Feature based SLAM using Side-scan salient objects

Josep Aulinas, Xavier Lladó and Joaquim Salvi
Computer Vision and Robotics Group
Institute of Informatics and Applications
University of Girona
17071 Girona, Spain
{jaulinas,llado,qsalvi}@eia.udg.edu

Yvan R. Petillot
Oceans Systems Lab
School of Engineering and Physical Sciences
Heriot Watt University
Edinburgh EH14 4AS, United Kingdom
Y.R.Petillot@hw.ac.uk

***Abstract*— Different underwater vehicles have been developed in order to explore underwater regions, specially those of difficult access for humans. Autonomous Underwater Vehicles (AUVs) are equipped with on-board sensors, which provide valuable information about the vehicle state and the environment. This information is used to build an approximate map of the area and estimate the position of the vehicle within this map. This is the so called Simultaneous Localization and Mapping (SLAM) problem. In this paper we propose a feature based submapping SLAM approach which uses side-scan salient objects as landmarks for the map building process. The detection of salient features in this environment is a complex task, since sonar images are noisy. We present in this paper an algorithm based on a set of image preprocessing steps and the use of a boosted cascade of Haar-like features to perform the automatic detection in side-scan images. Our experimental results show that the method produces consistent maps, while the vehicle is precisely localized.**

I. INTRODUCTION

Different underwater vehicles have been developed in order to explore underwater regions, specially those of difficult access for humans. In this sense, two different types of vehicle exist: Remotely Operated Vehicles (ROVs) and Autonomous Underwater Vehicles (AUVs). ROVs are linked to the ship by a tether and operated by a person aboard of the ship. The tether is a group of cables that carry electrical power, video and data signals back and forth between the operator and the vehicle. AUV technology does not require any umbilical cable, therefore they have complete autonomy. AUVs are equipped with on-board sensors, which provide valuable information about the vehicle state and the environment. This information is used to build an approximate map of the area and estimate the position of the vehicle within this map.

Some widely used sensors for land and aerial robots do not work or are not precise enough under the water. For instance, the use of cameras is difficult due to the lack of visibility and scattering; the laser range finders are imprecise working in these scenarios because of light attenuation; and GPS signal does not work underwater. The most commonly used sensors to measure navigation data on a AUV are the Inertial Measurement Unit (IMU) and the Doppler Velocity Log (DVL), while acoustic cameras or side-scan sonar are used to gather data from the environment. The IMU and the DVL do not give absolute localization, therefore if the vehicle is wrongly localized, nor the IMU neither the DVL will provide useful information to recover the right position. In addition, as the positioning is relative to past information, the localization problem is biased and the measurement noise produces drift. On the other hand, the detection of salient features in this environment is a complex task, since sonar images are noisy. This noise together with the lack of other navigation aids makes the mapping and localization a very difficult challenge.

A solution to the lack of GPS signal and the presence of noise are the Simultaneous Localization and Mapping (SLAM) algorithms, also known as Concurrent Mapping and Localization (CML) techniques. One of the main drawbacks of current SLAM algorithms is that they do not perform consistent maps for large areas, because of the increase in uncertainty for long term missions. In addition, as the map size grows the computational cost increases, making SLAM solutions not suitable for on-line applications. Introducing submaps in these techniques we can address both issues: 1) the reduction of computational cost, and 2) the improvement of map consistency. Following this idea, in this work we propose a technique that uses independent submaps together with a global level stochastic map. The basis of our approach lay on the EKF based SLAM. In particular, a sequence of EKF based submaps is built, while the links between submaps are stored in a global level map. This graph information allows to check the possibility of being in front of a loop closing event. Thus, a loop is closed when the vehicle is revisiting a certain number of previous observations, and as a consequence two submaps are joined and fused. Decide whether to fuse the submaps is made on the basis that fusing two submaps that share many landmarks will produce a better update than fusing two submaps that only share a few landmarks. These landmarks are detected from side-scan sonar images. This detection is automatically performed by means of two different algorithms: 1) using thresholding to segment bright spots an shadows in the image, and 2) using a boosted cascade of Haar-like features. Our experimental results show that both strategies perform similarly in terms of accuracy, but the second one is faster.

The paper is organised as follows: in Section II, a brief survey on SLAM is given, focusing on submapping techniques and on underwater applications; in Section III, underwater object detection strategies are listed and briefly detailed; in Section IV-A the implementation of our approach is

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presented; in Section V the experiments and results are provided; finally some conclusions are given in Section VI.

