Pose-Based SLAM with Probabilistic Scan Matching Algorithm using a Mechanical Scanned Imaging Sonar

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***Abstract*— *This paper proposes a pose-based algorithm to solve the full SLAM problem for an Autonomous Underwater Vehicle (AUV), navigating in an unknown and possibly unstructured environment. A probabilistic scan matching technique using range scans gathered from a Mechanical Scanning Imaging Sonar (MSIS) is used together with the robot dead-reckoning displacements, estimated through a Doppler Velocity Log (DVL) and a Motion Reference Unit (MRU). The proposed method utilizes two Extended Kalman Filters (EKF). The first, estimates the local path traveled by the robot while grabbing the scan as well as its uncertainty providing position estimates for correcting the distortions that the vehicle motion produces in the acoustic images. The second is an augmented state EKF that estimates and keeps the registered scans poses. The raw data from the sensors are processed and fused in-line. No priory structural information or initial pose are considered. The algorithm has been tested on an AUV guided along a 600m path within a marina environment, showing the viability of the proposed approach.*

***Keywords*— *Navigation, AUV, EKF, SLAM, Imaging Sonar*

I. INTRODUCTION

The last decades, a number of studies in mobile robotics had developed techniques to address the localization problem with very promising results. In particular, the so-called Simultaneous Localization and Mapping (SLAM) techniques have been broadly and successfully applied to indoor and outdoor environments. Hence, it is of interest to study how to adapt these techniques for their use in hostile underwater environments.

This paper is a contribution in this area, proposing a pose-based algorithm to solve the full SLAM problem of an AUV navigating in an unknown and possibly unstructured environment. A DVL and a low cost gyrocompass are used for dead reckoning while a mechanical scanning imaging sonar (MSIS) is used for sensing the environment. Scan matching is a technique that estimates the robot relative displacement between two configurations, by maximizing the overlap between the range scans normally gathered with a laser or a sonar sensor. [1]

The MSISpIC algorithm proposed in [2], is dealing with data gathered by an AUV utilizing MSIS. Is based in a reduced version of the pIC algorithm [3] and an EKF using a constant velocity model with acceleration noise updated with velocity and attitude measurements, is used to estimate the trajectory followed by the robot along the scan. This trajectory is used to remove the motion induced distortion of the acoustic image as well as to predict the uncertainty of the range scans prior to register them through the pIC algorithm.

In this paper we extend the MSISpIC algorithm in the pose-based SLAM framework. Now, each new pose of a scan is maintained in a second augmented state EKF (ASEKF) and is compared with previous scans that are in the nearby area. If there is enough data overlapping, a new scan match will put a constrain between the poses updating the ASEKF. These constrains help to identify and close the loops which correct the entire previously trajectory, bounding the drift. The proposed method has been tested with a real world dataset, including DGPS for ground truth, acquired during a survey mission in an abandoned marina located in the Girona coast. The results show substantial improvements in trajectory correction and map reconstruction.

The paper is structured as follows. In section II the probabilistic scan matching algorithm is described. Section III details the MSISpIC to be used in our SLAM algorithm which is described in section IV. Section V reports the experimental results before conclusions and future work.

II. PROBABILISTIC SCAN MATCHING

The geometric representations of a scan in the conventional ICP algorithm do not model the uncertainty of the sensor measurements. Correspondences between two scans are chosen based on the closest-point rule normally using the Euclidean distance. As pointed out in [3], this distance do not take into account that the points in the new scan, which are far from the sensor, could be far from their correspondents in the previous scan. On the other hand, if the scan data is very noisy, two statistically compatible points could appear far enough, in terms of the Euclidean distance. Both situations might prevent a possible association or even generate a wrong one. The spIC algorithm proposed in [4] is a statistical extension of the ICP algorithm where the relative displacement $\mathbf{q}$ as well as the observed points in both scans $\mathbf{r_i}$ and $\mathbf{n_i}$, are modeled as random Gaussian variables (r.g.v.).

