] also used potential attractive vectors in a planar dimension formalizing a group formation approach solely based on local feedback, such as the relative position and orientation of the other agents. However, the authors pointed out that this approach would be unstable in certain situations, especially when robots estimate different relative distances between measurements, causing an endless motion in the formation.

Another methodology of the potential field approach was presented in Balch et al.[180] paper, inspired in molecules biologic behaviours as "social potentials". In this behavior-based method, the closest agent is attracted to the formation instead of being attracted towards a particular location, like the molecular crystal formation, wherein molecules are drawn to attachment sites arranged with respect of their neighbours. In the same line, Gayle et al.[181] presented a new method to compute collision free paths for multiple robots using local coordination constraints. A social potential field was applied to a convex and non-convex polyhedra, integrated into the physics-based dynamics motion planning. The limitations referred in this approach is the inability to guarantee that the robot finds the path, even if one exists, by falling in a local minimum. Similarly, Monteiro et al.[182] published a study based on matrix displacement using attractor dynamics to formation control. By performing real experiments, the authors addressed some issues with respect to occlusion and missing sensory information (e.g. follower temporarily does not see its leader), pointing out the importance of group relative position in the global frame coordinates, though local minimum was still an unsolved problem. To minimize the local minimum issue, Nascimento et al.[183] proposed a nonlinear model predictive formation control, using as well potential functions, by penalizing the proximity with neighbours and obstacles with a potential repulsive barrier. These authors used a switching approach implemented inside the task formation, which is replaced by a controller with a modified path planning algorithm[184]. Rezaee et al.[185] adopted a similar approach, where a rotational repulsive potential field was applied to avoid falling in local minimum positions.

Other works in artificial potential functions were described in Hernandez et al. [170] survey. While simple attractive and repulsive behaviours have worked for a wide range of applications, including swarm robotics [186, 187], leader-follower approaches have been adopted by many authors to solve specific MRS applications.

For instance, in 2004, Takahashi et al.[102] stated the relevance of this leader following strategy in formation control, proposing a centralized algorithm to control a defined number of robots, without taking into account the initial deployment of the agents. However, real robots were unable to completely avoid obstacles, which is expected under centralized approaches that require a high level of data exchange between agents that cannot be guaranteed in real-world scenarios. Alternative approaches were proposed to tackle this and other issues, combining leader–follower with consensus-based estimation approaches, as presented by Ren et al.[103]. The proposed distributed formation control architecture accommodates an arbitrary number of group leaders and arbitrary information flow among agents, namely about the neighbours position. Approaches with multiple group leaders and an efficient inter-robot coupling are less prone to failures in the presence of limited information exchange within the formation, though consensus might be hard to achieve, as described in Ren et al.[104, 188] works.

Alternatively to leader-following, virtual structures (VS) have also been applied, for instance, Tan et al. [189] consider a group of robots which maintain a rigid geometric between each neighbour and to a frame of reference, as well as, presented in [190] work. The fundamental technique behind the VS is consider the formation as a pre-defined shape like a rigid body, and with the main objective to minimise the position error between all VS and maintain defined formation position.

Behaviour-based formation control was first proposed by [178]. It solves the formation control problem by using a hybrid vector-weighted control function, which is able to generate the control command based upon various kinds of formation missions.

Other interesting approaches have been presented very recently, including a few authors tackling some adaptive methods to solve motion coordinating problems [191, 105, 192], as it will be presented in more detail in the next section.

As it was possible to identified in the aforementioned approaches, they reveal several weaknesses and commonly focus in the same methodologies. For instance, [193] presents a general architecture following a hierarchical three layers model, as it is possible to observe in Figure 12, the task management layer, the path planning layer and the task execution layer.

- **Task management layer:** allocates missions to individual agents based upon the criteria of maximizing overall performance and minimizing the mission time.;

- **Path planning layer:** This layer generate a feasible trajectories for the formation, according to mission requirements. Therefore, this layer is divided in three sub-modules, more specifically the real-time trajectory modification module, the data acquisition module and the cooperative path planning module. Among them, the cooperative path planning module is the central point of the system and determines the optimised path for each agent. Since a number of uncertainties may occur along the trajectory in real world applications, the real-time trajectory modification module is added to the system to be able to avoid obstacles.

- **Task execution layer:** Generated paths will then be passed down to the task execution layer, which has the direct connection with the robot actuators and generates the control commands.;

In order to improve system performance, real-time information, for instance the agent position and velocity, is provided to the higher layer to modify the trajectory, which generates a closed loop.

For last, it is important to applied the appropriated formations terminologies and definitions used in MRS. [166] present a interesting survey describing several paradigms, by analysing and compare, in detail, formation hierarchies, congregations, congregations, teams, coalitions, federations, societies, markets, among other organizations types.

Table 2, summarizes some of the main approaches in the state-of-the-art, during the recent years. Among different features presented in the table, we consider the following ones to be the most relevant: all system will be deployed in ROS environment; the approach most be suitable to operate in 3 dimensional workspace, tackling the problem using a decentralized method, able to deal with dynamic uncertainties, such as obstacle avoidance. In terms of experiments, firstly it will be deploy in simulation environment and then supported with real field experiments.

