Underwater vehicle path planning using a multi-beam forward looking sonar.

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Abstract— [1] **This paper describes a new obstacle avoidance and path planning system for underwater vehicles based on a multi-beam forward looking sonar sensor. The real-time data flow (acoustic images) at the input of the system is first processed (segmentation and feature extraction) to create a representation of the workspace of the vehicle. This representation uses constructive solid geometry (CSG) to create a convex set of obstacles defining the workspace. We also take advantage of the real-time data stream to track the obstacles in the subsequent frames to obtain their dynamic characteristics. This will also allow us to optimise the preprocessing phases in segmenting only the relevant part of the images as well as to take into account obstacles which are no longer in the field of view of the sonar in the path planning phase. A well proven nonlinear search (sequential quadratic programming) is then employed, where obstacles are expressed as constraints in the search space. This approach is less affected by local minima than classical methods using potential fields. The proposed system is not only capable of obstacle avoidance but also of path planning in complex environments which include fast moving obstacles. Preliminary results obtained on real data are shown and discussed.**

Keywords: Path planning, Obstacle avoidance, Sonar, Underwater robotics

I. Introduction

We address here the general path planning and obstacle avoidance problem for an underwater vehicle using high resolution real-time sonar sensory data.

Although related problems such as 2D map building, environment modeling [1], [2] and motion estimation could be tackled in the framework of the presented system, we will focus on obstacle avoidance.

Until recently, most obstacle avoidance systems used low resolution or low frame rate sonar sensors yielding inaccurate estimations of the obstacles positions and movement. These systems were suitable for reactive obstacle avoidance ('reflex behaviour') but not for real path planning in a complex and changing environment.

[1]Presented at Oceans'98, Nice, September 98.

With the recent development of reliable high resolution multi-beam sonars, a new range of methods have emerged which allow for a more detailed description of the environment and has broaden the spectrum of techniques that can be used [3], [4], [5], [6], [7].

A. Target application

Our aim is to develop an obstacle avoidance system for the ARAMIS (Advanced ROV Package for Automatic Mobile Investigation of Sediments) tool-skid, where ROV stands for Remotely Operated Vehicles. ARAMIS (MAST-CT97-0083) provides a geological/scientific tool-skid which will be mounted on two different ROVs, VICTOR from IFREMER (France) and ROMEO from CNR-IAN (Italy), operating at a close distance from the seabed (2 meters) at depths ranging from 50 meters to 2000 meters. The cruising speed for both ROVs is around 1 knot and the movements of the ROVs are measured by several on-board sensors feeding the obstacle avoidance system with position, speed and orientation of the vehicle in world coordinates.

B. Obstacle avoidance system overview

The system we are currently designing (see figure 1) is modular in nature. Each module performs a distinct function :

B.1 Segmentation:

Considering the very nature of multi-beam sonar images, we have decided to discard the certainty grid approach [8] often used in air ultrasonic sensor based motion planning and to focus on an object oriented description of the workspace.

B.2 Feature extraction:

Once the image has been segmented, the visible obstacles with their main features (position, moments, area, ...) are identified. These features will be used

later to discard false alarms and track the obstacles and the vehicle.

B.3 Tracking:

This is one of the most important part of the system as it provides a dynamic model of the obstacles. Moreover, considering the amount of data to be processed, the tracking drives the segmentation and reduce the computational cost. It also enables us to create a world coordinates map of the obstacles surrounding the ROV including those that are no longer in the field of view of the sonar.

B.4 ROV dynamic modeling:

We have a dynamic and kinematic model of Angus 002, an ROV developed in Heriot-Watt University [9]. This model takes into account any type of sea current. It will be used until we have a model of the ROVs used in the project. In any case, the Angus model gives a realistic description of the behaviour of a typical ROV.

B.5 Workspace representation:

From the extracted obstacles and features of the current image, we can build an intra-frame workspace (frozen in time). Combining this intra-frame workspace with previous instances of intra-frame workspaces, a new dynamic workspace is built and constantly updated. It forms the basis for the path planning algorithm.

B.6 Path planning:

A nonlinear programming technique based on a constructive solid geometry representation of the obstacles is used for the path planning. Each obstacle in the workspace is represented as a constraint that has to be met in the search space (path not crossing the obstacle) while optimizing the Euclidean distance to the goal. This approach is based on our previous work [5], [6].

Each module will now be detailed and its main characteristics explained. Results will be presented for each module and the general path planner will be demonstrated in section V on real data.

II. Segmentation

Multi-beam sonar images are generally noisy and need to be filtered. A common segmentation procedure consists of median filtering followed by thresholding. The filtering part is generally very time-consuming. We have tried several techniques and found out that a good compromise between quality and speed was reached using the following scheme:

• **Filtering:** The filter used to remove the backscatter noise is a 7×7 mean filter which yields results almost as good as the median filter even on noisy images but at a reduced computational cost [10].

• **Threshold :** A single fixed threshold generally gives results which are highly dependent on the background level. We have used an adaptive thresholding technique based on the image histogram which is independent of the actual signal level. The idea is to estimate the noise probability density function assuming that the histogram of the studied image is a good estimate of it (thus assuming that obstacles are small in the image). The false alarm rate (FAR) is then fixed and used in conjunction with the histogram to derive the threshold value. Special cases where the images are mainly composed of obstacles (with high returns) or with a lot of backscatter noise from the seabed can easily be detected as they show a high variance. The process can then be adapted to these special cases. Although not as good as a real adaptive filter where the threshold value is *locally* derived with respect to the surrounding pixels, this technique gives results which match the real-time constraints. In the future, this scheme will be used on a subsampled image to detect potential obstacles in the scene while the tracking will allow the use of more elaborate techniques on selected parts of the scene.