II. SIMULTANEOUS LOCALIZATION AND MAPPING

SLAM is one of the fundamental challenges of robotics [1]. The SLAM problem involves finding appropriate representation for both the observation and the motion models, which is generally performed by computing its prior and posterior distributions using probabilistic algorithms, for instance Kalman Filters (KF), Particle Filters (PF) and Expectation Maximization (EM). These probabilistic techniques are very popular in the SLAM context because they tackle the problem by modelling explicitly different sources of noise and their effects on the measurements [2]. A well known and widely used SLAM approach is the Extended Kalman Filter SLAM (EKF-SLAM) [3]. EKF-SLAM represents the vehicles pose and the location of a set of environment features in a joint state vector. This vector is estimated and updated by the EKF. EKF provides a suboptimal solution due to several approximations and assumptions, which result in divergences [4]. Several alternatives exist aiming to address the linearisation approximations, for instance the Unscented Kalman Filter [5], which uses a sigma points representation to model noise distributions. In large areas, EKF complexity grows with the number of landmarks, because each landmark is correlated to all other landmarks. This means that EKF memory complexity is $O(n^2)$ and a time complexity of $O(n^2)$ per step, where n is the total number of features stored in the map. Different approaches aiming to reduce this computational cost have been presented, for instance, the Compressed Extended Kalman Filter [6] delays the update stage after several observations; while the Exactly sparse extended information filters [7] take advantage of the sparsity in the information matrix, reducing considerably the computational demand. The two following sections summarize the state-of-the-art SLAM approaches in A) submapping techniques, and B) underwater applications.

A. Submapping techniques

Using submaps addresses both issues, reduces computational cost and improves map consistency. An example of submapping approach is the Decoupled Stochastic Map [8], which uses non-statistically independent submaps, therefore the correlations are broken introducing inconsistency in the map. Something similar happens in [9], where local maps share information while kept independent, thus a long term mission diverges. Different techniques, such as the Constrained Local Submap Filter [10] or Local Map Joining [11] produce efficient global maps by consistently combining completely independent local maps. The Divide and Conquer [12] approach is able to recover the global map in approximately $O(n)$ time. The Conditionally Independent Local Maps [13] method is based on sharing information between consecutive submaps. This way, a new local map is initialised considering the a-priori knowledge. The Constant Time SLAM [14], the Atlas approach [15] and the Hierarchical SLAM [16] store the link between submaps by means of an adjacency graph. The later imposes loop constraints on the adjacency graph, producing a better estimate of the global level map. Finally, in [17] a Selective Submap Joining SLAM was proposed, this approach is detailed in further sections as it is the one used in our implementation.

B. Underwater approaches

Multiple techniques have shown promising results in a variety of different applications and scenarios. Some of them perform SLAM indoors where the scenario is structured and simpler as compared to outdoor environments. Underwater scenarios are still one of the most challenging scenarios for SLAM because of the reduced sensorial possibilities and the difficulty in finding reliable features. A SLAM solution for underwater environments tackles the problem using feature based techniques [18]. However, such approaches have many problems due to the unstructured nature of the seabed and the difficulty to identify reliable features. Many underwater features are scale dependant, sensitive to viewing angle and small. On the other hand, a non-feature based approach to SLAM that utilizes a 2D grid structure to represent the map and a Distributed Particle Filter to track the uncertainty in the vehicle state was presented in [19]. They named their method as the Bathymetric distributed Particle SLAM (BPSLAM) filter. BPSLAM does not need to explicitly identify features in the surrounding environment or apply complicated matching algorithms. On the other hand, they required a prior low-resolution map generated by a surface vessel.

Another approach utilizes a 3D occupancy grid map representation, efficiently managed with Deferred Reference Counting Octrees [20]. A particle filter is used to handle the uncertainty in the navigation solution provided by the vehicle. This approach was successful in minimizing the navigation error during a deep sea mapping mission. However, map based localization was only available after the map building process had been carried out. This prohibited any corrections in navigation during the map building process.

A vision-based localization approach for an underwater robot in a structured environment was presented in [21]. Their system was based on a coded pattern placed on the bottom of a water tank and an on-board down-looking camera. The system provided three-dimensional position and orientation of the vehicle along with its velocity. Another vision-based algorithm [22] used inertial sensors together with the typical low-overlap imagery constraints of underwater imagery. Their strategy consisted on solving a sparse system of linear equations in order to maintain consistent covariance bound within a SLAM information filter. The main limitation on vision-based techniques is that they are limited to near field vision (1-5m), and also deep water mission will require higher amounts of energy for lighting purposes.

Instead of vision, in [23] a mechanically scanned imaging sonar is used to obtained information about the location of vertical planar structures present in partially structured environments. In this approach, the authors extract line features from sonar data, by means of a robust voting algorithm. These line features are used into a Kalman filter base SLAM. In [24] a side-scan sonar was used to sense the environment. The returns from the sonar were used to detect landmarks in the vehicles vicinity. Reobserving these landmarks allows to correct the map and vehicle location, however after long distances the drift is too large to allow associating landmarks with current observations. For this reason, they proposed a method that combines a forward stochastic map in conjunction with a backward Rauch-Tung-Striebel filter to smooth the trajectory. Another approach using side-scan sonar is presented in [25]. In that paper, the whole scenario is built through EKF based submaps, producing a consistent map and localizing the vehicle efficiently. The same strategy is used in this paper together with the automatic detection of salient features from side-scan sonar images. As side scan sonars provide higher quality images than forward-look sonars, the object detection and the data association becomes easier.

