Range Extraction from Underwater Imaging Sonar Data

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Abstract

Nearly all advanced mobile robotic tasks require some knowledge of the robot location in the environment. Autonomous Underwater Vehicles *are usually endowed with acoustic devices to perform localization, because underwater scenarios pose important limitations to light based sensors. One of these acoustic devices is the* Mechanically Scanned Imaging Sonar *(MSIS). This sensor scans the environment by emitting ultrasonic pulses and it provides echo intensity profiles (beams) of the scanned area.*

Our goal is to obtain range scans instead of the beams as they are provided by the MSIS. Accordingly, the proposal of this paper is to process the acoustic images in order to compute accurate distances from the sensor to the relevant obstacles in the beam.

These range scans are suitable to be used in scan matching, SLAM or other approaches to estimate the robot pose.

1. Introduction

Nowadays, one of the major issues that centers the attention of the mobile robotics community is the one of estimating the robot position and attitude over time. This problem is known as the localization problem. For example, knowing the current robot pose is essential in order to plan a path to reach a specific target, or also, exploration tasks require some estimate of the robot location in order to decide whether a specific region has been already visited by the robot or not.

Broadly speaking, localization approaches, either incremental [7] or *Simultaneous Localization and Mapping* (SLAM) [3] rely on their ability to match recent sensor data against previously gathered measurements. In some cases, this involves the detection of features, such as straight lines or corners, and then performing the matching at the feature level. Besides, some other studies avoid the use of features, providing a more general approach not depending on the type of environment. Examples of matching techniques not depending on features are those inspired on the *Iterative Closest Point* (ICP) algorithm [6] and those based on the use of *Likelihood Fields* (LF) [9], both designed to work with range measurements. In the context of localization, these matching processes constitute the so called *measurement model*.

The scope of this paper is the one of those approaches that require range measurements.

Lasers and ultrasonic range finders, are very common in terrestrial robotics. However, in underwater environments, which are also the scope of this paper, it is more frequent the use of imaging sonars and profilers. Instead of providing ranges to the closest obstacles, these sensors provide acoustic profiles or acoustic images of the environment.

The sensor data used in this work has been obtained by a Mechanically Scanned Imaging Sonar (MSIS) sensor. This kind of sensors supplies echo intensity profiles of the scanned area (more information about the MSIS sensor can be found in section 2). Therefore, as usual techniques as measurement model or SLAM needs the range information provided by the sensors, the echo intensity profiles should be changed into range measurements.

This work discusses and compares various proposals to solve the problem of obtaining range information from the acoustic images of the environment.This is especially useful when providing self-localization capabilities to an Automomous Underwater Vehicle (AUV).

2. The MSIS sensor

The experiments conducted in this paper have been performed using the sensor data gathered by the *Ictineu AUV*. This AUV was designed and developed in the University of Girona (see [8] for more details).

The Ictineu is endowed, among other sensors, with an MSIS, the *Tritech Miniking Imaging Sonar*. This sensor scans the environment by emitting ultrasonic pulses and it provides echo intensity profiles of the scanned area.

In the particular configuration used in this paper, this sensor obtains 360^o scans of the environment (in the sensor reference frame) by rotating a sonar beam through 200 angular steps in about 13.8 seconds. At each angular position, a set of 500 values, named *bins*, is obtained representing a 50 m long echo intensity profile with a resolution of 10cm. Each of these sets of 500 bins will be referred to as *beam*. By accumulating this information, an acoustic

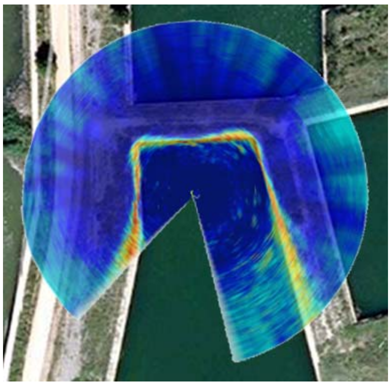

Figure 1. Acoustic image taking into account the robot motion, superimposed to a satellite view.

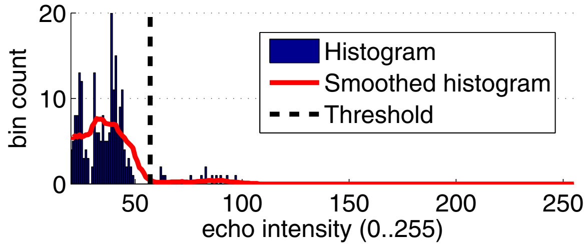

Figure 2. An example of the method 3 thresholding selection process.

image of the environment can be obtained. An example of one of these kind of images is shown in figure 3-(a).

According to this, different problems arise when using a MSIS to perform scan-based localization.

Firstly, as stated before, a MSIS does not provide range measurements but echo intensity profiles. Consequently, it is necessary to process the echo intensity profiles provided by the MSIS in order to obtain accurate range information.