III. MSISPIC ALGORITHM

Scan matching techniques are conceived to accept as input parameters two range scans with a rough displacement estimation between them. Most of the algorithms use laser range finders which gather scans almost instantaneously. However, for the underwater environment, commercially available scan sensors are based on acoustics with a mechanical head that rotates at fixed angular steps. At each step, a beam is emitted and received a posteriori, measuring ranges to the obstacles found across its trajectory. Thus, getting a complete scan that lasts few seconds while the vehicle is moving, generating deformed acoustic images. Therefore, a correction taking into account the robot pose when the beam was grabbed is necessary. A part of the MSISpIC algorithm forms a scan, corrected from the vehicle's motion distortion. MSISpIC uses an EKF with a constant velocity model and acceleration noise for the prediction step. Then, it updates with velocity and attitude measurements obtained from a DVL and a MRU respectively, in order to estimate the trajectory followed by the robot along the scan. This trajectory is used to remove the motion induced distortion of the acoustic image as well as to predict the uncertainty of the range scans prior to register them. After the corrected scan has formed, MSISpIC grabs two scans and registers them using the pIC algorithm. It is worth noting that the pIC takes as input two consecutive scans (S_{new} and S_{ref}) and its relative displacement ($\hat{\mathbf{q}}_{ref}$) and the output is an improved estimation of the robot displacement ($\hat{\mathbf{q}}_{new}$). MSISpIC algorithm, consist of three major parts: Beam segmentation, Relative vehicle localization and Scan forming.

A. Beam Segmentation and Range Detection

The MSIS returns a polar acoustic image composed of beams. Each beam has a particular bearing angle value and a set of intensity measurements. The angle corresponds to the orientation of the sensor head when the beam was emitted. The acoustic linear image corresponding to one beam is returned as an array of acoustic intensities detected at a certain distance. The beam is then segmented using a predefined threshold to compute the intensity peaks. Due to the noisy nature of the acoustic data, a minimum distance between peaks criteria is also applied. Hence, positions finally considered are those corresponding to high intensity values above the threshold with a minimum *distance* between each other.

B. Relative Vehicle Localization

The pIC algorithm needs a complete scan to be registered with the previous one in order to estimate the robot's displacement. Since MSIS needs a considerable period of time to obtain a complete scan, if the robot does not remain static, the robot's motion induces a distortion in the acoustic image (Fig. 1). To deal with this problem it is necessary to know the robot's pose at the beam reception time. Hence, it is possible to define an initial coordinate system I to reference all the range measurements belonging to the same scan. In our case, this initial frame is fixed at the robot pose where the first beam of the current scan was read. The localization system used in this work is a slight modification of the navigation system described in [5]. In this system, a MRU provides heading measurements and a DVL unit is used to estimate the robot's pose during the scan (navigation problem). MSIS beams are read at 30 Hz while DVL and MRU readings arrive asynchronously at a frequency of 1.5 Hz and 10 Hz respectively. An EKF is used to estimate the robot's 6DOF pose whenever a sonar beam is read. DVL and MRU readings are used asynchronously to update the filter. To reduce the noise inherent to the DVL measurements, a simple 6DOF constant velocity kinematics model is used.

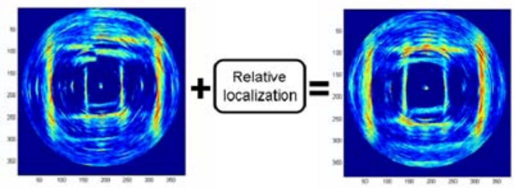


Fig. 1. The distortion produced by the displacement of the robot while acquiring data can be corrected with the relative displacement.

The model prediction is updated by the standard Kalman filter equations each time a new DVL or MRU measurement arrives.

