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ABSTRACT

The aim of this paper is to propose a technique for Simultaneous Localization and Mapping in underwater environments by means of acoustic sensors. The proposed procedure consists in the application of suitable Neural Network and Iterative Closest Point algorithms for objects detection, agent localization and map construction. General Regression Neural Network and improved ICP algorithms are implemented in order to process sonar data, to minimize the computational time and to maximize efficiency in localization tasks without using dynamical models of the agent. Experimental tests have been performed in a simple, structured static environment collecting data by means of a single-beam, mechanically scanning sonar. Results show good performances of the procedures in simple but meaningful situations.

KEY WORDS: sonar, Unmanned Underwater Vehicles, SLAM, ICP, GRNN.

INTRODUCTION

To localize oneself and to map the surrounding environment are important activities that an agent, especially an unmanned underwater vehicle, should be able to execute in order to operate safely and to perform general tasks. In this paper, we propose a Simultaneous Localization and Mapping (SLAM) technique, which can be employed by unmanned underwater vehicles equipped with single-beam mechanically scanning sonar in structured environments. The technique is based on the use of an Iterative Closest Point (ICP) algorithm in order to estimate the vehicle displacement and to localize it in the environment, while map building and updating is performed by a Kalman filter. The standard ICP algorithm has been improved by adding specific procedures for object detection and for optimizing the computation of optimal transformations. The optimization step increases the computational burden, but the object detection capabilities help in speeding up the process. The paper is divided in three Sections. The first one gives a short description of the SLAM Problem and of the state of the art of the related methodologies, including ICP algorithms. The second Section presents the proposed approach and the last Section discusses some experimental results.

SLAM: SIMULTANEOUS LOCALIZATION AND MAPPING

The problem of estimating the motion of an agent in an unknown environment, without any a priori information, is a well known and challenging one. Basically, it consists in constructing a map of the environment and, in the meantime, in estimating the position of the agent by exploiting the information collected, during the motion, by means of various sensors. In the literature this problem is known with the acronym SLAM (Simultaneous Localization and Mapping) and, since it was formally introduced in Smith, Self, and Cheeseman (1987), many different applications and solutions have been proposed. Actually, the possibility of giving a satisfactory solution to a SLAM Problem depends on several heterogeneous factors, which can be grouped into three categories: the environment's configuration (notably the presence of structure), the degree of knowledge about the agent's characteristics (notably about its dynamical model) and the kind and quality of its sensory equipment (which may include external and internal sensors, like e.g. cameras, sonar, laser, inertial measurement units, encoders, compasses, and so on).

Methodologies

In order to solve SLAM Problems, statistical approaches such as Bayesian Filters have found widespread acceptance in robotic. In the first approach proposed in Smith, Self and Cheeseman (1987), the authors use an Extended Kalman Filter (EKF). A similar methodology has been used in Williams, Newman, Dissanayake and Durrant-Whyte (2000); Newman and Leonard (2003); Newman, Leonard and Rikoski (2003); Newman (1999) and Leonard, Moran, Cox and Miller (1995). In these approaches, geometric objects (like points, lines, and circles chosen in order to match the environment's features or landmarks) are used to represent and to map the environment. A different approach was developed in Elfes (1987), where a statistical representation of the environment by means of cells and grid is proposed. This method has been used in many other situations by a number of authors (Conte, Gambella, Scaradozzi and Zanoli, 2006; Elfes, 1989; Gutmann, and Schlegel, 1996; Martin, and Moravec, 1996; Moravec, and Elfes, 1984; Schiele, and Crowley, 1994; Schultz, and Adams, 1998).
In general, all the mentioned approaches may show drawbacks that can compromise the convergence and the stability of the algorithms used

for processing the sensory data (Guivant and Nebot, 2001; Kortenkamp, Bonasso, and Murphy, 1998; Leonard and Feder, 1999; Lu and Milios, 1997; Thrun, Fox, and Burgard, 1998). These problems concern the computational complexity and the data association. In fact, with a large number of features or, in case of grid representations, a large number of cells, the computational complexity increases quickly for environments possessing; this could limiting, in many cases, the number of features or cells in the map. Moreover, wrong data association between new and past observations compromises the stability of the process and it causes failures of the localization and map building process.

