Real Time AUV Pipeline Detection and Tracking Using Side Scan Sonar and Multi-Beam Echosounder

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***Abstract*-. Robust pipeline tracking is critical for AUV technology to succeed in the commercial sector. This paper presents two techniques for reliably detecting and tracking pipelines using multi-beam echo-sounder and side-scan sonar systems. Because of the specific nature of the problem, a lot of prior knowledge can be used. Our algorithms use a model-based bayesian approach. They are both efficient and robust to variations of the model and noise. Results are shown on real data sets in both cases. The algorithms are compatible with real-time implementation.**

I. INTRODUCTION

With the advent of AUV technology in the offshore industry, major survey and inspection tasks are now possible at lower cost with faster execution time. Pipe inspection is of major interest in that respect as thousands of meters of pipelines are surveyed each year using traditional techniques (Surface vessel and Remotely Operated Vehicle) at a huge cost. Developing robust algorithms to detect and track pipelines and cables is the main objective of the AUTOTRACKER project sponsored by the European Union under Framework V.

In order to perform pipeline tracking efficiently, an AUV must

- Detect the pipeline
- Follow it to gather as much useful information as possible on the pipe condition (burial, corrosion, span).
- Do this robustly in variable terrain with possible re-acquisition phases.

This is currently achieved using a combination of sensors mounted on an ROV or a surface vessel. Pipeline inspection can be done using the CODA system [1] but detection is not covered. More traditionally, an ROV follows the pipe using a magnetic tracking system while a multi-beam echo-sounder checks the integrity of the pipeline. Sub-bottom profilers are also used when the pipeline is buried. None of current technologies address the online detection and tracking of pipeline without a trained human operator in the loop. This is what we propose to tackle in this paper.

Considering that a pipe is a very distinctive man-made structure on the (hopefully) unstructured seabed, and considering that a lot of prior information about the pipe (max curvature, max and min diameter) is available, a model based approach has been chosen. The pipe is detected on side-scan sonar images and tracked on multi-beam echo-sounder profiles. In each case, we use the a-priori information available to constrain our model. Part II will present the pipeline detection and tracking on side-scan sonar images while part III will concentrate on tracking in multi-beam echo-sounder tracks.

II. SIDE-SCAN SONAR PIPE DETECTION

Man-made objects such as pipelines produce distinctive shadow regions in Side-Scan Sonar imagery, which can be used for detection and classification purposes [2]. However, while the detection of these shadow regions is in itself, not very difficult, assessing the results to determine whether a pipe is present can prove more problematic. This section outlines a model which determines the probability of 1,2 or 3 pipes being present in an image. This model can be split into 3 components: Segmentation, Line-Fitting and Evaluation.

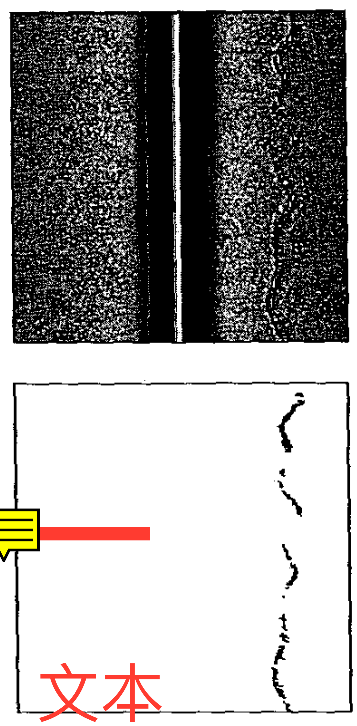


Figure 2.1: Example of detecting the pipe segments

A. Segmentation

Side-Scan Sonar images are generally very noisy making analysis of the raw image very difficult. To overcome this, an unsupervised Markov Random Field (MRF) model was used to segment the image into regions of shadow and non-shadow. The resulting binary image was then split into horizontal sections, which were individually searched through for pipe-like shadow regions using an adaptive non-linear filter. This introduces the idea that a pipe can be described simply as a collection of pipe-segments, a concept which is extended in the Evaluation section. Results for a Side-Scan Image can be seen in Figure 2.1 where each segment has been limited to a maximum of 3 detections.