										Control Variables					
References	Year	Main Approach	ROS Implementation	Dimensional Space	Decentralized	Simulation	Real experiments	Scalable	heterogeneity	Collision avoidance	CoMM Connectivity	Distance	Orientation	Displacement	Position
Alonso-Mora, J., Baker, S., & Rus, D. (2015, September). Multi-robot navigation in formation via sequential convex programming. In 2015 IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS) (pp. 4634-4641). IEEE.	2015	Convex Optimization	Y	2D/3D	Y	Y	Y	Y	Y	Dynamic	NA	Y	Y	N	Y
Han, D., & Panagou, D. (2017, December). Distributed multi-task formation control under parametric communication uncertainties. In 2017 IEEE 56th Annual Conference on Decision and Control (CDC) (pp. 405-410). IEEE.	2017	Parametric communication uncertainties	N	2D	Y	Y	Y	Y	NM	Static	NA	Y	N	N	N
Michael, N., Zavlanos, M. M., Kumar, V., & Pappas, G. J. (2008, May). Distributed multi-robot task assignment and formation control. In 2008 IEEE International Conference on Robotics and Automation (pp. 128-133). IEEE.	2008	Market base coordination (Bid)	N	2D	Y	Y	Y	Y	NM	Static	NA	Y	N	N	N
Wang, L., Ames, A. D., & Egerstedt, M. (2016, December). Multi-objective compositions for collision-free connectivity maintenance in teams of mobile robots. In 2016 IEEE 55th Conference on Decision and Control (CDC) (pp. 2659-2664). IEEE.	2016	Compositial barrier functions	Y	2D	N	Y	Y	NM	NM	Dynamic	NA	N	N	N	Y
Balch, T., & Arkin, R. C. (1998). Behavior-based formation control for multirobot teams. IEEE transactions on robotics and automation, 14(6), 926-939.	1998	Behavior-based for formation keeping	N	2D	N	Y	Y	NM	NM	Static	Y	N	N	Y	N
Alonso-Mora, J., Montijano, E., Schwager, M., & Rus, D. (2016, May). Distributed multi-robot formation control among obstacles: A geometric and optimization approach with consensus. In 2016 IEEE International Conference on Robotics and Automation (ICRA) (pp. 5356-5363). IEEE.	2016	Geometric and optimization with consensus	Y	2D/3D	Y	Y	Y	Y	Y	Dynamic	NA	Y	Y	N	Y
Jin, X. (2016). Fault tolerant finite-time leader–follower formation control for autonomous surface vessels with LOS range and angle constraints. Automatica, 68, 228-236.	2016	leader–follower strategy	N	2D	N	Y	N	NM	N	N	N	Y	Y	N	N
Vrohidis, C., Vlantis, P., Bechlioulis, C. P., & Kyriakopoulos, K. J. (2018). Reconfigurable multi-robot coordination with guaranteed convergence in obstacle cluttered environments under local communication. Autonomous	2018	leader–follower strategy	N	2D	Y	Y	N	Y	NM	Y	Y	Y	N	N	N
Yao, X. Y., Ding, H. F., & Ge, M. F. (2018). Formation-containment control for multi-robot systems with two-layer leaders via hierarchical controller–estimator algorithms. Journal of the Franklin Institute, 355(12), 5272-5290.	2018	leader–follower strategy	N	2D	Y	Y	N	N	NM	N	NA	Y	N	N	Y
Zhao, Z., & Han, D. (2018, March). Multi-task formation of multi-spacecraft via distributed hierarchical control. In 2018 IEEE Aerospace Conference (pp. 1-8). IEEE.	2018	Hierarchical formation	N	3D	Y	Y	Y	Y	NM	Y	Y	Y	N	N	N
Balch, T., & Hybinette, M. (2000). Social potentials for scalable multi-robot formations. In Proceedings 2000 ICRA. Millennium Conference. IEEE International Conference on Robotics and Automation. Symposia Proceedings (Cat. No. 00CH37065) (Vol. 1, pp. 73-80). IEEE.	2000	Social Potencial functions	N	2D	N	Y	N	Y	N	Y	NA	Y	Y	N	N
Desai, J. P., Ostrowski, J. P., & Kumar, V. (2001). Modeling and control of formations of nonholonomic mobile robots.	2001	Nonlinear control theory and graph theory	N	2D	N	Y	N	Y	N	Y	NA	N	Y	N	Y
Alonso-Mora, J., Naegeli, T., Siegwart, R., & Beardsley, P. (2015). Collision avoidance for aerial vehicles in multi-agent scenarios. Autonomous Robots, 39(1), 101-121.	2015	Convex optimization	Y	3D	Y	Y	Y	Y	Y	Dynamic	NA	Y	Y	N	Y
Hsieh, M. A., Kumar, V., & Chaimowicz, L. (2008). Decentralized controllers for shape generation with robotic swarms. Robotica, 26(5), 691-701.	2008	Potencial Field	N	2D/3D	N	Y	N	N	NM	N	N	Y	N	Y	N
Bazoula, A., Djouadi, M. S., & Maaref, H. (2008). Formation control of multi-robots via fuzzy logic technique. International Journal of Computers, Communications & Control, 3(3).	2008	Leader Follower	N	2D	N	Y	N	NM	NM	N	N	Y	Y	N	N

Table 2: Summary table with some multi-robot motion coordination approches.

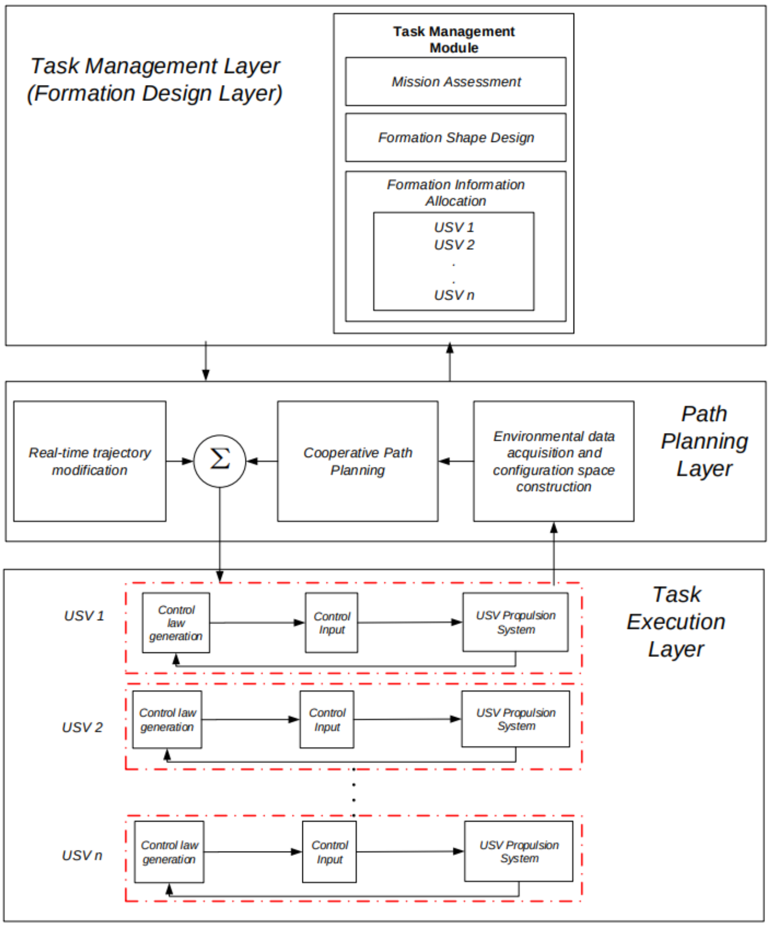


Figure 12: Multi-robot formation example architecture, from Liu et al. work.

Variable	Description
Distance/Range	The most used variable in formation control, that provides the inter-agents distance relation of neighbours with respect their own local coordinate systems.
Orientation	This metric is commonly combined with other variables presented in this table. It is able to supply the methods with the orientation of the individual agents to teammates, group centroids and goals.
Displacement	This variable provides a sense of relative displacement of the neighbours with respect to the global coordinate system.
Position	This variable is similar to displacement. However, it differs in the base reference coordinate system. The agents sense their own position to the global coordinate system, i.e., they are aware and able to localize themselves in the global frame (typically used when global positioning systems are available).
Collision avoidance	Usually this variable is designated as a constrain in the literature, be considered in most studies. This represent a static or dynamic constrain-agent (i.e. neighbour, teammate, obstacle) located in the global coordinate system.
Communication connectivity	This parameter is also presented as a constrain to the formation control approach. It is usually addressed when communication infrastructures are unavailable, in order to maintain the network connectivity. A typical approach include set of rules imposed by the group in relative and global system coordination.

