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Multi-Robot Path Planning based on Self-Organized Map for Autonomous Robots (SOMAR)

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INGENIARIUS

Introduction

Endowing a multi-robot system (MRS) with the ability to maintain a given predefined geometric shape over time has been applied in a wide range of applications, namely in infrastructure inspection and maintenance, cooperative mapping, search and rescue, and others. Despite the panoply of multi-robot formation control approaches available in the literature, many challenges are still left untackled or lead to a suboptimal performance, especially when robots need to operate in real-world scenarios, wherein moving obstacles and other constraints need to be taken into account.

This work reports preliminary steps towards extending the self-organizing map (SOM) neural network method for autonomous robot formation maintenance, leading to the Self-Organizing Map for Autonomous Robots (SOMAR) architecture. In this work, SOM is improved with an obstacle-free convex region with a preferred direction of motion for safe local navigation. The proposed approach endows robots with the ability to efficiently avoid collisions, while maintaining, as much as possible, a given formation. SOMAR is validated under a realistic Gazebo-based aquatic multi-robot simulator.

Keywords: SOM, Multi-Robot systems, Path Planning Tracking, Artificial Neural Network.

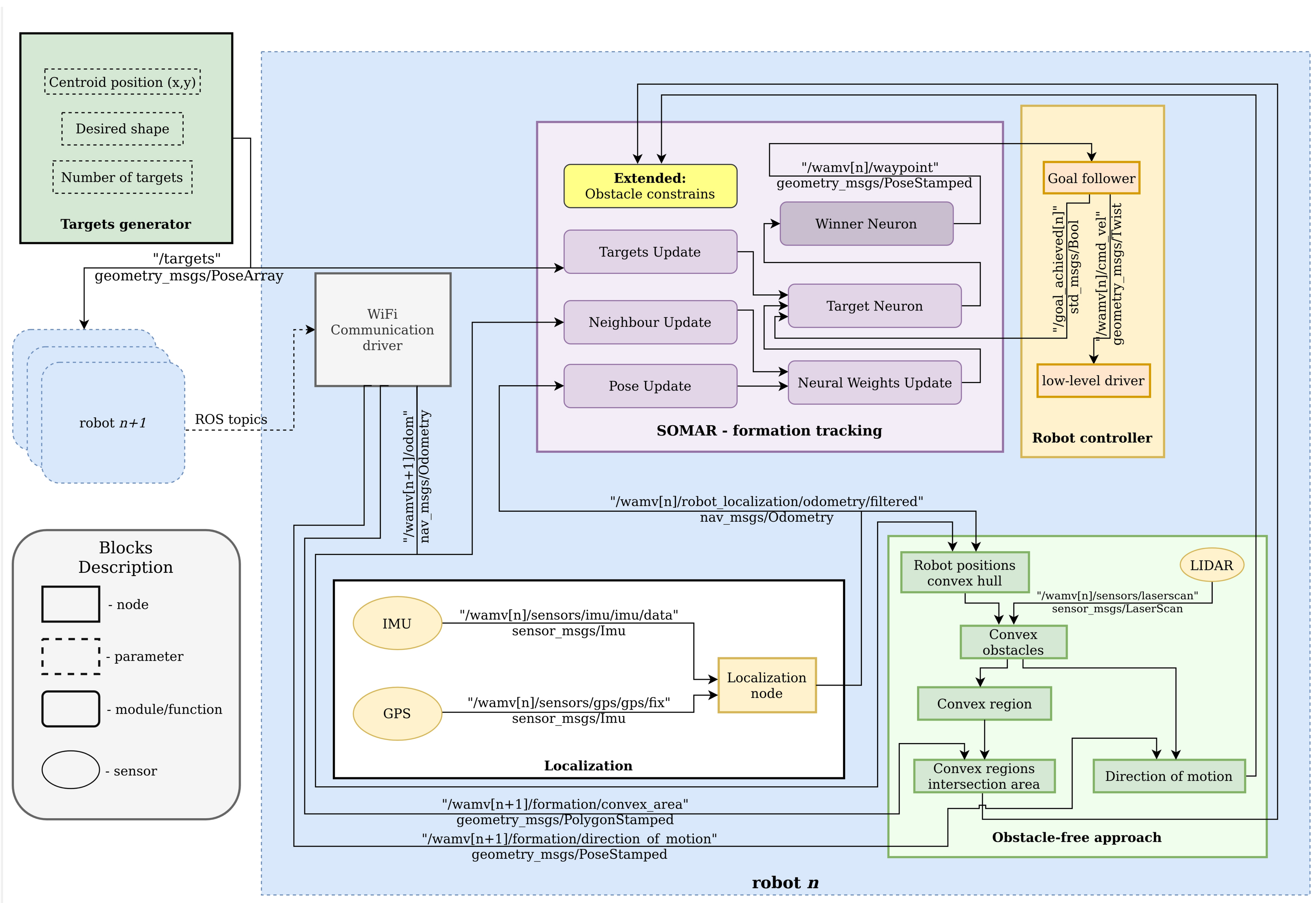
Self-Organized Map for Autonomous Robots (SOMAR)