Another problem is related to the MSIS scan time. As the sensor needs a few seconds to gather a full scan, it can not be assumed that a scan has been fully gathered at a single robot pose. Instead, the robot motion during the scan acquisition has to be considered. Some considerations regarding this issue using terrestrial Polaroid sensors are provided in [1]. Moreover, a recent study by [5] shows the feasibility of underwater scan matching using a MSIS. Figure 1 shows an example of an acoustic image obtained by the MSIS taking into account the robot motion.

This paper is focused in the process that obtains range information from the MSIS intensity profiles. Let it be named the *beam segmentation*.

3. Beam Segmentation

Our goal is to obtain range scans instead of the beams as they are provided by the MSIS. Accordingly, the beam segmentation is in charge of computing the distance from the sensor to the largest obstacle in the beam. Although in some cases, this distance corresponds to the bin with the largest intensity value and it is easy to find it, in some other cases it does not. To deal with these last situations, the following procedures are proposed, so that the correct distance can be found as the maximum intensity value in the beam. Let the bin with the largest echo intensity value be named the *range reading*.

3.1. Method 1: Enhancement and image processing techniques

The goal of this method is to isolate the high intensities areas of the intensity profile which are susceptible to be obstacles in the environment. In this case, the image is modified using the standard image processing techniques [4] , without considering that it has been registered by the MSIS sensor. Next steps are needed:

Enhancement: The intensity of the gray-scale profile is transformed taking into account the whole image. The original image is adjusted mapping its intensity values to new values such that 1% of data is saturated at its low and high intensities.

Thresholding: The resulting image is converted to binary image by thresholding. After the enhancement a threshold of 0.5 seems to be a good approximation to preserve the high intensities areas.

Morphological operations: The resulting binary image is modified by means of the standard closing morphological operation, which means a dilatation followed by a erosion using a rectangular 3×5 structural element. The effect is that the small gaps are filled in and the outer edges of the objects are smoothed. Next, to remove false measurements, small objects are ruled out. The rest are pruned, which means to remove its end points without removing small objects completely. The result of these operations is a binary image which is used as a mask over the original intensity profile.

3.2. Method 2: Enhancement depending on the range

This second option enhances the image taking into account the behavior of the MSIS. It can be visually observed that when the MSIS provides a new beam, the larger the range is the less contrasted is the signal obtained by the sensor. See figure 3-(a) carefully to notice this effect.

Consequently, the proposed solution to solve this problem is to enhance the echo intensity profile depending on the range. To do this, the image is processed column by column, expanding the gray scale region of each column from $[low\_threshold \quad 1]$ to $[0 \quad 1]$. Being $low\_threshold$ a gray-level value depending on the position of the column, that is depending on the range.

3.3. Method 3: Dynamically Thresholding

This beam segmentation method also processes the image considering the behavior of the sensor and adding an erosion.

Thresholding : An echo intensity threshold is dynamically selected as follows. Firstly, the histogram of echo intensities corresponding to the beam under analysis is computed. Secondly, the histogram is smoothed. Afterwards, the threshold is located at the largest echo intensity value that locally minimizes the smoothed histogram. Figure 2 exemplifies the threshold selection process. In this way, the threshold separates two clearly defined areas in the echo intensity space. Finally, those bins whose intensity is below the threshold are discarded.

Erosion : The remaining bins are eroded. That means that those bins that, after the thresholding, do not have another bin in their immediate neighborhood, are removed. The purpose of this step is to remove spurious measurements.

Notice that after putting into practice any of the methods described above, the original image is transformed into a new gray-scale image which is used to obtain the range reading of each beam. This new processed image is used to select, for each beam, the bin with the largest echo intensity value. The distance corresponding to this bin will be the range reading for the beam under analysis.

The results of selecting the maximum intensity bin and those of applying these methods or its combinations are exemplified in section 4.

4. Experimental Results

Figure 3 shows the experimental results obtained after using the proposed methods with one of the images obtained by the imaging sonar. Some other results can be downloaded from [2].

Henceforward, M1 means method 1, M2 method 2, M3 method 3 and letters between brackets always refer to figure 3.

The first row of this figure shows in (a) the original image used as it has been gathered by the MSIS and in (b) the maximum intensity per row. The rest of the figure shows in the column on the left the results of processing (a) using the different methods detailed in section 3 and some of its combinations. While the column on the right shows the maximum value per row of each processed image, which represents the range reading of each beam.

Second, third and fourth rows of the figure present the obtained results from M1, M2 and M3 respectively. Figure (c) shows how M1 isolates the the high intensities areas of (a), (e) shows the enhanced and not very noisy image obtained from the original one using M2 and (g) shows the obtained image after applying M3.

The range readings obtained with M1, see (d), and M3, see (h), are much better than the ones obtained in (b). Nevertheless the results in (f) are quite similar to (b), which suggests that M2 should be considered as a method to be used in combination with the other two.

The results of combining the methods are shown in the following order: 5th row shows the results of applying M1+M2, 6th M1+M3, 7th M2+M3 and 8th M1+M2+M3. The best results are obtained in (j), (l) and (p).