B. Line Fitting

Although the movement of the sonar fish can induce curves in the pipeline shadow, the model assumes that the pipe can be described as a linear line. To robustly fit 1,2 or 3 lines to the pipe-segments detected in section A, a Least Median Squared algorithm was implemented. Outliers for each fitted line are removed as suggested, after which a Least Squares algorithm is fitted to the remaining inliers. This produces robust results for 1,2 and 3 pipes as shown in Figure 2.2.

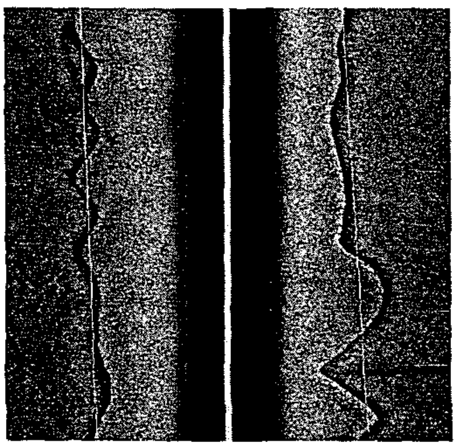


Figure 2.2: Fitting 2 lines to data containing 2 pipes.

C. Evaluation

After 1,2 or 3 lines have been fitted to the data, it is necessary to evaluate the probability of this solution. Bayes theorem provides a suitable mechanism for incorporating prior information into this probability measure such that

$$P(X \mid Y) \propto P(Y \mid X)P(X) \qquad (2.1)$$

where Y is the pipe-segment detection data and X is the model drawn from X={1,2,3} pipes. Probability P(Y|X) is the likelihood while P(X) is used to incorporate any available a priori information.

1) The Likelihood Model

The likelihood model developed is based on the premise that a collection of pipe-segment detections has pipe-like characteristics if the detections are close together and aligned. This is demonstrated in Figure 2.3.

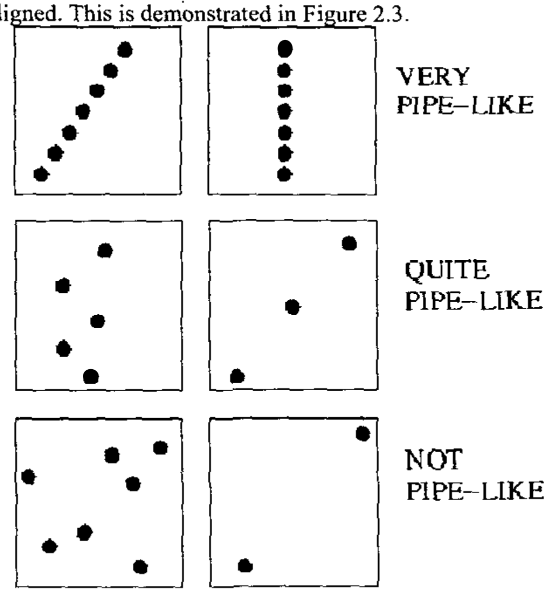


Figure 2.3: Examples to demonstrate how a pipe is made up of closely space and aligned segments.

This leads to the following formulations for P(Y|X), X={1,2,3}.

$$P(y \mid 1) = P_{pipe}(y_1 \mid 1)P_{num}(y_1 \mid 1) \qquad (2.2)$$

$$P(y \mid x) = \frac{1}{x}\sum_{i=1}^{x} P_{pipe}(y_i \mid x)P_{num}(y_i \mid x) \qquad (2.3)$$

where y_i is the pipe-segment detection data associated with each pipe i. Probability $P_{pipe}(y_i|x)$ is described by

$$P_{pipe}(y_i \mid x) = \frac{1}{N_i}\sum_{y_i}\frac{1}{Z}\exp\left(-\frac{3\,|\Delta\theta_i\,|}{\pi} - \frac{3\,|\,d_i\,|}{d_{max}}\right) \qquad (2.4)$$

where Z is a normalizing constant, N_i is the number of data points allocated to pipe i, $|\Delta\theta_i|=|\theta_{i-1}-\theta_i|$. d_{max} is a constant which determines the penalty for adjacent pipe detections being separated by distance d. This is explained in Figure 2.4, which shows 3 adjacent pipe-segment detections in a pipe.