III. OBJECT DETECTION AND MATCHING

A great number of papers discussing image segmentation, classification, registration, and landmark extraction have already been published. Thresholding and clustering theory has been used in [26] to segment the side-scan sonar image into regions of object-highlight, shadow, and background. Similarly, the system in [27] utilizes an adaptive thresholding technique to detect and extract geometric features for both the shadow and the object. Another unsupervised model for both the detection and the shadow extraction as an automated classification system was presented in [28]. Using spatial information on the physical size and geometric signature of mines in side-scan sonar, a Markov random field (MRF) model segments the image into regions. A cooperating statistical snake (CSS) model is used to extract the highlight and shadow of the object. Features are extracted so that the object can be classified. A more recent approach [29], first extracts texture features from side scan images. A region based active contour model is then applied to segment significant objects.

The Viola-Jones object detection framework is capable to provide competitive object detection rates [30]. It can be trained to detect a variety of object classes. In this paper, we implemented two different methods to detect objects from side-scan sonar images, one based on thresholding and the other one based on Viola-Jones (further details are given in Section IV-B).

IV. IMPLEMENTATION

The method presented in this paper is represented in the block diagram on fig. 1.

A. *Selective Submap Joining SLAM*

The Selective Submap Joining SLAM was presented in [17]. The main idea of this SLAM approach is to use

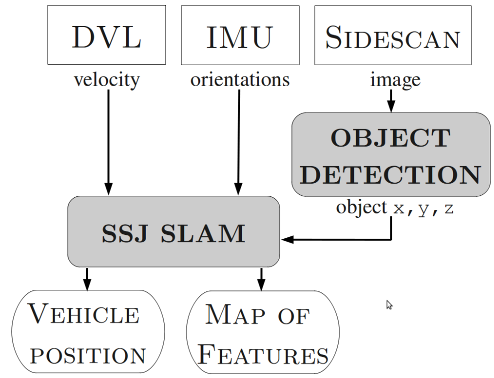


Fig. 1. Schematic representation of our system

Algorithm I: Selective Submap Joining SLAM

begin mission
while navigating **do**
  $\widehat{\mathbf{x}}_i, \widehat{\mathbf{P}}_i$ = EKF SLAM() $\leftarrow$ (*Build submap* $\mathcal{M}_i$)
  $\widehat{\mathbf{x}}_G, \widehat{\mathbf{P}}_G$ = build global map($\widehat{\mathbf{x}}_i$, $\widehat{\mathbf{P}}_i$)
  $\mathcal{H}_{Loop}$ = check possible loops($\widehat{\mathbf{x}}_G$, $\widehat{\mathbf{P}}_G$)
  for $j = \mathcal{H}_{Loop}$ **do**
    refer $\mathcal{M}_i$ and $\mathcal{M}_j$ to a common base reference
    $\mathcal{H}_{ij}$ = data association($\widehat{\mathbf{x}}_i, \widehat{\mathbf{x}}_j, \widehat{\mathbf{P}}_i, \widehat{\mathbf{P}}_j$)
    if $\mathcal{H}_{ij} > threshold$ **then**
      $\widehat{\mathbf{x}}_{ij}, \widehat{\mathbf{P}}_{ij}$ = map fusion($\widehat{\mathbf{x}}_i$, $\widehat{\mathbf{P}}_i$, $\widehat{\mathbf{x}}_j$, $\widehat{\mathbf{P}}_j$, $\mathcal{H}_{ij}$)
      $\widehat{\mathbf{x}}_G, \widehat{\mathbf{P}}_G$ = update global map($\widehat{\mathbf{x}}_{ij}, \widehat{\mathbf{P}}_{ij}$)
    endif
  endfor
endwhile

the EKF to build local maps. The size of these local maps is bounded by the total number of features and by the level of uncertainty. The relative topological relationship between consecutive local maps is stored in a global level map. The global level is used to search for loop closure, i.e. the vehicle is revisiting a region. Once a loop is detected, the data association between those maps that are closing the loop is computed. The loop closing strategy involves a decision on whether to fuse local maps depending on the amount of found correspondences. This correspondences are computed by means of a Joint Compatibility Branch and Bound [31] data association algorithm. The whole process is presented in *Algorithm I*.

The AUV REMUS-100 was used to gather the experimental data (see fig. 2). The vehicle was equipped with a DVL and IMU, giving navigation data relative to the vehicle reference frame, such as, velocities, orientations and depth. In addition, the vehicle was carrying a side-scan sonar pointing both ways, starboard and port. The state of the vehicle is defined by a 9-vector, composed by a 6-DOF vehicle pose and the vehicle frame linear velocities. The scenario is composed of objects, rocks and other detectable features. This feature's state is defined as 3D points in our map. These features are extracted from side-scan images (see fig. 3). In addition to feature information, the side-scan sonar provides a measure of the altitude (see fig. 4), i.e. the distance

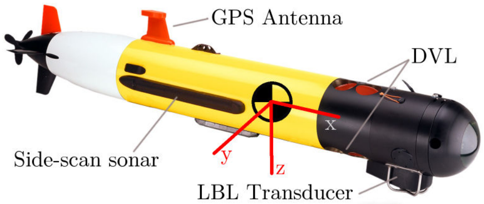


Fig. 2. The REMUS-100 AUV is the one used in our experiments.