C. Scan Forming

The navigation system presented above is able to estimate the robot's pose, but the uncertainty will grow without limit due to its dead-reckoning nature. Moreover, we are only interested in the robot's relative position (and uncertainty) with respect to the end of the scan (I-frame). Hence a slight modification to the filter is introduced making a reset in position (setting x, y, z to 0 in the vector state) whenever a new scan is started. Note that it is important to keep the yaw (ψ) value (it is not reset) because it represents an absolute angle with respect to the magnetic north and a reset would mean an unreal high rotation during the scan. The same thing happens with roll (ϕ) and pitch (θ). Since we are only interested in the uncertainty accumulated during the scan, the reset process also affects the x, y, and z terms of the covariance matrix ($\mathbf{P}$). Now, the modified filter provides the robot's relative position where the beams where gathered including its uncertainty accumulated during the scan. Hence, it is possible to reference all the ranges computed from the beams to the frame I, removing the distortion induced by the robot's motion.

IV. SLAM ALGORITHM

The proposed pose-based SLAM algorithm uses an ASEKF for the scan poses estimation. In this implementation of the stochastic map [6], the estimate of the positions of the vehicle at the end of each full scan $\{\mathbf{x}_1 \ldots \mathbf{x}_n^B\}$ are stored in the state vector $\hat{\mathbf{x}}$:

$$\hat{\mathbf{x}}_k^B = \left[\hat{\mathbf{x}}_{n_k}^B \ \ldots \ \hat{\mathbf{x}}_{1_k}^B\right]^T$$

and the covariance matrix for this state is defined as:

$$\mathbf{P}_k^B = E([\mathbf{x}_k^B - \hat{\mathbf{x}}_k^B][\mathbf{x}_k^B - \hat{\mathbf{x}}_k^B]^T)$$

Note that, a full scan is defined as the final 360° polar range image obtained after compounding, along the path, the robot pose with the range and bearing data, which is the output from the MSISpIC algorithm.

A. Map Initialization

All the elements on the state vector are represented in the map reference frame B. Although this reference frame can be defined arbitrarily, we have chosen to place its origin on the initial position of the vehicle and orient it to the north.

The pose state $\mathbf{x}_i$ is represented as:

$$\mathbf{x}_i^B = [x\ y\ \psi]^T$$

where, x, y and ψ is the position and orientation vector of the vehicle in the global frame B. The state and the map are initialized from the first full scan obtained by the MSISpIC algorithm.

B. Prediction

Let

- $\hat{\mathbf{x}}_{n_k}^B$ be the last robot pose and
- $\hat{\mathbf{q}}_n^{B_n} \equiv N(\hat{q}_n^{B_n},\ \mathbf{P}_{q_n})$ be the robot displacement during the last scan, estimated through dead reckoning.

the prediction / state augmentation equation is given by:

$$\hat{\mathbf{x}}_k^{B+} = \hat{\mathbf{x}}_k^B \odot \hat{\mathbf{q}}_{n_k}^{B_n} =$$
$$\left[\ \hat{\mathbf{x}}_{n-1_k}^B \odot \hat{\mathbf{q}}_{n_k}^{B_n} | \ \hat{\mathbf{x}}_{n-1_k}^B \dots \hat{\mathbf{x}}_{i_k}^B \dots \hat{\mathbf{x}}_{1_k}^B\ \right]$$

where given that B and B_n frames are aligned, the operator $\odot$ is defined as:

$$\mathbf{x} \odot \mathbf{q} = \begin{bmatrix} a \\ b \\ c \end{bmatrix} \odot \begin{bmatrix} d \\ e \\ f \end{bmatrix} = \begin{bmatrix} a+d \\ b+e \\ f \end{bmatrix}$$

Hence, the predicted pose uncertainty represented as $\mathbf{P}_k^{B+}$ and is estimated as:

$$\mathbf{P}_k^{B+} = \mathbf{F}_k \mathbf{P}_k^B \mathbf{F}_k^T + \mathbf{G}_k \mathbf{P}_{q_i}^B \mathbf{G}_k^T$$

where $\mathbf{F}_k = \left. \frac{\partial \hat{\mathbf{x}}_k^B \odot \hat{\mathbf{q}}_{n_k}^{B_n}}{\partial \hat{\mathbf{x}}_k^B} \right|_{(\hat{\mathbf{x}}_{n_k}^B, \hat{\mathbf{q}}_{n_k}^{B_n})}$

and $\mathbf{G}_k = \left. \frac{\partial \hat{\mathbf{x}}_k^B \odot \hat{\mathbf{q}}_{n_k}^{B_n}}{\partial \hat{\mathbf{q}}_{n_k}^{B_n}} \right|_{(\hat{\mathbf{x}}_{n_k}^B, \hat{\mathbf{q}}_{n_k}^{B_n})}$