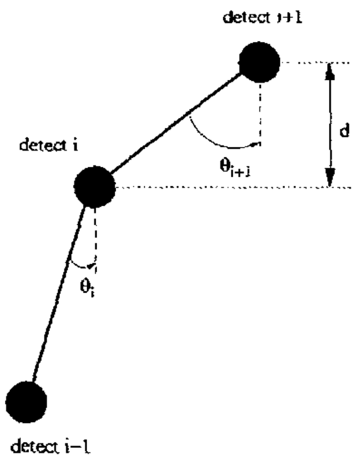


Figure 2.4: Explanation of the likelihood term.

This term assumes that each pipe-segment detection's probability of belonging to the pipe is dependant only on its neighbours, with the overall final probability $P_{pipe}(y_i|x)$ simply being the mean of these individual values.

Probability $P_{num}(y_i|x)$ contributes to the overall likelihood term by considering the number of pipe-segment detections allocated to each pipe. For example, if there were only one pipe present in the image, it would be expected that all the data would be well described by 1 line, with few outliers needing to be removed. The form of this probability function can be seen in Figure 2.5 where N_T is the total number of pipe-segment detections found before outliers have been removed.

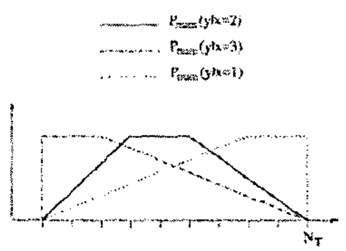


Figure 2.5: The form of the numbers probability function.

The flat-topped nature of the $P_{num}(y_i|x)$ functions allows the adaptive filter to pick up false alarms and is also robust to multiple pipe situations where one pipe has more of the detections than the rest.

2. The Prior P(X)

With navigational information and detailed knowledge of the pipeline field, it is possible to envisage constructing a powerful prior P(X) which could immediately discard certain solutions proposed by the line-fitting algorithm. However, in our situation we use it simply to discard unlikely multiple-pipe solutions where the model attempts to fit multiple lines over the same pipeline. For this $|\Delta m|$ and $|\Delta h|$, the difference in the 2 lines gradient and mean column position are used. The prior probability values can be seen in Table 1.

TABLE 1
PRIOR PROBABILITY VALUES P(X)

Δm Δh	$< t$	$> t$
< 0.5	0.2	1.0
> 0.5	1.0	1.0

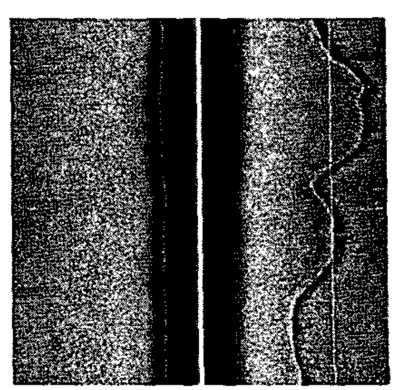
This prior simply models the belief that pipes of roughly the same orientation must be at least a minimum distance (t pixels here) apart. The P(X=3) solution is computed by simply deducing the product of the separate 2 pipe combinations.

D. Results

The model was tested on multiple Side-scan images containing pipes with the results of 3 of these images shown here. The images containing 2 and 3 pipes had to be generated from images containing only 1 pipe due to lack of available data. However, the applicability of the model is still clearly demonstrated.
The images with the best solution overlaid are shown in Figure 2.6. The probability results for 1,2 or 3 pipes being present in each of the images are in Table 2. As can be seen, the model predicted the correct result in all cases.