Table 2: Main types of controlled variables in Formation control methods.

5.2.2 Adaptive Methods Applied to Motion Coordination

As is possible to verify from the current state-of-the-art, formation control algorithms are often not adaptive and require a high parameterization and tuning. However, some authors like [191], [105] and [192], propose a decentralized adaptive control approaches to solve the consensus problem of multi-agent systems. Also by adopting adaptive neural network schemes it was possible to counteracted the effect of some environment disturbances in real world applications. However, the collision avoidance problem is not considered, as well as dynamic uncertainties. Moreover, the 3D workspace capability stated, it was consider just as a fixed frame applied to multiple robotic manipulators.

Another active research group, that have been continuously working in this field, is Alonso et al., by adopting several combined methods, as shown in their studies [106, 194, 107, 108, 195]. The authors presented decentralized approaches with a capability to deal with static and dynamic obstacles environments in 3D workspaces. The followed strategy was based on a sequential convex optimization approach to compute a convex region in free position-time space and on non-convex optimization methods to compute the configuration of the team of robots with obstacle avoidance constraints [109, 196]. However, in their last work it was stated that deadlocks may arise due to disagreements occurring when each robot computes an independent global path [108].

More recently, some authors like [197], started to apply combined methods with reinforcement learning (Deep Double Q-Networks (DDQN) and Proximal Policy Optimization (PPO)) and behavior-based to formation control, by optimizing the reward function it is possible to modify the entire dynamics of the group [197]. The authors, in this work it was deployed a team of 3 robots along several scenarios blocked with fixed obstacles, with defined starting points and goals. It was possible to verify, that best performance results in these experiments, were mostly in situations which did not change between the layout of environment. These results were achieved, by tune the reward function, and consequently the robots were able to increased the level of confidence reached the goals faster, by avoiding the obstacles and increasing the navigation speed. However, the work suggest that the hidden layers of deep reinforcement learning models are helpful in complex experiments, but computationally costly and in most simple experiments, the addition of a hidden layer was not beneficial. Furthermore, the performed experiments were in simulation and did not consider the dynamic uncertainties.

Artificial neural network (ANN), such as the self-organising map (SOM), have also been considered to address multi-task allocation for unmanned vehicles. For example, Zhu et al. [110] used the SOM approach to plan tasks for multi-AUV systems and develop a velocity synthesis method for path planning according to the assigned tasks. In [111], the authors incorporated a biologically inspired neural network (BINN) into the task-allocation algorithm to address the dynamics constraints of the robot when generating the path. More recently, and still the same authors [112, 3], presented a new study, this time considering the orientation of the AUVs as well, which resulted in an improved path planning taking in consideration the kinematics of the AUV. Also, [198] work apply a SOM-based approach, to formation tracking. During the formation there is not defined a leader neither a follower, all group are treated equally. The desired locations are set as input vectors of SOM neural network. Self-organizing competitive calculations are carried out with workload balance taken into account. Output vectors of the SOM network are the corresponding AUVs' coordinates, so that a group of AUVs are controlled to reach the designated locations. Bucknall et al. [113] expanded the utilisation of the SOM to USV platforms, additionally integrating a potential field approach to achieve improved collision avoidance. A different research group, though still within the same line of research, was presented by [199], who applied the SOM for AUV systems and have specifically investigated SOM application in data collection missions.

However, in presented approaches were performed with ideal conditions and without consider dynamic uncertainties, focusing in a specific environment aerial or aquatic, among the other limitations referred in this section. This give us the opportunity to improve in this line of research, by applying these recent SOM-based approaches as a starting point.

In the same line of the previous comparative table, it was created a new table (Table 3) but this time focusing the main research works using adaptive methods. For this research, we consider the following features the most relevant to be achieved during this work. The approach will be based in SOM, able to deal with obstacle avoidance and dynamic uncertain, in a certain 3 dimensional workspace focused in the formation coordination problem. In terms of experiments, we intent to deploy our approach in real field experiments.

Authors	Tittle	Year	Approach	Problem to solve	Plataform Type	Real Tests	3D workspace	Formation coordination	Path Plannig	Task assigment	Obstacle avoidance	Dynamics uncertainties
Hou et al.	Decentralized Robust Adaptive Control for the Multiagent System Consensus Problem Using Neural Networks	2009	Radial basis function neural network (RBFNN)	Consensus problem of multiagent systems	Manipulators	N	3D Fixed frame	N	N	Y	N	N
Cheng et al.	Neural-network-based adaptive leader-following control for multiagent systems with uncertainties	2010	Radial basis function neural network (RBFNN)	Leader-following control and Track the leader's time-varying state	N.A.	N	N	N	N	Y	N	Agent's dynamics
Cheng et al.	Recurrent neural network for non-smooth convex optimization problems with application to the identification of genetic regulatory networks	2011	Recurrent neural network (RNN)	Non-smooth convex optimization problem with the convex inequality and linear equality constraints.	N.A.	N	N	N	N	N	N	N
Alonso-Mora et al.	Multi-robot navigation in formation via sequential convex programming	2015	Collision-free Convex polytope , followed by a constrained optimization via sequential convex programming	Navigating a team of robots in formation in 2D and 3D environments with static and dynamic obstacles	Hololomic Mobile Robots	Y	Y	Y	Y	N	Y	Y
Alonso-Mora et al.	Local motion planning for collaborative multi-robot manipulation of deformable objects	2015	Convex optimization Collision avoidance and manipulation	Manipulation of soft objects by robot teams	Hololomic Mobile Robots + Manipulators	Y	3D Fixed frame + 2D	Y	Y	N	Y	N
Alonso-Mora et al.	Collision avoidance for aerial vehicles in multi-agent scenarios	2015	Distributed convex optimization | centralized non-convex optimization | concept of velocity obstacles (VO)	Local motion planning, or collision avoidance, for a set of decisionmaking agents navigating in 3D space	UAVs	Y	Y	N	Y	N	Y	Y
Hai et al.	Distributed Multi-Robot Formation Splitting and Merging in Dynamic Environments	2019	Obstacle-free convex regions + intersection graph based	Distributed method for splitting and merging of multi-robot formations in dynamic environments with static and moving obstacles	UAVs	Y	Y	Y	N	N	Y	Y
Zhu et al.	Dynamic task assignment and path planning of multi-AUV system based on an improved self-organizing map and velocity synthesis method in three-dimensional underwater workspace	2013	Improved Self-Organizing Map (SOM) + Velocity synthesis approach	Dynamic task assignment and Path planning of a group of AUVs	AUVs	N	Y	N	Y	Y	N	N
Zhu et al.	Formation tracking and transformation control of nonholonomic AUVs based on improved SOM method	2017	Improved Self-Organizing Map (SOM) + Virtual targets	Formation Tracking of a group of AUVs	AUVs	N	N	Y	N	N	N	N
Xin et al.	An adaptive SOM neural network method for distributed formation control of a group of AUVs	2017	Improved Self-Organizing Map (SOM) + Distributed approach	Formation control of a group of AUVs	AUVs	Y	Y	Y	N	N	Y	N
Zhu et al.	Biologically inspired self-organizing map applied to task assignment and path planning of an AUV system	2017	Biologically inspired Self-Organizing Map (BISOM)	Task assignment and Path planning of a group of AUVs	AUVs	N	Y	N	Y	Y	Y	N
Faigl et al.	Autonomous data collection using a self-organizing map	2017	Growing Self-Organizing Map (GSOM)	Solve the traveling salesman problem (TSP)	N.A.	N	N	N	Y	N	N	N
Faigl et al.	An Application of Self-Organizing Map for Multirobot Multigoal Path Planning with Minmax Objective	2016	Self-Organizing Map (SOM)	Multiple Traveling Salesman Problem (MTSP) with minmax objective	N.A.	N	N	N	Y	N	Y	N
Zhu et al.	Multi-AUV SOM task allocation algorithm considering initial orientation and ocean current environment	2019	Improved Self-Organizing Map (SOM) + Orientation approach	Task assignment and Path planning of a group of AUVs	AUVs	N	Y	N	Y	Y	N	N
Cao et al.	Multi-AUV cooperative target search algorithm in 3-D underwater workspace	2017	Self-Organising Map (SOM)+ Glasius Bioinspired Neural Network (GBNN)	Improve the efficiency of multi-AUVs cooperative target search	AUVs	N	Y	N	Y	N	Y	N