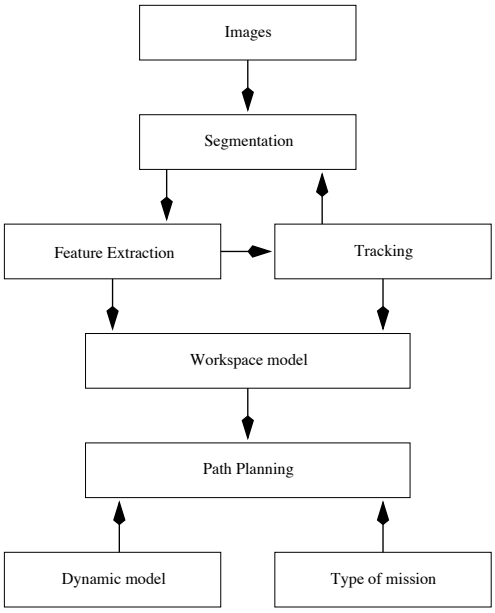

Fig. 1: Principle of sonar based real time path planning.

Two examples of the same segmentation process on a clear and a noisy images are given in figure 2. It should be noted that no tuning parameter is needed and that the process is fully automatic.

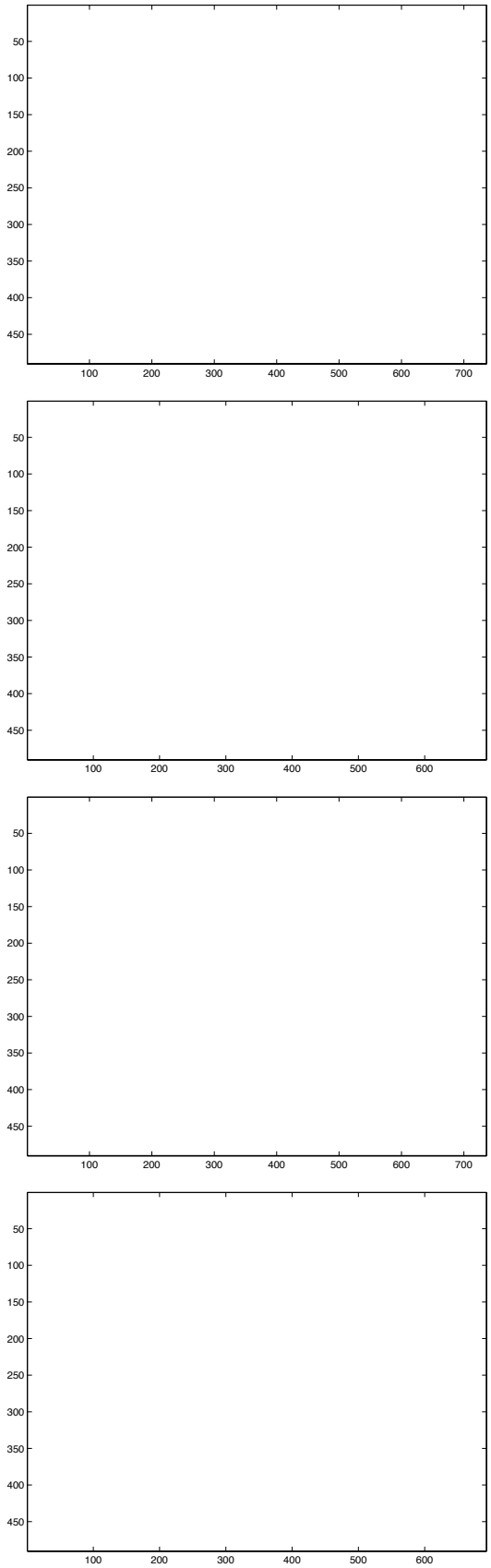

Fig. : Segmentation of multi-beam high-resolution sonar images containing pier legs and a diver with a clear image (top) and a noisy image (bottom). Scans were obtained from a Seabat 6 1 from Reson.

III. Feature extraction and rac ing

Once segmented, the different regions representing the obstacles in the image are labeled using a standard labeling algorithm, and the major features of each obstacle are extracted (area, perimeter, moments). In order to track the obstacles in a sequence of images, the first step is to associate the new observations (obstacles) of the image under study with the tracks of the previously identified obstacles. This is known as the data association phase. We employ a nearest neighbour algorithm to associate the predicted position of the tracked obstacles with the new observations. Three cases are then possible :

- There is a new observation matching the predicted position. A Kalman filter is then applied, a new state vector derived and new internal values computed.
- No new observation matches the prediction. The obstacle prediction is then updated using the Kalman filter internal values which are not updated. If no match is found between the observations and a given tracked obstacle on a predefined number of frames, the obstacle is discarded as a false alarm.
- An observation is not associated to any prediction, a new obstacle is created and its corresponding Kalman filter initialized.

This scheme has been successfully tested on simulated data but not yet on real segmented data. This will be done in the near future. For real data, the extracted features will be used as a consistency test in the data association algorithm. Obstacles will also be merged if they appear to be the result of several returns from the same obstacle, a very common situation with moving obstacles when using multi-beam sonars(see figure 2(b)). We are currently developing and testing standard Kalman filter and extended Kalman filters for tracking realistic underwater targets. More details on tracking and data association schemes can be found in [11].

I . Wor ace re re entation and ath lanning

The choice of a workspace representation is intimately linked with the path planning technique which will be applied. Most path planning algorithms assume a convex representation of the obstacles to ensure that the goal will be reached. When dealing with a changing environment which is sensed on the fly, it is better to use a reactive path planning technique which does not need a complete description of the workspace from the current position to the goal for:

- Only partial information is available (due to the limitations of the sensor).