In recent years, new approaches, which reduce the drawbacks, based on improved statistical methods and iterative algorithms, have been developed. Among these are, for example, those which use particles filters. On the base of results in Murphy (1999), Montemerlo, Thrun, Koller and Wegbreit (2002) developed a new approach, called FastSLAM, which factorizes the problem of estimating both the vehicle's position and the landmarks' ones and which combines particles filters and Kalman filters. Thanks to the factorization of the posterior probability distribution, it is possible to deal efficiently with a large number of features and, using particle filters, accuracy in data association can be improved. However, this kind of approach, in particular the prediction step of the Bayesian filter, relies on the knowledge of a mathematical model of the agent's dynamics. In case the agent is an unmanned underwater vehicle, this is not always available (Brutzman, 1994; Fossen, 1995).

Recently, iterative algorithms have been used in SLAM Problems. Iterative Closest Point (ICP) algorithms are the most popular ones (Choi and Oh, 2006; Muller, Surmann, Pervolz and May, 2006; Nuchter, Lingemann, Hertzberg and Surmann, 2005; Ohno and Tadokoro, 2005; Singh, Roman, Pizarro and Eustice, 2007; Wang and Thorpe, 2002; Murino, Ronchetti, Castellani, Fusiello, 2001). They have been first proposed in Besl and McKay (1992) and they consist essentially of alignment methods. From two clouds of points in two different coordinate systems and an initial hypothesis of coordinate transformation (translation and rotation), the ICP algorithm iteratively estimates the (locally) optimal rigid body transformation that aligns the clouds of points in the best possible way. Algorithms of this kind can be used to reconstruct 3D surfaces from different scans, to match in real-time geometric models with measures and, in particular, to localize robots. The algorithm itself is very simple and, even if computational complexity grows exponentially with the number of points of the meshes one consider, it can be combined with other techniques in order to be used in time critical applications. Advantages of such algorithms are given by the fact that they do not require the knowledge of a model of the vehicle's dynamics and that the iterative data association gives, in general, very accurate results.

Here, we propose an approach for dealing with SLAM Problems in an underwater environment based on the use ICP techniques. In particular, we develop a suitable version of the ICP algorithm, in order to improve the local optimum, to estimate the global transformation and to localize the vehicle on the map. A General Regression Neural Network (GRNN) is also included in the global procedure in order to classify detected objects and to reduce the number of points in the map, causing the computational burden to decrease and speeding up the process.

ICP and improved ICP

The ICP algorithm is a popular method for aligning three-dimensional objects represented by clouds of points, using only geometric information. In particular, it is widely used for registering data collected by 3D scanners from different point of view. From two meshes and an initial guess of the relative rigid-body transformation from one to the other, the algorithm iteratively refines the transformation by repeatedly matching pairs of corresponding points on the meshes and by minimizing a suitably computed error. The algorithm was first proposed in Besl and McKey (1992) and then many modifications and improvements of its basic form have been developed (Almhdie, Leger, Deriche and Ledee, 2007; Bae and Lichti, 2004; Brown, 1992; Chetverikov, Svirko, Stepanov and Krsek, 2002; Dias, Sequeira, Vaz and Goncalves, 2003; Godin, Laurendeau and Bergevin, 2001; Greenspan and Yurick, 2003; Kapoutsis, Vavoulidis and Pitas, 1999; Liu and Chen, 2004, Mitra, Gelfand, Pottmann and Guibas, 2004; Puli, 1999, Shang, Jasiobedzki and Greenspan, 2005; Sharp, Lee and Wehe, 2002; Umeda, Godin and Rioux, 2004; Weik, 1999; Zinsser, Schmidt and Niemann, 2003; Zitova and Flusser, 2003).