Table 3: Summary table with the presented adaptative approches.

5.2.3 Self-Organizing Map (SOM)

Self-organizing map (SOM), it is highly used for clustering information from big data, as a type of artificial neural network (ANN) it categorised as a self-organizing method. It is differentiated from other ANN as is trained using unsupervised competitive learning, instead error-correction learning. SOM use a neighborhood function to preserve the topological properties of the input space. Also, by using this method it is possible to to produce a low-dimensional, two dimensions typically, by discretizing the representation of the input space of the training samples, called a map, and is therefore a method compute dimensionality reduction.

The SOM neural network method was first introduced by T. Kohonen in the 1980s and extended later [200, 201, 202]. It is based on the idea that there is a special order of processing units in the mammalian brain. Each unit is dedicated to a specific task and each group of neurons is sensitive to a particular type of input signals. The units are determined by parameters that can be changed in certain processes to produce meaningful organizations. This algorithm soon became a valuable tool and was used to solve many kinds of problems. In recent years, this method has been applied to solve task assignment problems and control of multi-robot systems [203].

In summary SOM approach, recognizes each point in the data set by competing for representation in the map. This competitive representation is initialized by randomly sample a vector and update the map of weight vectors. It is computed each weight that best represents that sample. Each weight vector has neighboring weights that are close to it, then the weight that is chosen is rewarded by being able to become more like that randomly selected sample vector. The neighbors of that weight are also rewarded by being able to become more like the chosen sample vector.

5.3 Preliminary Approach

In an early stage of this project, potential fields were considered as a preliminary formation tracking approach, as described in the following section. From there it was possible to identify a series of drawbacks, which subsequently led us to the SOM-based method.

5.3.1 Potential Field

The developed preliminary MRS formation control was based on the Potential Field [177] method with attractive behaviour in regards to the center of mass of the group, commonly designated in the literature as centroid [204]. In this work, the formation control algorithm follows solely the principles of attractive forces, in which the behaviour of each robot n follows a system of difference equations (1):

$$\begin{cases} v_n[t] = -k.(x_n[t] - x_{t_n}[t]) \\ x_n[t+1] = x_n[t] + v_n[t] \end{cases} \tag{1}$$

wherein k assigns weight to the convergence rate, with k¿0. $v_n[t]$ and $x_n[t]$ represents the velocity and position vector of robot n, respectively. While $\| v_n[t] \|$ is limited to the maximum allowed velocity of V_{max} for robots, i.e.,$\| v_n[t] \| \leq V_{max}$, $x_n[t]$ depends on the scenario dimensions. In the beginning, robots' velocities are set to zero ($v_n[t] = 0$) and their position is randomly set within the boundaries of the scenario (Algorithm 1). $x_{t_n}[t]$ is the target position for robot n computed as the minimum Euclidean distance between its current position and the desired target positions.

To easily find the target position of a given robot n, an Euclidean distance matrix $E_c = [e_{ij}] \in R_{>0}^{N_R \times N_T}$, with $R > 0$ as a set of positive real numbers, can be calculated based on the Euclidean distance between all N_R robots to all N_T targets, as (2):

$$e_{ij} = \| x_i[t] - x_{j_i}[t] \| \tag{2}$$

In this work, we assume that the number of robots and the number of targets are the same, $N_R = N_T$. The target of a given robot n will then be the one with the smallest Euclidean distance ((3)):

$$t_n = \arg\min_{t \in N_T} e_{n,t} \tag{3}$$

It is noteworthy that the size of the vectors (ϖ) depends on the dimensionality R of the physical space being explored, e.g., $\varpi = 2$ for planar problems and $\varpi = 3$ for three-dimensional problems. This work considers the formation control of surface robots, thus defining $\varpi = 2$.

Matlab was used in a first stage due to its simplicity in testing the algorithm. Algorithm 1 presents the overview of the method as pseudo-code:

Algorithm 1: Method overview for formation control in MRS.

```
define n robots;
initialize robot poses and velocities; // Seeded by random numbers [x_min, x_max]
while defined iterations do
    i. Calculate the Euclidean distance matrix (eq. (2));
    ii. Compute individual cost function as the smallest Euclidean distance (eq. (3));
    iii. Update robot velocity if over velocity threshold then
        establish min/max threshold (eq. (1));
    end
    iv. Update robot position (eq. (1));
    v. Publish a new pose to each robot;
end
```

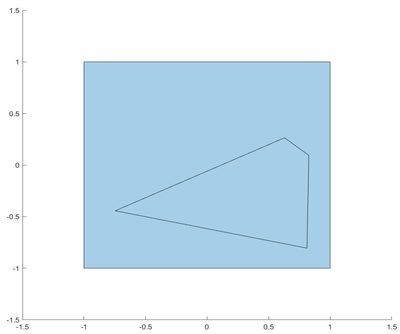
Figure 13 presents the visual validation of the implemented method. It is possible to verify a blue shape, where the vertices represents the desire position of all four robots, forming the square type shape. Inside the blue shape area, it is shown the actual shape of the robot formation, where the vertices represent the position of the robots. By following the sequence in Figure 13a, we can observe the initial random deployment of the vertices, originating that formation shape. After approximately 14 iterations (Fig. 13d) the group reach the desire position and consequent formation shape.