C. Loop Closing Candidates

Each new pose of a scan is compared against the previous scan poses that are in the nearby area defined by a threshold, and if there is enough data overlapping, a new scan match will put a constrain between the poses updating the ASEKF. These constrains close the loops which correct the whole trajectory, bounding the drift.

Let

- $\hat{\mathbf{x}}_{n_k}^B$ be the last scan pose and S_{n_k} the corresponding scan
- $Overlap_k = \left\{ S_{i_k} \ / \ \left\| \hat{\mathbf{x}}_{n_k}^B - \hat{\mathbf{x}}_{i_k}^B \right\| < threshold \right\}$ the set of overlapping scans and $\mathbf{O}_k = [S_{1_k},\ S_{2_k}\ \dots\ S_{m_k}]$ the sequence of overlapping scans belonging to $Overlap_k$ set but sorted from maximum to minimum distance order

then

- $\forall\ [S_{i_k}, \hat{\mathbf{x}}_i^B] \in \mathbf{O}_k$, we perform a new scan matching between the scan poses $(\hat{\mathbf{x}}_{n_k}^B, \hat{\mathbf{x}}_{i_k}^B)$ with the corresponding scans (S_{n_k}, S_{i_k}) where
- $[\mathbf{q}_i^{I_i}, \mathbf{R}_{q_i}^{I_i}]$ be the result of the scan matching and its uncertainty

and then we carry out a state update.

D. Scan Matching

In order to execute the pIC algorithm, given two overlapping scans (S_i, S_n) with related poses $(\hat{\mathbf{x}}_i^B, \hat{\mathbf{x}}_n^B)$, an initial guess of their relative displacement is necessary. This initial guess $[\hat{\mathbf{q}}_i^{I_i}, \mathbf{P}_i^{I_i}]$ can be easily extracted from the state vector using the tail-to-tail transformation [6]:

$$\hat{\mathbf{q}}_i^{I_i} = \ominus \hat{\mathbf{x}}_i^B \oplus \hat{\mathbf{x}}_n^B$$

Since the tail-to-tail transformation is actually a nonlinear function of the state vector $\hat{\mathbf{x}}_k^B$, the uncertainty of the initial guess can be computed by means of the Jacobian of the non linear function:

$$\mathbf{P}_{q_i}^{I_i} = \mathbf{H}_k \mathbf{P}_k^B \mathbf{H}_k^T$$

where

$$\mathbf{H}_k = \left. \frac{\partial \ \ominus \hat{\mathbf{x}}_i^B \oplus \hat{\mathbf{x}}_n^B}{\partial \ \mathbf{x}_k^B} \right|_{(\mathbf{x}_k^B = \hat{\mathbf{x}}_k^B)}$$

Moreover, as shown in [6], the Jacobian for the tail-to-tail transformation $\mathbf{x}_{a_c} = \ominus \mathbf{x}_{b_a} \oplus \mathbf{x}_{b_c}$, is:

$$\frac{\partial \ \ominus \mathbf{x}_{b_a} \oplus \mathbf{x}_{b_c}}{\partial \ (\mathbf{x}_{b_a} \mathbf{x}_{b_c})} = [\mathbf{J}_{1\oplus} \mathbf{J}_{\ominus} \quad \mathbf{J}_{2\oplus}]$$

where the $\mathbf{J}_{1\oplus}, \mathbf{J}_{2\oplus}$ and $\mathbf{J}_{\ominus}$ are the Jacobian matrices of the compounding and inverse transformations respectively.