The structure of the algorithm consists of six steps, which in some case can be reduced to three. After having defined a global reference system (points in the global reference system are called "model points"), the target is to estimate the transformation that aligns the points in the local reference systems (points in the local reference system are called "data points") to those in the global one. The first step consists in selecting points from the two meshes (model points and data points) (this step is not always necessary). The second step consists in creating pairs by matching the selected points and the third step consists in weighting the pairs (this step is not always necessary). Then, some of the weighted pairs are rejected (this step is not always necessary). Finally, an error metric is defined and a minimization algorithm is applied to the remaining pairs in order to minimize the error and to compute the best alignment between the two meshes.

A thorough description of the ICP steps and variants is given in Rusinkiewicz (2001). Here we describe only the significant features of the algorithm in the version we use.

Indicating by p_{m_j} and p_{d_i}, respectively, a model point and a data point and by

$$d\left(p_{m_j}, p_{d_i}\right) = \sqrt{\left(x_{m_j} - x_{d_i}\right)^2 + \left(y_{m_j} - y_{d_i}\right)^2 + \left(z_{m_j} - z_{d_i}\right)^2} \qquad (1)$$

the Euclidean distance, first we match each data point with the nearest model point. In other terms, for each data point, we define the matching by the equation

$$m(p_{d_i}, p_m) = min_{j=1,\ldots,N_m}\left(d\left(p_{m_j}, p_{d_i}\right)\right) \qquad (2)$$

where N_m is the number of model points. The weighting step and the rejection step are not performed, because experimental tests do not show, in our case, any improvements. The error is defined by means of the sum of squared distances between corresponding points

$$err = \frac{1}{N_d}\sum_{i=1}^{N_d} d\left(p_{m_i}, R \cdot p_{d_i} + T\right)^2 \qquad (3)$$

where N_d is the number of data points and R and T are respectively the rotation matrix and the translation vector. In order to determine the rigid-body transformation that minimizes the error, we use the closed form solution of the optimization problem proposed in Horn (1987) and based on quaternions.

The basic version of the ICP algorithm described so far is improved by performing perturbations to avoid local solutions and by implementing objects detection and classification tools to filter noisy data.

It is known, in fact, that the algorithm may converges to a local solution (Besl and McKey, 1992), giving an unsatisfactory result. To contrast this possibility, we perturb the initial hypothesis on the transformation from data points to model points. Different transformations consisting of bounded random translations and of regular spaced rotations are considered. The ICP algorithm is then applied to each hypothesis,

solutions are compared and the best one is chosen. In practical implementation, since the environment is static and the maximum displacement is bounded, the error tends to zero and the translation values are limited, so it is possible to decide which initial transformation gives the best solution.
This technique has the drawback that it increases the computational time, since the entire ICP algorithm is applied repeatedly more times. A possible way to overcome this difficulty by speeding up the algorithm consists in choosing data points in such a way to reduce the effect of noise and measurement errors. In case the environment is structured, this can be done by exploiting the additional information provided by the structure. Practically, in our case, we use information about the presence of objects in the environment and about their geometric characteristics in order to select data points and to reduce the number of those processed by the ICP algorithm, without losing information.
In the next Section the proposed approach is described in detail.