It is clear that our approaches are able to obtain a much more accurate range scan than the simple maximum intensity selection showed in (b), with the only one exception (f), as it has been explained above.

5. Conclusions and Future Work

This paper presents different methods to enhance the image profile in order to obtain accurate range readings instead of the beams as they are provided by the MSIS.

We have presented one method only based on standard image processing techniques, although the image has been obtained by an imaging sonar, and two more which take into account the behavior of the MSIS. All of these methods can be used in scan matching or scan based SLAM to perform localization using underwater sonar data.

The experimental results, although preliminary, show the potential benefits of the presente approach.

Future research would be looked at using these presented methods in underwater scan matching and SLAM, to compare the results of applying the different combinations in localization.

Acknowledgements

This work is partially supported by DPI 2008-06548-C03-02, FEDER funding and FP7-TRIDENT Project SCP8-GA-2010-248497. The authors are grateful to the members of the Underwater Robotics Lab, in Universitat de Girona, for the data sets.

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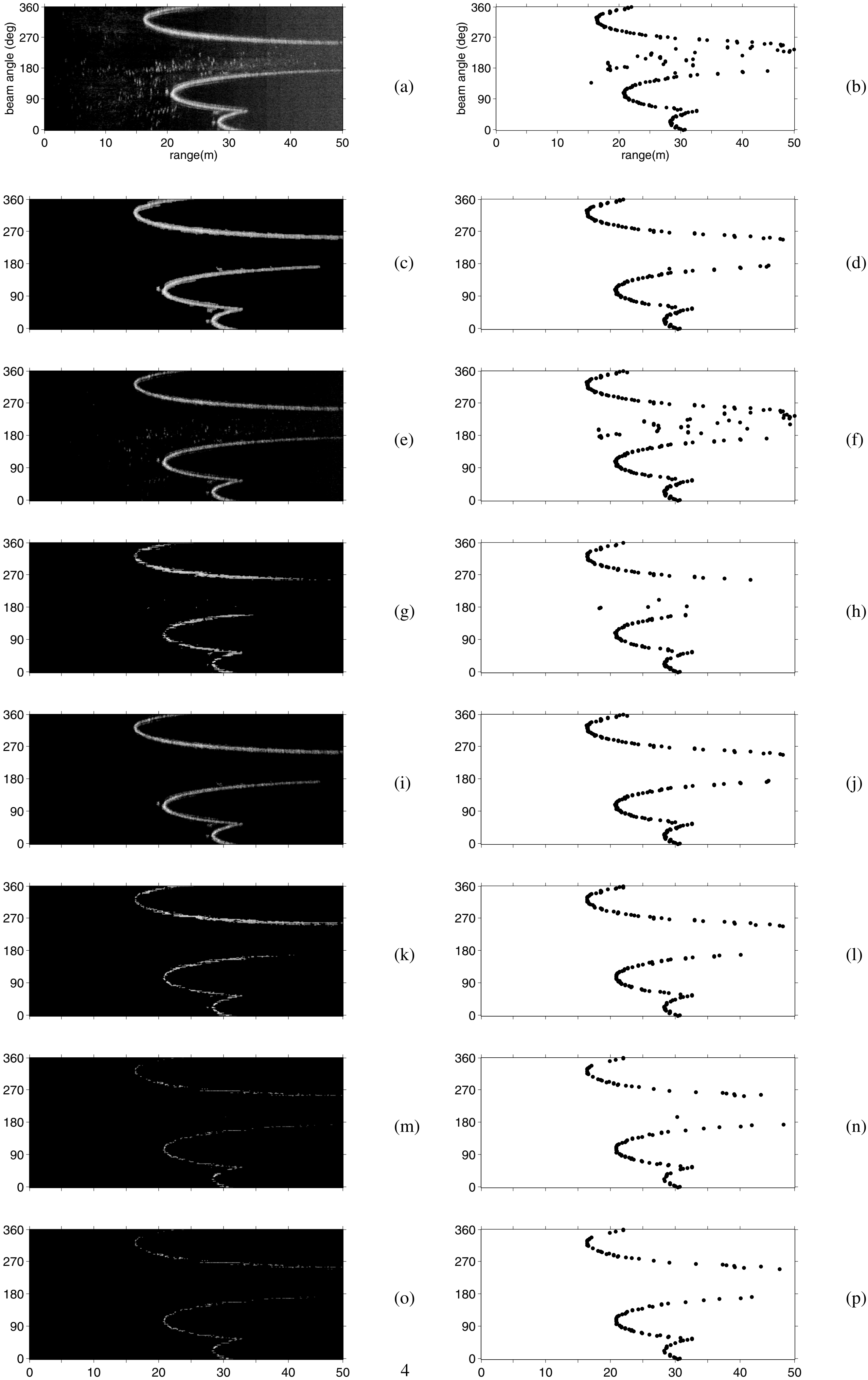

Figure 3. Experimental results: processed images (left) and their maximum intensity per row (right).