A ROS node was developed as a second step, *mrs_formation_control*, made available in the github repository. The Matlab code was then migrated to C++ language, subscribing position topic (*/robot_n/p3d_odom*) to feed the algorithm with actual pose of each robot, as well as the goal pose of the centroid provided by a specific topic (*/robot_0/mrs_centroid/goal*), computing the new pose by publishing a set of positions in the world map, in the topics (*/robot_n/move_base_simple/goal*).

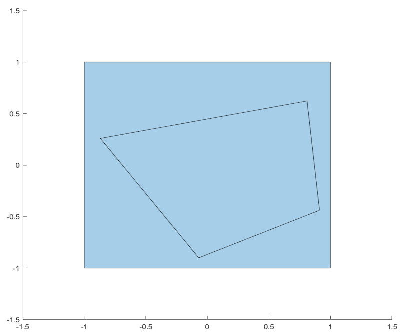
Aside from planning constraints, and as stated in the literature for complex environments, the system cannot solely rely in potential field based approaches, due to the trap situations caused by local minima (cyclic behavior), no passage between closely spaced obstacles, oscillations in the presence of obstacles, and oscillations in narrow passages.Therefore, as previously justified, the key contribution intends to fall in a novel SOM-based method. Next section presents the fundamental description of the SOM-based method to be consider as a starting point and a future comparative method to benchmark with the upcoming implementation of thisresearch.

5.3.2 SOM-based

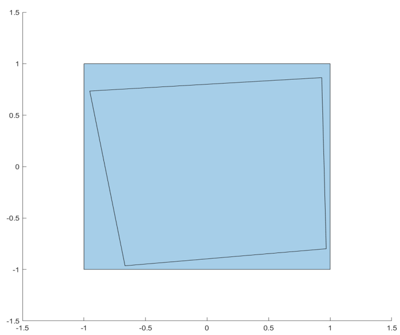
As a preliminary implementation of a SOM-based approach it was followed the work of [3]. It will be consider as a starting point algorithm to be used as benchmark reference of the upcoming improvements. For this implementation, it was used Matlab, but for future work



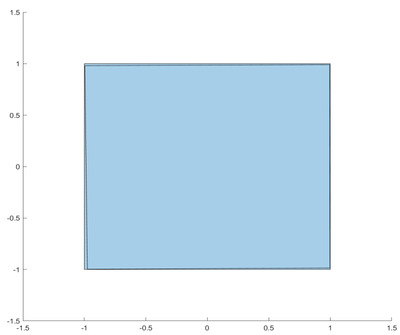
(a) Initial deployment, iteration n= 1.



(b) Converging to desire position, iteration n= 6



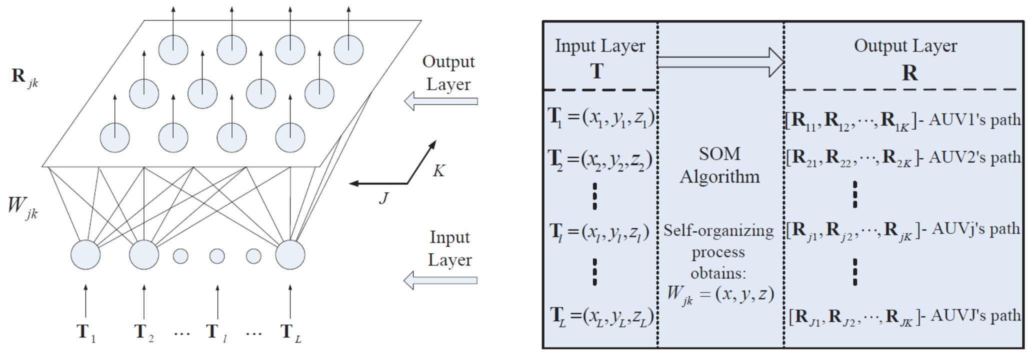
(c) Converging to desire position, iteration n= 10



(d) Final position, iteration n= 14

Figure 13: Sequence of method converge to desire positions. Blue square vertices representing the desire final formation, and interior black shape vertices the actual position.

is indented to migrate to ROS framework, to be possible deploy in Gazebo simulation. In Figure 14a, it is present the SOM-based neural network model followed and the mapping relationship is shown in Fig. 14b. Initially, there are J robots randomly distributed in the 3D workspace, where $J \in N^+$, however, we will consider a 2D workspace for this implementation. L points are set at the key positions of the expected formation shape.



(a) (b)

Figure 14: SOM neural network **(a)** structure and the **(b)** mapping relationship of the two layers, presented in [3] work.

The first layer is the input layer, including L neurons, where $J \in N^+$. These neurons represent the Cartesian coordinates of the points in the 2D workspace. T is a $2 \times L$ matrix which denotes the coordinates of the target points as input neurons. Each input neuron has three parameters (x_l, y_l) according to the coordinates of its corresponding point, where $l = 1, 2, ..., L$. All the coordinates form the input dataset.

The second layer is the output layer. Neurons in the output layer represent the coordinates of the robots and the corresponding path for each robot. Each neuron of the output layer is fully connected to the neurons of the input layer. There are K neurons to establish an optimal path for each robot, where $K \in N^+$, resulting in $K \times J$ neurons. The connection weight of each output neuron, i.e. the weight $W_{j_k} = (x, y)$, is given by a 1×3 weight vector, which is initialized as the coordinates of the initial robot position. The network is initialized with the weight vector $R_{j_k} = W_{j_k} = (w_{j_{k_x}}, w_{j_{k_{yy}}}$, where $j = 1, 2, ..., J$ and $k = 1$. R_{j_k} changes with W_{j_k} during every computation iteration. After the iterations, we get a $2 \times J \times K$ matrix R which denotes the coordinates of the output neurons, i.e., the trajectories of the robots. The input data set is given sequentially to the network in a random order, i.e., target coordinates are inputs of the network one by one until the last target. This input strategy with the random order of the input data results in the robustness of the algorithm and reduces its dependence on initial workspace configuration. During this process of formation, the visiting sequence of the points is gradually worked out, and the points would attract output neurons to form a formation for the robots. The iterations end until all of the robots reach the desired points.

In order to deploy the following approach, a pseudo-code, also described in Algorithm 2 presents main steps of this implementation:

- **Winner Selection and Neighborhood Function Design:** The first step in the SOM approach is to select the winner node. For an input neuron (the target point in formation), the output neurons compete to become the winner node [203]. Let D_{kjl} be a weight value at a time instance related to Euclid distance between the j^{th} AUV neuron and l^{th} input node neuron in the k^{th} iteration. The neighborhood should be a circle in 2D space with radius γ. The center of the neighborhood sphere is the winner

Algorithm 2: SOM-based method implementation pseudo-code overview, following the approach presented in [3] work.