THE PROPOSED APPROACH

The SLAM procedure we realized implements the improved ICP algorithm described in the previous Section. The underwater environment we consider is assumed to be structured and static. This is a realistic assumption, since very often the environment where ROV's or AUV's operate includes artificial objects in known relative positions (as, e.g., in the case of off-shore installations) or it can be easily structured (for example by means of passive or active acoustic targets and buoys).
The vehicle used as test-platform is a Deep Ocean Engineering Phantom-S2 ROV (Conte, Gambella, Scaradozzi and Zanoli, 2006) and the proposed approach only requires the use of the onboard sonar (a 675 KHz single-beam, mechanically scanning, imaging sonar, which emits a 2.7° conic beam) and standard sensors (depth meter, compass, inclinometers or cheap inertial measurement unit). In normal operation, the sonar is set in vertical position, so that, by scanning the environment while the vehicle depth is kept constant and pitch and roll motions are absent, it provides an acoustic image of the region that surrounds the vehicle in the horizontal plane in which it moves. In this condition, during each acquisition phase, it is possible to construct a two-dimensional map which describes the environment and provides useful information for navigating the vehicle amongst obstacles (Newman, 1999; Newman and Leonard, 2003; Williams, Newman, Dissanayake and Durrant-Whyte, 2000).
Therefore, in order to implement a two dimensional version of the proposed ICP algorithm, we assume that the vehicle moves at constant depth and that pitch and roll angles are kept equal to 0. Practically, depth can be kept constant by actuating the vertical thrusters and using a simple depth meter. Pitch and roll angles are generally not controllable in small ROV's like ours, but 0 represents an asymptotically stable equilibrium point for them and simple sensors (inclinometers or cheap inertial measurement unit) can be used to evaluate possible perturbations. In case, the acquired sonar data can be discarded. The parameters that describe the vehicle position in this case are the coordinates of its center of mass in the plane and its orientation. Orientation can be determined, with respect to geographic North, by means of a compass.
Since the sonar needs time to perform a 360° mechanical scans, we assume that the vehicle, in order to explore the environment, moves to a location, then it stops for the time required to perform a complete acquisition, and then it moves to a new location. In real situations waves and currents may affect vehicle's motion, however, in deep water waves are absent and, in a static environment, the presence of current can be detected by simple tests, using the sonar to check relative motion with respect to objects when horizontal thrusters are off. Constant currents can then be balanced by activating the thrusters in order to keep the vehicle in a stationary position during the acquisition phases.

Object Classification: GRNN

The objects classification algorithm has been implemented by means of a Neural Network, in particular a General Regression Neural Network (GRNN) (Specht, 1991).
Neural Networks can be applied to the solution of many heterogeneous problems (Varchmin, Rae and Ritter, 1997; Cohen, 2005; Heittmann and Ramacher, 2003; Kun, Hong and Ying, 2006; Rowley, Baluja and Kanade, 1998; Takahashi, Karungaru, Fukumi and Akamatsu, 2006; Tan, Xia and Wang, 2000) that range from system identification and control to game-playing and decision making, as well as from pattern recognition to sequence recognition. They are also widely used in medical diagnosis, financial applications, data mining, visualization and e-mail spam filtering. In recent years, GRNN have also been applied to sonar data processing for objects classification (Perry and Guan, 2004a; Perry and Guan, 2004b; Ward and Stevenson, 2000).
GRNN's originates from Radial Basis Function Networks (RBFN): the first layer units adopt a Gaussian kernel as nonlinear transfer function while the second layer consists of summation units. In RBFN's the centers and widths of the Gaussian kernels are determined iteratively by clustering procedures, while in GRNN's the same parameters are represented as deterministic functions of the training data. So, no iterative training procedure is required and GRNN's perform quickly.
Since no iterative training procedure is implemented, an experimental off-line determination of the neural network parameters is required. In our case of objects classification, after having determined a set of sample observation (o_p, Ω_p) where $p = 1, \dots, N$ (N is the number of different objects), o is the observation sample (a vector of M object features) and Ω is the corresponding GRNN output, N RBF units (one for each different object) are applied

$$\beta_p = e^{-\frac{(o^* - o_p)^T (o^* - o_p)}{2\sigma^2}} \quad p = 1, \dots, N \tag{4}$$

where o^* is the neural network input, i.e. the real observation, and σ is a user defined parameter. Then, the output of the GRNN is

$$y^* = \sum_{p=1}^{N} \alpha_p \Omega_p, p = 1, \dots, N, 0 \le \alpha_p \le 1, \sum_{p=1}^{N} \alpha_p = 1 \tag{5}$$

$$\alpha_p = \frac{\beta_p}{\sum_{p=1}^{N} \beta_p} \tag{6}$$

If the o^* features of the real observation are close (by Euclidean distance) to an o_p sample observation, the corresponding weight α_p is dominant in Eq. 5. Hence, the output of the GRNN tends to Ω_p and the input object can be correctly classified.