Being in our case $\hat{\mathbf{x}}_{n_k}^B$ and $\hat{\mathbf{x}}_{i_k}^B$ components of the full state vector, the Jacobian of the measurement equation becomes:

$$\mathbf{H}_k = \frac{\partial \ominus \hat{\mathbf{x}}_{i_k}^B \oplus \hat{\mathbf{x}}_{n_k}^B}{\partial \ \mathbf{x}_k} =$$
$$[\mathbf{J}_{2\oplus 3x3} \quad \mathbf{0}_{3x3(n-i-1)} \quad \mathbf{J}_{1\oplus} \mathbf{J}_{\ominus 3x3} \quad \mathbf{0}_{3x3(i-1)}]$$

Once the initial displacement guess is available, the pIC algorithm can be used to produce an updated measurement of this displacement.

E. State Update

When two overlapping scans (S_i, S_n) with the corresponding poses $(\hat{\mathbf{x}}_i^B, \hat{\mathbf{x}}_n^B)$ are registered, their relative displacement defines a constrain between the both poses. This constrain can be expressed by means of the measurement equation:

$$\mathbf{z}_k = h(\mathbf{x}_k, \mathbf{v}_k)$$

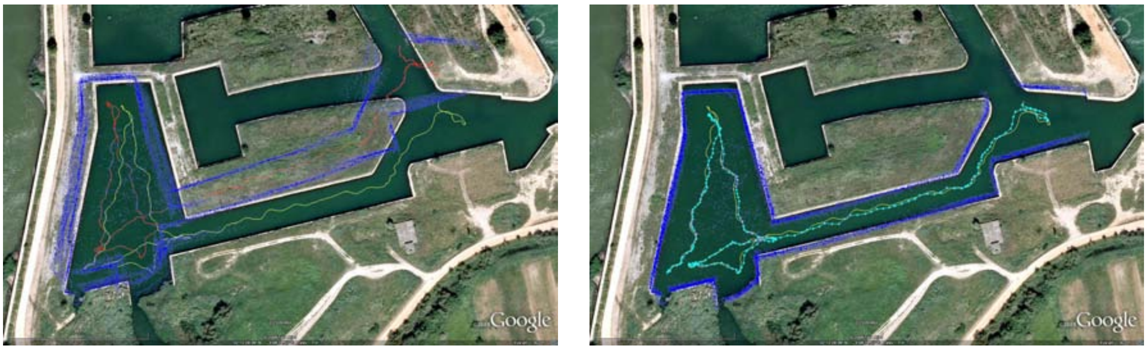
which again, in our case becomes to:

$$\mathbf{z}_k = \ominus \hat{\mathbf{x}}_{i_k}^B \oplus \hat{\mathbf{x}}_{n_k}^B$$

where $\hat{\mathbf{x}}_{i_k}^B$ is the scan pose which overlaps with the last scan pose $\hat{\mathbf{x}}_{n_k}^B$. Now, an update of the stochastic map can be performed with the standard extended Kalman filter equations.

V. EXPERIMENTAL RESULTS

The method described in this paper has been used with a dataset obtained in an abandoned marina located in the Catalan coast [7] [8]. This dataset corresponds to structured environment but our algorithm does not take into account any structural information neither features and with the current sensor suit, can been used wherever there is enough vertical information. The survey mission was carried out



a) b)

Fig. 2. Results: a) Trajectory and map generated with odometry (red). DGPS trajectory (yellow) used as a ground truth. b) Map and trajectory (dotted cyan) generated with the SLAM algorithm.

using ICTINEU$^{\mathrm{AUV}}$ [9] traveling along a $600m$ path. The MSIS was configured to scan the whole $360°$ sector and it was set to fire up to a $50m$ range with a $0.1m$ resolution and a $1.8°$ angular step. Dead-reckoning was computed using the velocity reading coming from the DVL and the heading data obtained from the MRU sensor, both merged using the described EKF.