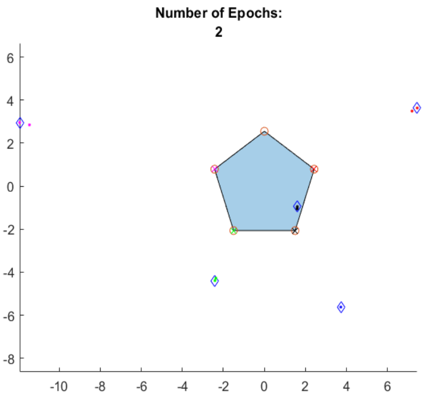
Input:
Define number of robots n_{robots};
Define number of targets $n_{targets} = n_{robots}$;
Define desire shape formation $shape\_array = xy_{points[]}$;
Random initial position of robots $rand(xy_{rob})$;
i. $robot\_n_{random}$ → randomly select $robot_n$;
ii. $compute\_euclidean\_distance()$ → to all neurons;
iii. $select\_winner\_neuron()$ → from all candidates;
iv. $compute\_neighborhood\_influence()$ → winner and neighbor neurons;
v. $update\_neural\_weights(xy_{rob})$;
if $robot_n <= D_{min}$ **then**
| $xy_{rob} = xy_{target}$ → goal reached;
end
Output:
Desire shape D_{shape};

node. The neighborhood function determines the influence of the input target on the winner neuron and its neighbor nodes. The winner was put on the highest attractive force, which diminishes as the distances of the neighbor neurons to the winner increase.

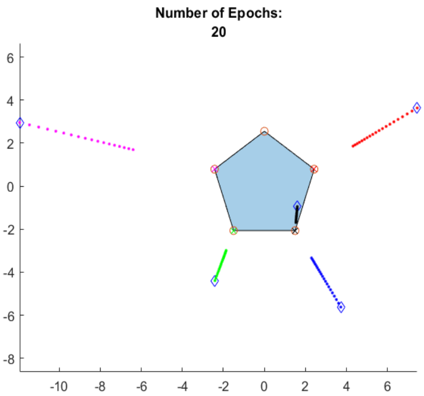
- **Strategy for Workload Balance of the robots:** The benefit of workload balance control is that the energy consumption of each robot could be equalized, making use of the robot team as a whole formation. Workload balance control is mainly determined by the robots' actual moving length and the safety length preset.
- **Neural Weights Updating Function:** After the winner neuron and its neighbors are selected, the next step is to move the winner neuron and its neighbors toward the input neuron (the target), whereas the other neurons stay still.
- **Formation Tracking Strategy:** A virtual formation is assumed, which is totally the same as the actual one. The virtual formation has the same key points as the real formation and, when formation tracking is implemented, the virtual formation moves first.

Figure 15 present the experimental results of the implemented approach.
In terms of parameters for this experiment, it was consider the following:
$n_{robots} = 5$;
$n_{targets} = n_{robots}$;
$S_{max} = 12$;
$S = 0.2 * S_{max}$;
$gama = 3$;
$mu = 5$;
$G_0 = 0.2$;
$D_{min} = 0.1$;
$acc_s = 0.1$;
$acc_f = 1.2$;
$alpha = acc_s * 0.5$;

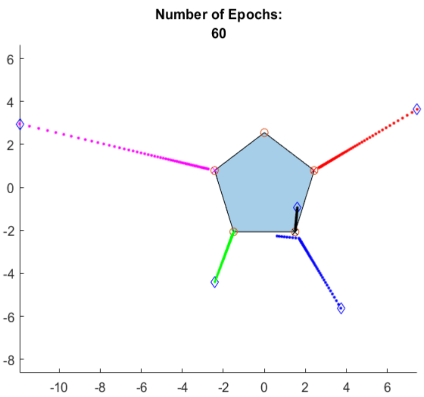
Where n_{robots} define the number of robots in environment, $n_{targets}$ the number of targets to visit, S_{max} maximum allowed traveling length, S it is a safe distance where it can vary between 20% and 80% from S_{max}, $gama$ define the neighbourhood radius, mu and G_0 is the neighbourhood velocities coefficient, D_{min} its the stop threshold condition, where defines the



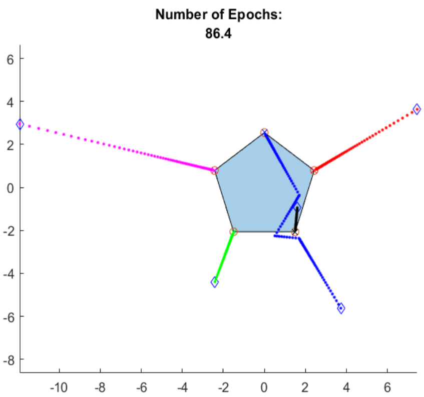
(a) Initial deployment, epoch number 2.



(b) Converging to desire goal, epoch number 20



(c) Converging to desire goal, epoch number 60



(d) All robots reach final goals, epoch number 86.4

Figure 15: Sequence of SOM-based method, with a team of 5 robots converging to desire goals (circles) in a pentagon shape formation; Starting point is marked as diamond markers.

acceptable distance to goal. Finally, acc_s, acc_f and $alpha$ is the corresponding acceleration factor and leaning rate.

In the experimental results a 2D workspace was configured where a team of 5 robots was randomly deployed (Fig. 15a) represented by diamond markers, and defined a associated color for each robot. For the desire goals (circles) it was placed a pentagon formation shape (blue). The velocities of all robots are adjusted (Fig. 15b) to maintain a certain coherence in terms of time of arrival to the goals. We can verify in Figure 15c, the competitive feature of the method, where the black and blue robot competed for the same goal, and the blue robot redirect its path to another goal and ending on the final goal position, as shown in Figure 15d.

5.4 SOM Implementation and Experimental results

The SOM implementation is described in the following section, and is called Self-Organized Map for Autonomous Robot (SOMAR). The focus is to merge SOM with the obstacle susceptibility required when operating in real-world scenarios. The proposed approach is based on obstacle-free convex regions with a preferred direction of motion local navigator by Alonso-Mora et al. [108], which allows robots to adjust the SOM-based formation, while avoiding collisions with static and moving obstacles when progressing towards their goal.

The implementation steps are as follows:

- Development of SOMAR for real-world robotic formation by delineating the first extension of the SOM method using the obstacle-free convex region with a preferred direction of motion approach proposed in [108];
- ROS implementation of the SOM method previously proposed by Li and Zhu [3] for robotic formation, and extension it to 3D;
- Setting up a ROS-compatible Gazebo simulation environment, involving one remotely operated wheeled vehicle and multiple aerial drones, including relevant real-world models, such as robot dynamics, and radio frequency communication modeling to account for communication constraints.

The next paragraphs introduce development procedures, prepared to evaluate the proposed approach.

5.4.1 SOMAR Implementation

SOMAR is a SOM adaptation with extension to distributed way of sharing data and cooperation between formation members. A formation consists of a group of unmanned aerial vehicles (UAVs) which are supposed to maintain the desired shape, and an unmanned ground vehicle (UGV) is considered to be a centroid or a leader of the formation. A formation comprise a group of $j \in J = \{1, ..., n\} \subset \mathbb{N}$ robots.