SLAM with improved ICP

This subsection describes the whole SLAM procedure based on the improved ICP algorithm. The solution of the SLAM Problem requires to perform a sequence of operations every time the vehicle moves from one position to another and it stops to acquire new sonar data. The sequence of operations consists of: data acquisition and low level processing, objects detection, localization and two-dimensional map updating.
In the first step, the sonar performs a 360° acquisition. Acquired data are then filtered and principal returns (identified by (x, y) coordinates) are estimated (Conte, Gambella, Scaradozzi and Zanoli, 2006; Gambella, 2005; Newman, 1999). So, a preliminary two-dimensional local map of principal returns is obtained.

Then, in the second step, in order to detect significant objects in the map, a clustering procedure is performed, so to group principal returns that are close to each other. Clustering is based on the use of two thresholds that concern minimum relative distance and angle (Newman, 1999). Clusters' features are then evaluated and the GRNN described in the previous subsection is applied for classifying detected objects.
In the third step, in order to reduce the computational time and to increase the efficiency, only the points belonging to detected objects are processed by the described improved ICP algorithm. The estimated optimal transformation can be easily associated to the relative vehicle displacement, so the localization (x, y, θ) of the vehicle in the global reference system is performed.
At the last step, the two-dimensional global map has to be updated. This operation is performed by using a Kalman filters. Since the environment is assumed to be static, mean values and covariance of objects in the map can be easily and rapidly predicted and updated by applying a Kalman filter for each object. At the same time, newly observed objects are included directly into the map.
In the next Section experimental results of simple field tests are described.

EXPERIMENTAL RESULTS

Experimental tests have been performed in a pool (16 m diameter, 1.4 m depth), structuring the environment by three PVC pipes (20 cm diameter, 1.40m length) placed in vertical position and in a triangular configuration, avoiding symmetry (Fig. 1). In fact, a symmetric arrangement of the objects may give rise to ambiguity and make impossible to solve the SLAM Problem. The experimental framework simulates real situations like those found in off-shore installations (Murino, Ronchetti, Castellani and Fusiello, 2001; Berger, Brackett and Mittleman, 1983).


Fig. 1 Experimental test environment

The reduced depth of the pool does not allow a safe underwater navigation of the vehicle; so, since the only sensor needed for testing the procedure is the sonar, the sonar head has been manually placed in different positions, emulating the vehicle's stop-and-go motion. In order to validate the results (obstacles' and sonar's positions on the constructed map), effective positions have been measured by a laser device with an accuracy of $\pm$ 1,5 mm.
The GRNN used for object classification has been instructed in order to distinguish the objects (PVC pipes) in the scene. The sonar actually detects the PVC pipes and the pool's edges, but it also displays false objects, due to environmental noise and multiple reflections. So the environment, from the sonar point of view, contains three different kinds of objects: pipes, edge and false objects. Since these largely differ one from the other, each sample observation o_p (one for each type of object) contains few features: dimension, number of principal returns and covariance. This is sufficient for an efficient application of the GRNN. As an example, Fig. 2~4 show some partial results of the SLAM procedure. The "+" symbols indicate different positions of the sonar head, while dots indicate positions of principal returns. Fig. 2 shows a preliminary map with raw principal returns. A simple threshold is applied to filter sonar data and Fig. 3 shows the result of the filtering and clustering operations (clusters' mean values and covariance are shown by black "+" and red ellipses). At the end, Fig. 4 shows the result of GRNN objects classification: only the principal returns corresponding to objects of the kind "pipe" are found.