The SOM method is an artificial neural network (ANN) approach introduced by Kohonen and inspired by the idea that there is a special order of processing units in the mammalian brain [1]. Each ANN unit is dedicated to a specific task and each group of neurons is sensitive to a particular type of input signals. SOM has been adopted for MRS and adapted to multi-robot applications mostly with the purpose of maintaining a formation. SOMAR goes one step further by adding obstacle avoidance convex hull free area. The method provides a preferred motion direction and improves the neural weights updating function to promote the deployment of robots under real-world applications. Following the same notation of the original work [2], Equation (1) is the modified neural weights updating function, wherein Q_x, Q_y and Q_z denote the rotation matrix of the preferred direction vector $\boldsymbol{u}$ for roll, pitch and yaw, respectively. This equation provides a novel method to obtain the updated weights of the neural network, which takes into account the obstacle-free path. The previous features have been introduced before with the intent to adapt SOM to multi-robot applications. SOMAR goes one step further by implementing the all-encompassing architecture presented in the following figure.

$$\boldsymbol{w}_{k+1} = \boldsymbol{w}_k + Q_z(\theta^*_{jz}).\,Q_y(\theta^*_{jy}).\,Q_x(\theta^*_{jx})\,.\,\boldsymbol{d}_{l,w(k+1)} \quad (1)$$

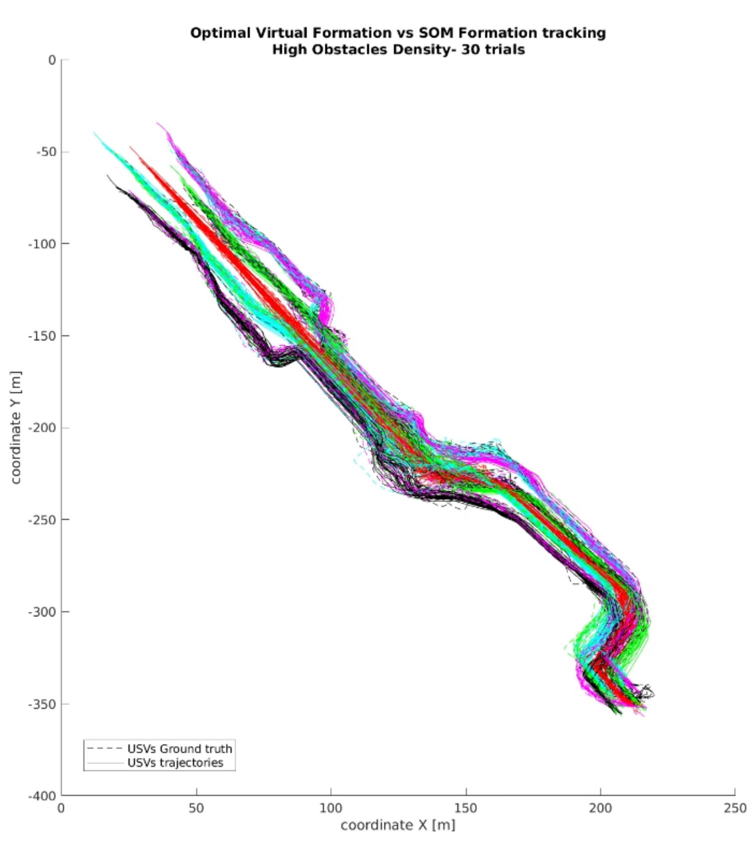
Contributions

- 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 proposed in [3];
- Implementation in ROS of the SOM method previously proposed by Zhu [2];
- Setting up a ROS-compatible Gazebo simulation aquatic testbeda, involving one remotely operated underwater vehicle (ROV) and multiple unmanned surface vehicles (USV), including relevant real-world properties, such as robot dynamics, underwater acoustic propagation for ROV positioning estimation, and Wi-Fi modeling to account for communication constraints.



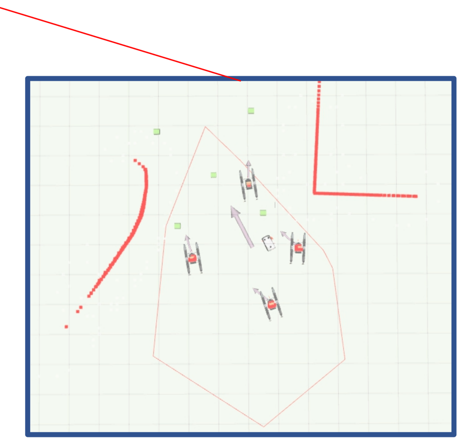
Results

A set of 120 simulation trials, using four different densities of obstacles, has been conducted under the realistic simulated aquatic testbed b to demonstrate the performance of the proposed SOMAR architecture 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. Nonetheless, it is not a significant difference, namely when taking into account that the average travel length of the group in the worst scenario is 385.74 meters, with a RMSE of 3.696 ± 2.158 meters.



video

Obstacles	mean RMSE	std RMSE	RMSE min	RMSE max	avg travel
None	1.477	0.486	1.005	3.422	361.42
Low	2.630	1.098	1.982	8.773	366.05
Medium	0.103	2.149	2.126	9.114	379.92
High	3.696	2.158	2.148	10.703	385.74



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