Robots should have an opportunity to move as a group and avoid obstacles. For achieving that, a common free from the obstacles area is shared between each of them. Obstacle free area is calculated using the convex approach, based on the work of Alonso Mora [108], the diagram of which is presented on Fig. 16. The UAV is equipped with Lidar, which is used to detect obstacles. The point cloud data is reorganised in a way, that each obstacle is clustered and simplified to be presented as a convex 3D polytope. The UGV has a separate planner and obstacle avoidance system, using merged cloud from Lidar and RealSense camera.

Computation of a large obstacle-free convex region is performed by each robot. The first step is to scan for available neighbour robots to generate the convex hull of theirs positions, which is also used for estimation of a direction of motion when UAVs face obstacles. Secondly, the obstacle free convex areas are being calculated in a distributed way on each robot as intersection polytope received from neighbouring UAVs to ensure that the group was not split.

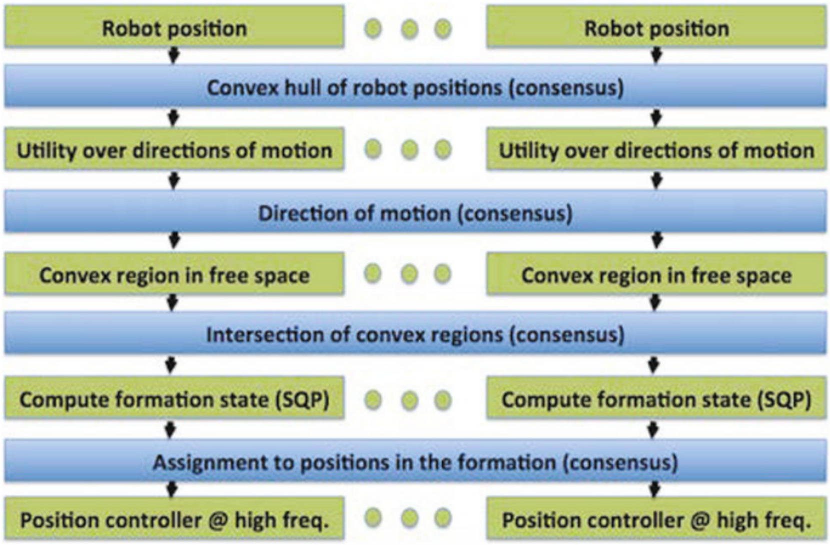


Figure 16: Schema of the convex obstacle free method.

As stated before robots should never split and move as a whole in the same direction, to ensure both the tracking of UGV and in order to not loose any member of the group. A preferred direction of motion is computed on each j^{th} robot. In order to compute that direction $\theta^* \in \mathbb{R}^3$ in a distributed fashion, each robot handles a vector $\mathbf{u}_i \in \mathbb{R}^k$ to compute the global utility for all the angles in $\Theta = \theta_1, ..., \theta_n$.

The vector is initialized as $\mathbf{u}_i(0) = [\mathbf{u}_i(\theta_1), ..., \mathbf{u}_i(\theta_k)]$ and, subsequently, all the robots execute the following iterative rule:

$$\mathbf{u}_j(k+1) = \min_{i \in N_j} (\mathbf{u}_j(k), \mathbf{u}_i(k)) \tag{1}$$

The polygon P on a 2D plane centered at UGV position, where the z or height coordinate is limited only by communication range between ground robot and aerial ones. The direction V is calculated from UAV's change in position over the time step t. The generated polygon is built around an incircle with radius R, representing maximum radius between UAVs.

Taking into account the actual pose of the robot in the formation, $\mathbf{R}_j \in \mathbb{R}^3$, each individual is capable to distributively calculate the distances and angles matrix D towards the ideal robot position P_j provided by SOM. The proposed approach considers the discrete set of angles Θ, containing n possible incremental directions of motion, assuming that a global orientation frame is available to all the robots, with origin in $\mathbf{R}_j$. The obstacles point clouds are converted into a set of convex hull polygons O for the simplification purposes. The algorithms also require formation centroid f_c calculated out of UAVs positions, where they first converted into convex 2D polygon and then f_c is calculated from that polygon center.

Each robot is capable of computing a utility value, $\mathbf{u}_j$ (1) for every $\theta \in \beta$ that describes how good is a given direction of motion is.

$$u(\theta) = \min_{j \in J} u_j(\theta) \tag{2}$$

From equation (2), the optimal direction of motion, i.e., the one leading to the best global utility, can be calculated as:

$$\theta^* = arg \max_{\theta \in \Theta} u(\theta) = arg \max \min_{j \in J} u_j(\theta) \tag{3}$$

All vertices of a desired formation must be inside an obstacle free area A. The FODPSO (4) optimizes the ideal targets polygon P_{ideal} to fit in area A in k iterations by minimizing the euclidean distances d_i between original vertices and optimized ones as long as they do not fit in obstacle free area A - 3D convex polygon, as described in Alg. 4. The maximized ellipse E_{max} must touch surfaces of convex obstacles O, which then are converted into planes I and intersected between each other resulting in a 3D polygon A.

$$PSO(P) = min(\sum_{i=1}^{k} d_i) \tag{4}$$

Algorithm 3: Distributed direction of motion - Robot j

Initialize discrete set of angles Θ;
while *not ROS shutdown* **do**
  receive robot neighbour positions;
  receive O;
  receive P_{ideal};
  receive j winning node from SOM for current robot;
  compute distances and angles matrix D_j towards P_j;
  send D_j to all robots;
  receive D and calculate group direction of motion θ;
  compute robot direction of motion θ^* towards P_j;
end

Algorithm 4: Distributed obstacle free area - Robot j

Initialize discrete set of angles Θ;
while *not ROS shutdown* **do**
  receive O;
  generate minimum ellipsoid E around f_c;
  if *obstacles points not in E* **then**
    calculate E_{max} [5];
    build planes I;
    build A from I intersections;
  end
end

The FODPSO (5) maximizes the inner ellipsoid E as in Equation 5 to touch the surfaces of the neighbouring obstacles O in k iterations by maximizing the ellipsoid radiuses a, b and c between original values and optimized ones as long as they do not cross one of the planes. One must be careful to setup the initial formation without any obstacles between the robots.

$$PSO(E) = max(E_{fit}) \tag{5}$$

Algorithm 5 describes the desired formation shape generation, the vertices of which will be the ideal positions for the group. Later those vertices will be fed into SOM to select the ideal position for each drone and plan a path to it.

The SOMAR function subscribes to targets P_{fit} and calculates robot's desired j target id, fed to robot local planner, which publishes command velocities to the robot ensuring reaching the P_j position in P_{fit}, where P_c is a current position on a path to P_j. The SOMAR is initialized with general SOM parameters described in section 5.2.3.