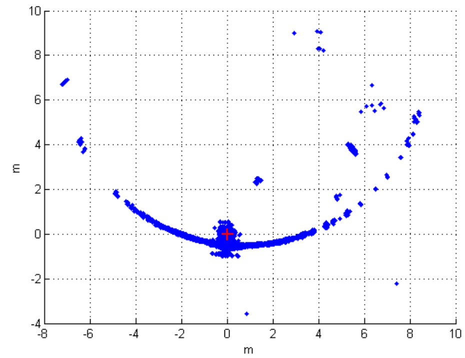

Fig. 2 Raw principal returns map

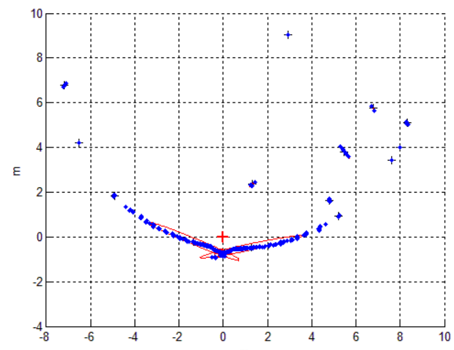

Fig. 3 Filtered map and clusters

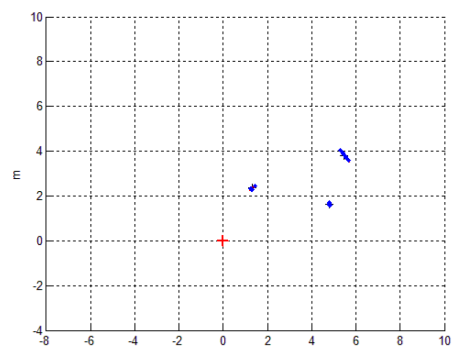

Fig. 4 Map after GRNN application

The results of the improved ICP algorithm are shown in Fig. 5~7. Fig. 5 displays model points (in the global reference system): circles denote the points and "+" symbols indicate different positions of the sonar head. Fig. 6 displays data points (in the local reference system) coming from a new acquisition. Fig. 7 shows the result of the application of the ICP algorithm: data points and model points are aligned and the relative displacement of the sonar head is evaluated (the new sonar position is represented by the "+" symbol).

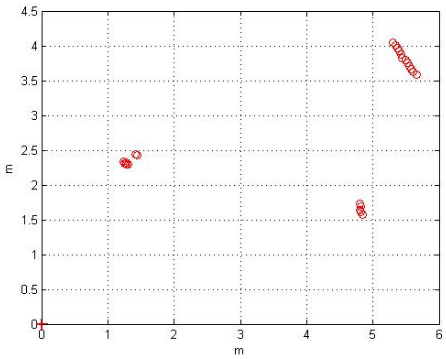

Fig. 5 Model points

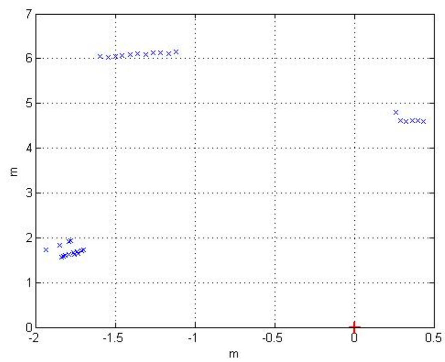

Fig. 6 Data points

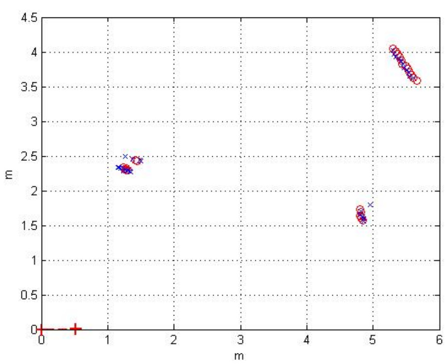

Fig. 7 Improved ICP algorithm's result

The SLAM procedure has been repeatedly applied moving the sonar head to several different positions and the final result is showed in Fig. 8.

In Table 1 numerical results about localization are displayed and compared with the correspondent real measures.

Fig. 9~11 display obstacles' localization errors during experimental tests: the error is the relative error between the real and the estimated positions. For each object, relative x and y coordinates errors are shown.