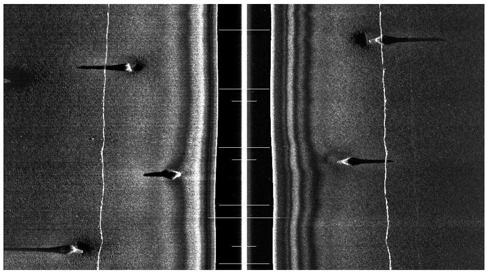


Fig. 3. Example of side-scan image. Metallic objects are well characterised by a bright spot together with a large oriented shadow. The dark vertical area in the center of the figure corresponds to the vehicle shadow.

from the sensor to the seabed. Therefore, the joint state vector estimate contains both vehicle state and map information.

B. Object Detection

Our initial approach to object detection was based on preprocessing the image followed by thresholding, as shown in fig. 5. First, a median filter is applied to remove the salt an peper effect of the sea floor (fig. 5(b)). Second, a low intensity threshold is used to binarize the image and find shadows (fig. 5(c)). The resulting image is run through the morphological operation 'erode' in order to magnify shadow sizes, while at the same time joining small noise areas together. In this way, selecting only dark regions with a certain size, which depends on image range, are accepted as object shadow candidates (fig. 5(e)). Third, the process is repeated for bright spots. A high intensity threshold is applied in order to binarize the image and find high reflective metallic objects (fig. 5(d)). In order to magnify this small spots, a 'dilate' is applied and these spots are selected as possible object candidates (fig. 5(f)). Finally, only those

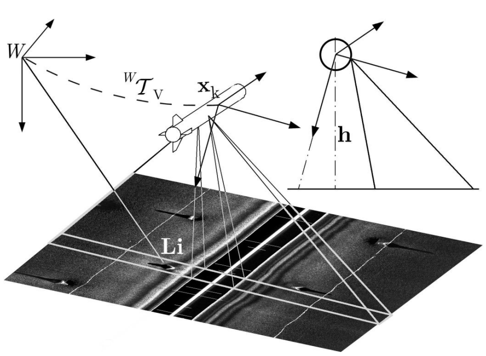


Fig. 4. Schematic representation of the side-scan sonar measurement procedure.

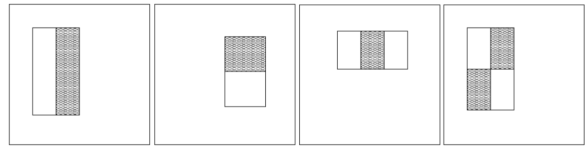


Fig. 6. Examples of rectangular features [30]. Left examples are two-rectangle features, while in the right there are a three-rectangle and a four-rectangle feature examples.

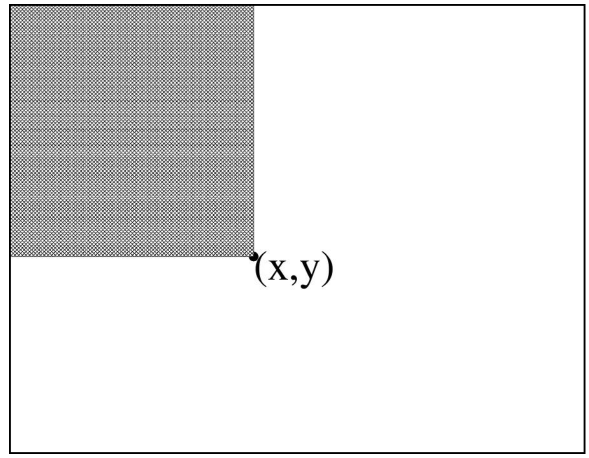
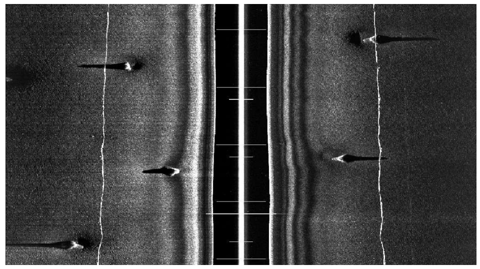


Fig. 7. The value of the integral image at (x, y) is the sum of all pixels in the shades area [30].

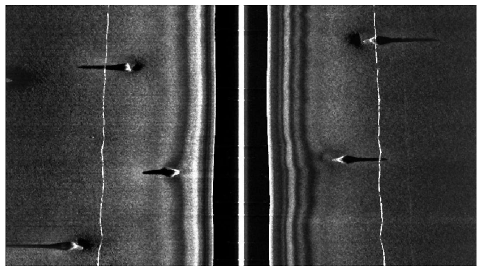
areas with both, shadow and metallic object candidates are accepted as real objects (fig. 5(g)).