Algorithm 5: Formation shape generation

Define $n\_targets$;
while *not ROS shutdown* **do**
 receive n_robots;
 receive A;
 receive direction of motion $\mathbf{u}$;
 compute waypoint $\mathbf{w}$ at $\mathbf{u}$ direction;
 generate polygon P_{ideal} at f_c ;
 P_{fit} = PSO(P_{ideal});
end

Algorithm 6: SOMAR

Initialize SOM parameters;
while *not ROS shutdown* **do**
 receive P_{fit} and R_{max};
 receive f_c;
 receive robot position R_i;
 calculate winning j node by SOM;
 if P_c *did not reach* R_i **then**
  move robot to P_j;
 end
end

5.4.2 Robotics Simulator Setup

To test the approach a Gazebo [205] simulation was used, as it has existing open source solutions that include most of the necessary realistic features needed, including vehicle models, actuators and controllers, sensors and world models. The Husky robot [9] was chosen to represent a ground vehicle as it has necessary physics parameters. Moreover, Husky model has already implemented tools for localization, navigation and control that are very useful for this project. The husky navigation stack [10] is based on the [11] that links together a global and local planner to reaching a given target in a world.

We also integrate use the UAV Simulator, named *Hector Quadrotor*[12] from Johannes Meyer et al. [206], open-source development simulator and testing tool, based on Gazebo, providing UAVs flight dynamics, onboard sensors like IMUs, external imaging sensors and complex environments. The LIDAR-based and visual SLAM approaches are also available as open source software. The UAV is able to move to a desired position using the MoveIt motion planning framework [13], a 3D autonomous navigation stack for a Quadcopter.

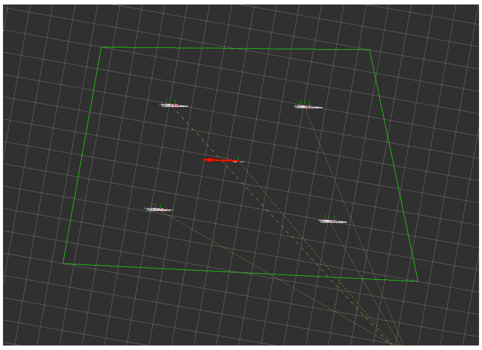
The simulation setup with UGV and four UAVs is shown in Figure 17(a) and the created obstacle-free polygon in 2D view in rviz can be seen there, red arrow represents the direction of motion for the group. In Figure 17(b) the ideal free of the obstacles area is created as none of the UAVs detect an obstacle, same for the direction of motion pointing forward.

In Figure 18 the setup when approaching the mountain is shown. In this case the convex area is deforming due to the fact that one of the UAVs face an obstacle. The direction of motion has also changed its' orientation to allow obstacle avoidance for the whole group.

The obstacle free area is published in both 2D and 3D representations. A plugin to view 3D polygon in *rviz* was created as depicted in Figure 19.

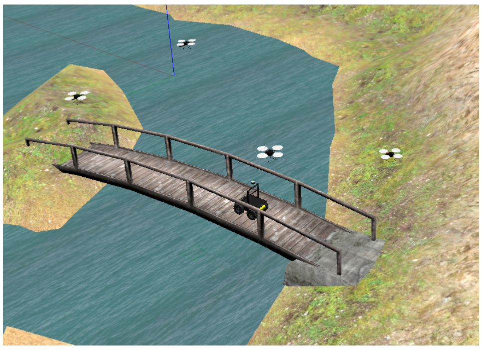
[9]http://wiki.ros.org/Robots/Husky
[10]http://wiki.ros.org/husky_navigation
[11]http://wiki.ros.org/move_base
[12]http://wiki.ros.org/hector_quadrotor
[13]https://github.com/tahsinkose/hector-moveit

(a) Gazebo - setup with four UAVs and one ground vehicle.

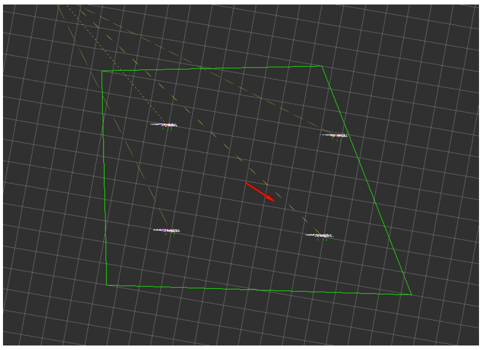


(b) rviz - Ideal obstacle-free area and direction of motion.

Figure 17: Simulation view with no obstacles.



(a) Gazebo - a formation of four UAVs and one UGV approached a mountain.



(b) rviz - obstacle-free area deformation and changed direction of motion.

Figure 18: Simulation view when approaching an obstacle (mountain).

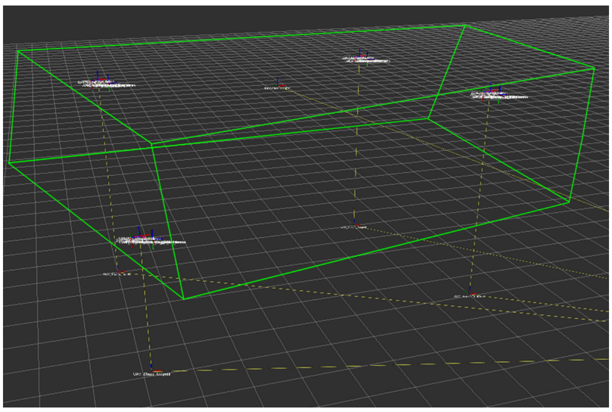


Figure 19: Obstacle-free area in 3D view

A root-mean-square error (RMSE) analysis has been carried out to measure the accumulated differences between the real position of the robot and the one generated by SOMAR. As expected, the RMSE increases with the density of obstacles (Tab.3.). Nonetheless, it is not a significant difference, namely when taking into account that the average travel length of the group in the worst scenario (4) is 385.74 meters, with a RMSE of 3.696±2.158 meters.

Designation	**mean rmse**	**std rmse**	**rmse min**	**rmse max**	**avg travel**
No obstacles	1.477	0.486	1.005	3.422	361.42
Low obstacles	2.630	1.098	1.982	8.773	366.05
Medium obstacles	3.103	2.149	2.126	9.114	379.92

Table 3: RMSE analyses in meters of overall team in different obstacle density scenarios.

6 Conclusion

This deliverable addresses the multi-robot exploration, patrolling and localization system within SEMFIRE. We analyzed the literature and reported on the developments and existing results within SEMFIRE on all three topics in this final version (b) of deliverable E4.1.

We started by describing the multimodal localization (Section 2) system of the Ranger, which is already in a mature phase of implementation and is paramount to the success of the other tasks (patrolling and exploration), we then moved on to the multi-robot exploration for cooperative reconnaissance (Section 3) and the ranger patrolling approach for forest clearing under cooperative monitoring of the Scouts in formation control (Section 4), which have been carefully delineated. Ongoing developments and augmented results on the multi-robot tasks have also been presented, when compared to the initial version (a) of this deliverable.

During the upcoming months of the projects, we will start the preparation to apply recent developments on the final trials of the SEMFIRE project.

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