Fig. 2.a shows the trajectory and the map estimated using the dead-reckoning method. Fig. 2.b shows the trajectory and the map estimated with our SLAM algorithm. In those figures, the estimated trajectory is plotted on an ortophotomap together with the DGPS ground truth for comparison. It can be appreciated that the dead-reckoning estimated trajectory suffers from an important drift which is drastically reduced when our algorithm is used. In Fig. 2.b it can be appreciated that the mapped size of the polygonal channel is smaller than the actual size whilst in the long, almost horizontal, water channel some times is smaller and some longer. This problem arises because during part of the trajectory, the robot traverses an area where the scan only observes one or two walls parallel to the robot path, being able to correct the lateral displacement but still drifting in the forward direction.

VI. CONCLUSIONS

This paper proposes an extension to the MSISpIC algorithm in the pose-based SLAM framework. To deal with the motion induced distortion of the acoustic image, an EKF is used to estimate the robot motion during the scan. The filter uses a constant velocity model with acceleration noise for motion prediction and velocity (DVL) and attitude measurements (MRU) for updating the state. Through the compounding of the relative robot position within the scan, with the range and bearing measurements of the beams gathered with the sonar, the acoustic image gets undistorted. Assuming Gaussian noise, the algorithm is able to predict the uncertainty of the sonar measurements with respect to a frame located at the position occupied by the robot at the end of the scan. Each full scan pose is maintained in a second filter, an augment EKF and is cross registered with all the previous scan posses that are in a certain range applying the pIC algorithm. The proposed method has been tested with a real world dataset including DGPS for ground truth acquired during a survey mission in an abandoned marina located in the Girona coast. The results show substantial improvements in trajectory correction and map reconstruction.

VII. FUTURE WORK

Currently we are working on the calculation of the real uncertainty of the scan matching algorithm which will depend of the uncertainties of the input scans. Next step will consist of gathering a new dataset in an complete unstructured environment to check how the algorithm performs.

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REFERENCES

[1] D. Hahnel, W. Burgard, D. Fox, and S. Thrun, “An efficient fastslam algorithm for generating maps of large-scale cyclic environments from raw laser range measurements,” *Intelligent Robots and Systems, 2003. (IROS 2003). Proceedings. 2003 IEEE/RSJ International Conference on*, vol. 1, pp. 206–211 vol.1, 27-31 Oct. 2003.

[2] E. Hernandez, P. Ridao, D. Ribas, and J. Batlle, “Msispic: A probabilistic scan matching algorithm using a mechanical scanned imaging sonar,” *Journal on Physical Agents (JoPhA)*, vol. 3, no. 1, pp. 3–12, 2009.

[3] L. Montesano, J. Mínguez, and L. Montano, “Probabilistic scan matching for motion estimation in unstructured environments,” *Intelligent Robots and Systems, 2005. (IROS 2005). 2005 IEEE/RSJ International Conference on*, Aug. 2005.

[4] A. Burguera, Y. Gonzalez, and G. Oliver, “A probabilistic framework for sonar scan matching localization,” *International Journal of the RSJ, Advanced Robotics*, 2008.

[5] D. Ribas, J. Neira, P. Ridao, and J. Tardós, “Auv localization in structured underwater environments using an a priori map,” in *7th IFAC Conference on Manoeuvring and Control of Marine Crafts*, Lisbon, Portugal, september 2006.

[6] R. Smith, M. Self, and P. Cheeseman, “Estimating uncertain spatial relationships in robotics,” in *Autonomous robot vehicles*. New York, NY, USA: Springer-Verlag New York, Inc., 1990, pp. 167–193.

[7] D. Ribas, “David ribas homepage,” http://eia.udg.edu/∼dribas, Online March 2009.

[8] D. Ribas, P. Ridao, J. Tardós, and J. Neira, “Underwater SLAM in man made structured environments,” *Journal of Field Robotics*, vol. Accepted for publication, 2008.

[9] D. Ribas, N. Palomer, P. Ridao, M. Carreras, and E. Hernandez, “Ictineu AUV wins the first SAUC-E competition,” in *IEEE International Conference on Robotics and Automation*, Roma, Italy, apr 2007.