Unfortunately, this approach is computationally expensive. Therefore we looked for a fast detector capable of producing consistent results for on-line applications. The Viola and Jones detector was initially designed to detect faces, but it can be used for any sort of object. In this algorithm, feature detection is done by means of a boosted cascade of Haar-like features (see fig. 6). All these features rely on more than one rectangular area, and the value assigned to them is the sum of the pixels within clear rectangles subtracted from the sum of pixels within shaded rectangles. The advantage of these features is that they are sensitive to vertical and horizontal changes. With the use of an image representation called the integral image, rectangular features can be evaluated in constant time. The integral image at location x, y contains the sum of the pixels above and to the left of x, y (see fig. 7). Using the integral image any rectangular sum can be computed as shown in fig. 8.

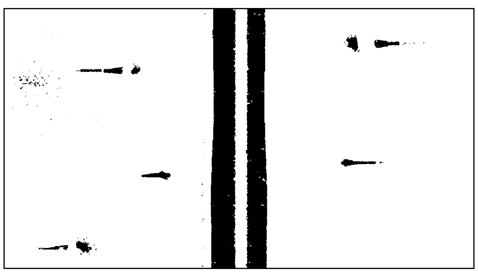
The learning process would be prohibitively expensive if we wanted to evaluate all possible features. In order to speed up the process, a variant of AdaBoost is used to select the best features and to train proper classifiers. Strong classifiers are arranged in a cascade in order of complexity (see fig. 9). In this way, each successive classifier is only trained on the examples which passed through the preceding classifiers. OpenCV libraries are used to first pre-process the images, mainly apply a median filter, then train the system and finally run the object detector.



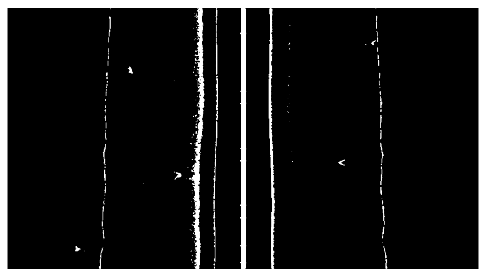
(a) original image



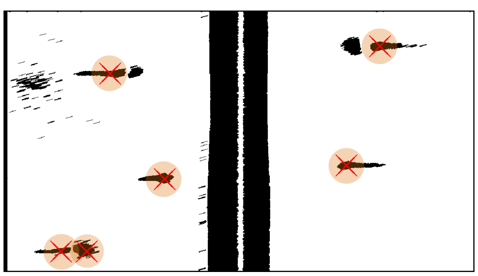
(b) image after median filter



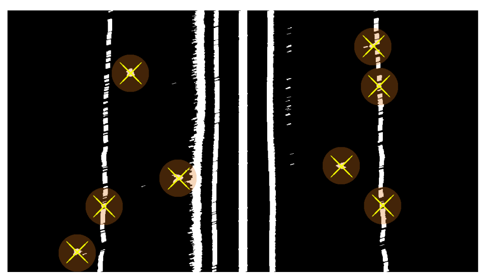
(c) high intensity threshold binary image



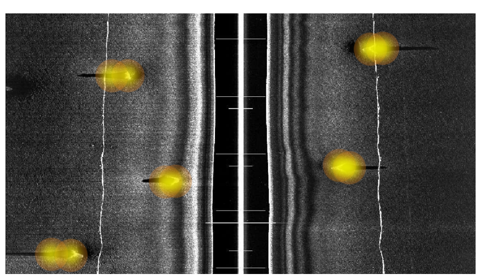
(d) low intensity threshold binary image



(e) shadow candidates detection



(f) metallic spot candidates detection



(g) final detection = shadows + metallic spots

Fig. 5. Example of the automatic detection performance.

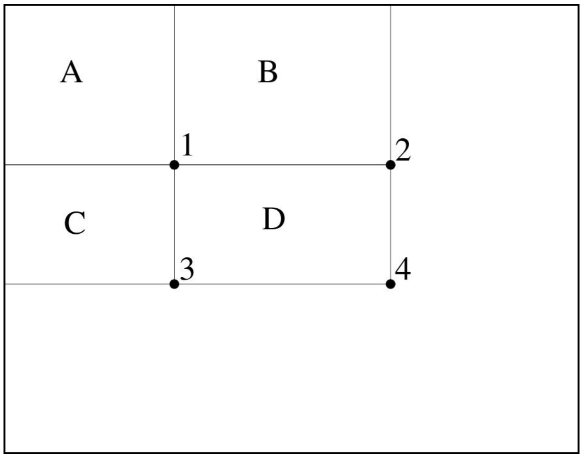


Fig. 8. The sum of pixels within rectangle D can be computed as the combination $4 + 1 - (2 + 3)$ of the integral images at points 1 to 4.

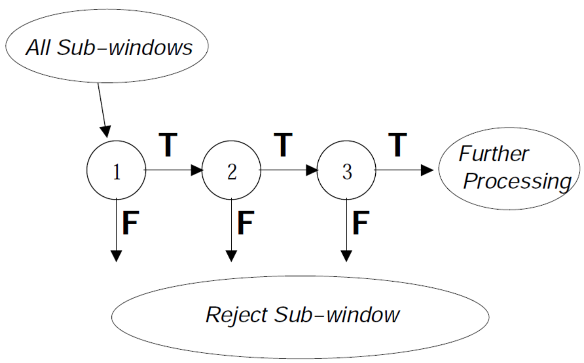


Fig. 9. Schematic representation of a detection cascade [30]. Subwindows of the image are run through a series of classifiers. Further processing means additional stages of the cascade.