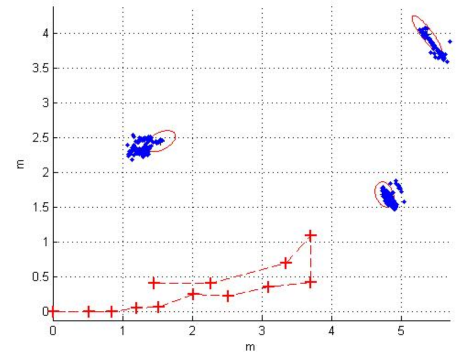

Fig. 8 Final global map and sonar head displacement

Table 1 Localization results

Estimated sonar position (x,y)	Real sonar position (x,y)
(0 m, 0 m)	(0 m, 0 m)
(0.512 m, 0.001 m)	(0.377 m, 0.021 m)
(0.850 m, 0.003 m)	(0.698 m, -0.035 m)
(1.200 m, 0.048 m)	(1.062 m, -0.032 m)
(1.522 m, 0.063 m)	(1.499 m, -0.016 m)
(2.012 m, 0.249 m)	(1.858 m, 0.077 m)
(2.513 m, 0.223 m)	(2.362 m, 0.227 m)
(3.098 m, 0.359 m)	(2.850 m, 0.422 m)
(3.695 m, 0.419 m)	(3.288 m, 0.698 m)
(3.700 m, 1.098 m)	(3.801 m, 1.051 m)
(3.337 m, 0.704 m)	(3.608 m, 0.563 m)
(2.268 m, 0.409 m)	(2.267 m, 0.296 m)
(1.446 m, 0.407 m)	(1.586 m, 0.227 m)

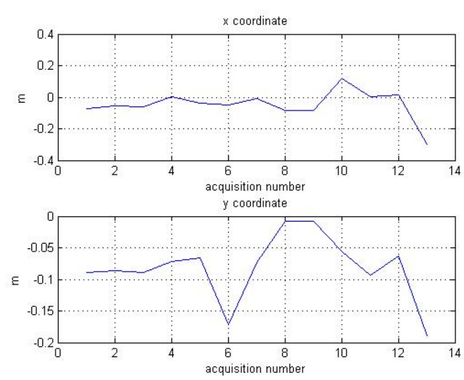

Fig. 9 Obstacle 1 localization error

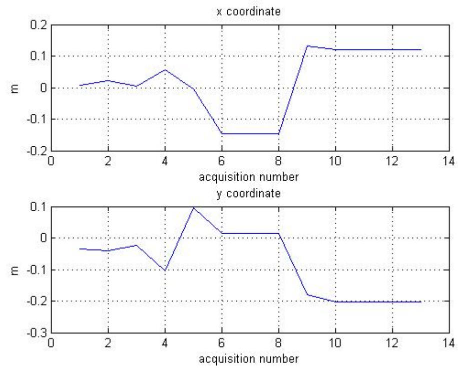

Fig. 10 Ostacle 2 localization error

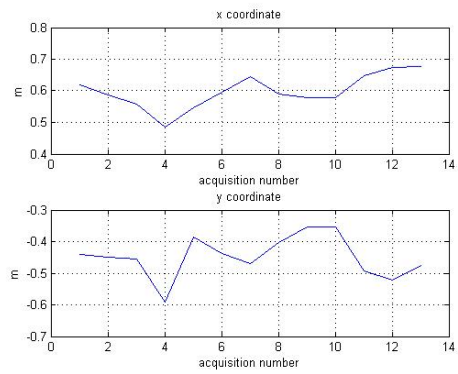

Fig. 11 Obstacle 3 localization error

CONCLUSION

We have proposed a procedure for dealing with SLAM Problems that can be applied in underwater environments by unmanned vehicles equipped with single-beam mechanically scanning sonar. The procedure is based on an improved ICP algorithm and on the use of a GRNN for object classification. Experimental tests show that the proposed approach gives satisfactory results in a simple, structured environment. Both the position of the agent and those of the main objects in the environment are determined with small errors, whose magnitude is comparable with the dimension (about 20 cm) of the objects in the horizontal plane. This is an expected result, since the procedure is based only on the geometry of the observations.

Moreover, satisfactory results may be obtained also in case some of the objects are not detected by the classification algorithm. In fact, although three objects are present, in our situation it has been sufficient to detect correctly two of them to localize the agent in the map.

Regarding the computational time, in the tests we performed, after the acquisition phase, the agent's localization and the construction of the updated map took generally less than two seconds. This time is smaller than the time required for moving the vehicle from one position to another and for stopping its motion. Therefore, the proposed approach can be applied in real situations.

Further work for improving object recognition and for performing more complex field experiments in order to validate the results is planned for the next future.

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