V. EXPERIMENTAL RESULTS

The experiments were conducted in a real environment. The AUV was sent underwater to perform a recognition mission. During the mission the vehicle navigated a large surface, about 300m x 400m. The whole navigation consisted in a large number of loops, i.e. revisiting the same area several times (see fig. 11). The vehicle's depth was almost constant around 12 meters, and some intervals at 14 meters, while the sea floor with respect to the water surface was oscillating 16 meters. The total navigation time was almost 4 hours. This scenario sea floor was considerably flat, but with several salient objects.

Table I summarises numerical results from both implementations. Notice that these results were obtained from Matlab implementations in a computer equipped with a Core 2 Duo CPU at 2.66 GHz. With this data both object detectors were able to find about 80% of all existing landmarks, with a similar rate of false positive around 9 for the whole mission. This detection rate is well suited in the context of SLAM, if we consider that in SLAM applications is very important to have a very low rate of false positives. Detecting false objects would create a false landmark and false associations, causing divergences. For this reason, the algorithm is tuned

TABLE I
DETECTOR PERFORMANCE COMPARISON

	Thresholding	Viola-Jones
True Positive (%)	81.2	82.1
False Positive (objects)	9	8
Time per image (s)	2.56	0.58

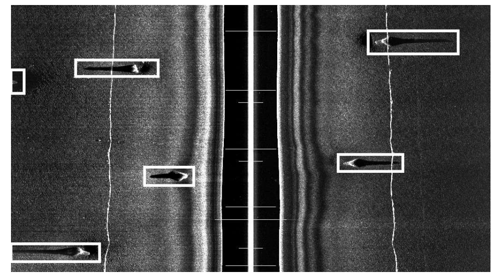


Fig. 10. Example of the automatic detection performance. The image has 6 objects that have been properly detected.

in order to obtain detections with a very high probability of being a real object. This constraint is very restrictive, thus some objects that could have been detected are discarded, reducing the amount of true positives. Both approaches produce similar results in terms of accuracy. However, the Viola-Jones approach is much faster. An example for the threshold approach is given in fig. 5. The method is shown to be very robust, as the condition of having shadow horizontally aligned with a closed bright spot is very restrictive. The Viola and Jones algorithm is able to perform automatic detection in side-scan images (see fig. 10) with a very low rate of false positives. The training process is computationally expensive. However, once the training have been done off-line, the detection can be conducted in real-time.

VI. CONCLUSION AND FUTURE WORK

A. Conclusions

In this paper we have presented and compared two object detection strategies. These object detection strategies are used to segment objects located on the sea floor and sensored through side-scan sonar. These detected objects are then used as landmarks for the map building process. In the meantime, the vehicle is located within the map, by means of the selective submap joining SLAM algorithm.

After seeing the results, we can conclude that both detectors perform very similar in terms of accuracy, but the algorithm based on the Viola and Jones detector is faster. However, this approach requires a very expensive training stage, which must run off-line. Identifying a set of features able to discriminate typical objects that appear in side-scan images is a complex task. In addition, a big dataset is necessary for the training to be efficient and produce a proper detector.

B. Future Works

Several points remain for further study:

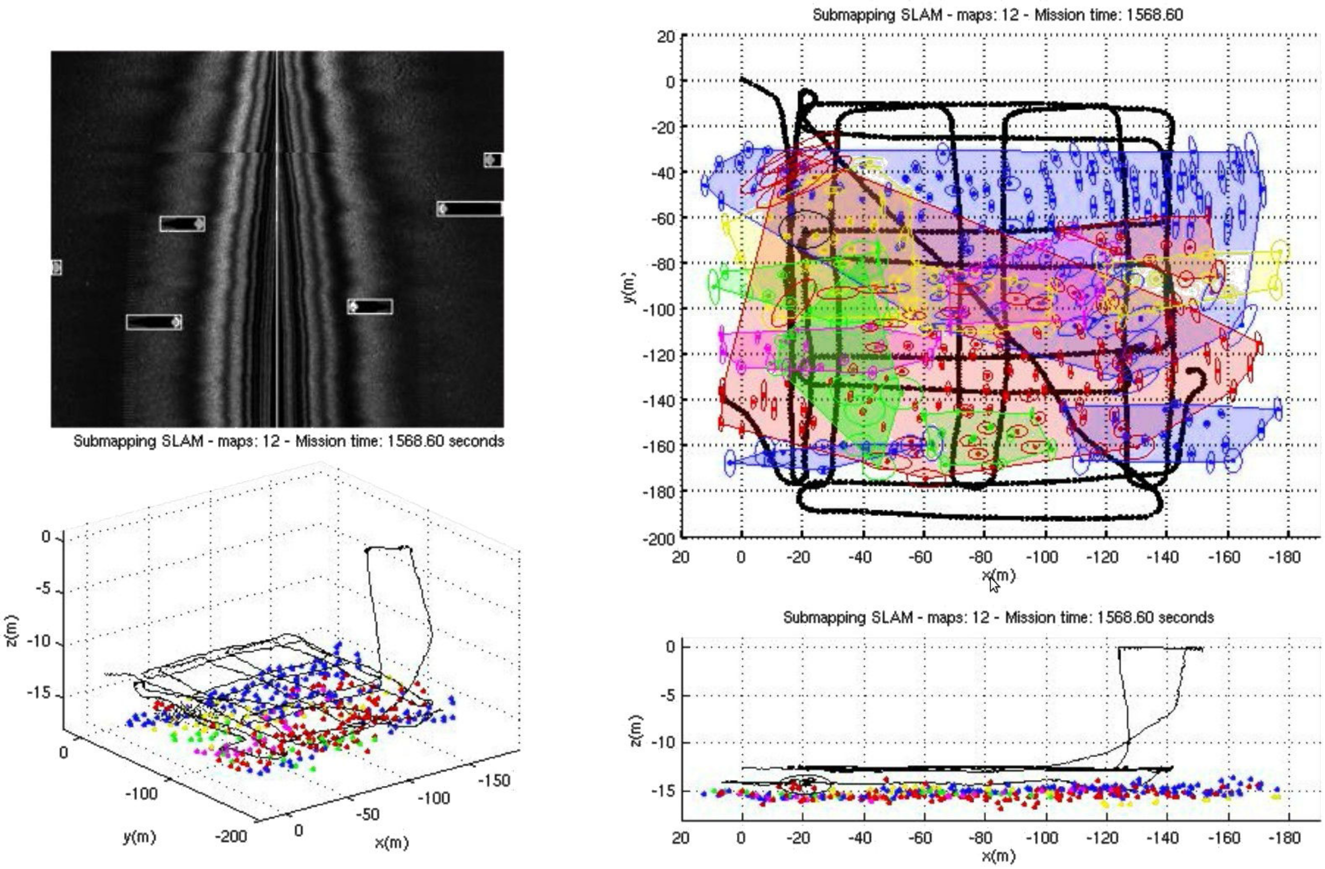


Fig. 11. Plot of the execution at a certain step during the mission. Top-left: side-scan image with several detected objects. Bottom-left: 3D plot of the map and the trajectory of the vehicle. Top-right: XY top view of the map and trajectory. This plot shows the submaps in different colours, together with its corresponding landmarks and uncertainty ellipses. Bottom-right: XZ frontal view of the execution. In this plot, it is easy to see that the vehicle has been navigating at around 12 meter deep, then it has gone to the surface, and it has dived back to around 14 meters deep

- to analyse the performance of the detector using only some specific features, taking advantage of the geometric constraints given by the regular pattern bright-shadow of the metallic objects in a side-scan sonar image.
- to analyse the performance of the detector under different training datasets.
- to add the possibility to automatically classify detected objects. This would ease the data association process.
- to test the SLAM algorithm under different real datasets.

VII. ACKNOWLEDGEMENTS

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REFERENCES

[1] H. Durrant-Whyte and T. Bailey, "Simultaneous localization and mapping (SLAM): Part I", *IEEE Robotics and Automation Magazine*, vol. 13, num. 2, pp 99–108, 2006.

[2] S. Thrun, D. Burgard and W. Fox, "Probabilistic Robotics", *MIT Press*, 2005. ISBN-10: 0-262-20162-3.

[3] R. Smith, M. Self, and P. Cheeseman, "A Stochastic map for uncertain spatial relationships", *4th International Symposium on Robotics Research*, O. Faugeras and G.Giralt (Editors), the MIT Press, pp. 467–474, 1988.

[4] J. A. Castellanos, R. Martínez-Cantón, J. Neira, and J. D. Tardós, "Robocentric map joining: Improving the consistency of EKF-SLAM", *Robotics and Autonomous Systems*, vol. 55, num. 1, pp. 21–29, 2007.

[5] E. Wan and R. van der Merwe, "Kalman Filtering and Neural Networks, Chapter 7: The Unscented Kalman Filter". *Wiley*, 2001. ISBN: 978-0-471-36998-1.

[6] J. E. Guivant and E. M. Nebot, "Optimization of the simultaneous localization and map-building algorithm for real-time implementation", *IEEE Transaction on Robotics and Automation*, vol. 17, num. 3, pp. 242–257, 2001.

[7] M.R. Walter, R.M. Eustice and J.J. Leonard, "Exactly sparse extended information filters for feature based SLAM", *International Journal of Robotics Research*, vol.26, num. 4, pp 335–359, 2007.

[8] J. J. Leonard, H. Feder, "Decoupled stochastic mapping", *IEEE Journal of Oceanic Engineering*, 26(4), 561571, 2001.

[9] J. Aulinas, J. Salvi, X. LLado, Y. Petillot, "Local map update for large scale SLAM", *Electronic Letters (ELT)*, 46(8), 564-566, 2010.

[10] S. B. Williams, G. Dissanayake, and H. Durrant-Whyte, "An efficient approach to the simultaneous localisation and mapping problem",

IEEE Int. Conf. on Robotics and Automation, vol. 1, pp. 406–411, 2002.

[11] J. D. Tardós, J. Neira, P. M. Newman, and J. J. Leonard, "Robust mapping and localization in indoor environments using sonar data", *International Journal on Robotics Research*, vol. 21, num. 4, pp. 311–330, 2002.

[12] L. M. Paz, J. D. Tardós, and J. Neira, "Divide and conquer: EKF SLAM in O(n)", *IEEE Transaction in Robotics*, vol. 24, num. 5, pp. 1107–1120, 2008.

[13] P. Piniés and J. D. Tardós, "Large Scale SLAM Building Conditionally Independent Local Maps: Application to Monocular Vision", *IEEE Transactions on Robotics*, vol. 24, no. 5, October 2008.

[14] P.M. Newman and J.J. Leonard, "Consistent, convergent, and constant-time SLAM", *Int. Joint Conf. on Artificial Intelligence (IJCAI)*, pp. 1143–1150, 2003.

[15] M. Bosse, P. M. Newman, J. J. Leonard, and S. Teller, "SLAM in large scale cyclic environments using the atlas framework", *Int. Journal in Robotics Research*, vol. 23, num. 12, pp. 1113–1139, 2004.

[16] C. Estrada, J. Neira, and J. D. Tardós, "Hierarchical SLAM: real-time accurate mapping of large environments", *IEEE Transaction in Robotics*, vol. 21, num. 4, pp. 588–596, 2005.

[17] J. Aulinas, X. LLadó, J. Salvi, Y. Petillot, "SLAM base Selective Submap Joining for the Victoria Park Dataset", *7th IFAC Symposium on Intelligent Autonomous Vehicles (IFAC/IAV)*, Lecce (Italy) September 6-8, 2010.

[18] S.B. Williams, "Efficient Solutions to Autonomous Mapping and Navigation Problems", *PhD thesis*, Australian Centre for Field Robotics - The University of Sydney, 2001.

[19] S. Barkby, S.B. Williams, O. Pizarro, M. Jakuba, "Incorporating prior bathymetric maps with distributed particle bathymetric SLAM for improved AUV navigation and mapping", in *Proceedings MTS/IEEE Oceans Conference and Exhibition*, Biloxi (USA), 2009.

[20] N. Fairfield, D. Wettergreen. Active localization on the ocean floor with multibeam sonar, In Proceedings of MTS/IEEE OCEANS, 2008.

[21] M. Carreras, P. Ridao, R. Garcia, and T. Nicosevici, "Vision-based localization of an underwater robot in a structured environment", *IEEE International Conference on Robotics and Automation*, 2003. ICRA 03, vol. 1, pp. 971–976, 2003.

[22] R. Eustice, O. Pizarro, and H. Singh, "Visually Augmented Navigation for Autonomous Underwater Vehicles", *IEEE Journal of Oceanic Engineering*, 33(2):103 – 122, April. 2008.

[23] D. Ribas, P. Ridao, J.D. Tards and J. Neira, "Underwater SLAM in Man Made Structured Environments", *Journal of Field Robotics*, 25(11-12):898–921, 2008.

[24] I. Tena-Ruiz, S. Raucourt, Y. Petillot, and D. Lane, Concurrent mapping and localization using side-scan sonar, *IEEE Journal of Oceanic Engineering*, vol. 29, no. 2, pp. 442–456, 2004.

[25] J. Aulinas, C.S. Lee, J. Salvi, Y. Petillot, "Submapping SLAM based on acoustic data from a 6-DOF AUV", *8th IFAC Conference on Control Applications in Marine Systems (IFAC/CAMS)*, Rostock-Warnemnde (Germany), September 15-17, 2010.

[26] S. G. Johnson and M. A. Deaett, The application of automated recognition techniques to side-scan sonar imagery, *IEEE Journal of Oceanic Engineering*, vol. 19, pp. 138–144, 1994.

[27] C. M. Ciany and J. Huang, Computer aided detection/computer aided classification and data fusion algorithms for automated detection and classification of underwater mine, in *Proc. MTS/IEEE Oceans Conference and Exhibition*, vol. 1, pp. 277–284, 2000.

[28] S. Reed, Y.R. Petillot, J. Bell, "An Automatic Approach to the Detection and Extraction of Mine Features in Side-scan Sonar", *IEEE Journal of Oceanic Engineering*, vol. 28, no. 1, pp. 90–105, 2003.

[29] M. Lianantonakis, Y. petillot, "Side-scan Sonar Segmentation Using Texture Descriptors and Active Contours", *IEEE Journal of Oceanic Engineering*, vol. 32, pp. 744–752, 2007.

[30] P.A. Viola, M. J. Jones, "Rapid Object Detection using a Boosted Cascade of Simple Features", *IEEE Conference on Computer Vision and Pattern Recognition (CVPR)*, vol. 1, pp. 511–518, 2001.

[31] J. Neira and J.D. Tardós, "Data Association in Stochastic Mapping Using the Joint Compatibility Test", *IEEE Transaction on Robotics and Automation*, vol. 17, num. 6, pp. 890–897, Dec 2001.