TABLE 2
PROBABILITY RESULTS FOR THE 3 POSSIBLE SCENARIOS
FOR EACH OF THE 3 IMAGES PRESENTED

OVERALL PROBABILITY	*1 pipe image*	*2 pipe image*	*3 pipe image*
P(1 pipe)	*0.751*	*0.600*	*0.304*
P(2 pipes)	*0.122*	*0.713*	*0.632*
P(3 pipes)	*0.005*	*0.145*	*0.787*



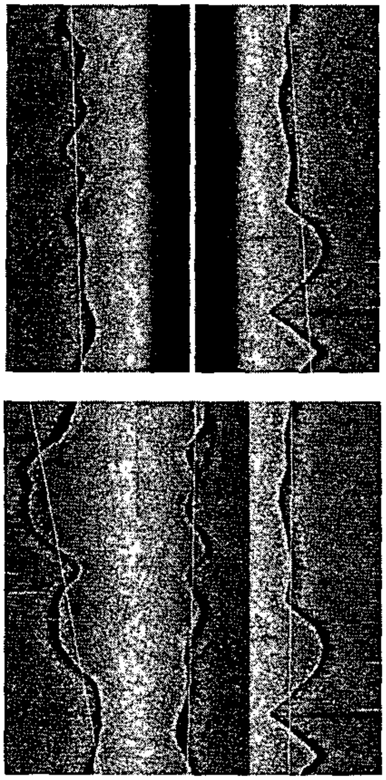


Figure 2.6: Displaying the most likely outcome as predicted by the model for images containing 1,2 and 3 pipes respectively.

III. TRACKING IN MULTI-BEAM ECHO-SOUNDER RETURNS

Once the pipe has been detected in the sonar image, the vehicle can be driven on top of the pipe where multibeam data can be gathered. Typical plots of pipes profiles obtained by a multi-beam echo-sounder are shown in figure 3.1

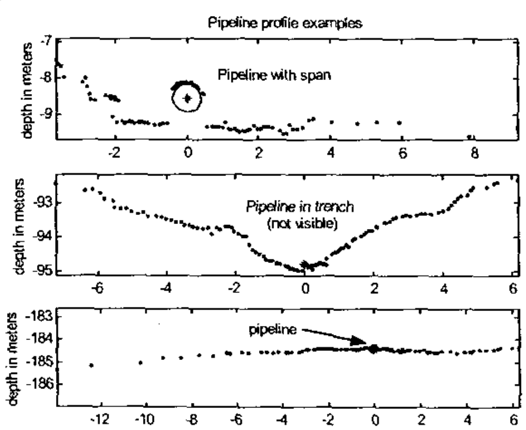


Figure 3.1: example of pipe profiles illustrating a variety of cases.

Due to the large variety of possible scenarios (pipeline *partially exposed, span, pipeline in trench)* it is very difficult to design a filter that will cover all possible cases. However, there is a common denominator to all those scenarios: the pipeline or the trench are circular (or elliptical) profiles of a approximately known size. If we can model this property together with an accuracy of the fit between the model and the observed data, we should have a robust tracking system.

A Problem Modeling

The problem can be stated as an optimization problem. Let first define the parameters Θ of the model that we wish to estimate. We have chosen to model the pipeline profile as a segment of ellipse. Other parameterization are possible and do not change the principle of the algorithm.
The set Θ is composed of:

- Center of the pipeline: $[c_x, c_y]$
- Bottom depth: bo_d
- Burial depth: bu_d
- Major and minor axis of the ellipse: $[a, b]$

Let P(X) be the probability of the model also called prior probability. This will integrate all the prior knowledge available (pipe diameter, type of laying, estimated pipe position). Let Y be the observed data (pipeline profile). We wish to find the set of parameters X (unknown) that optimizes the posterior distribution E(f(X)/Y) where E( ) is the expectation operator and f relates X to the observed data in some meaningful way. Using Bayes theorem, this can be rewritten as:

$$E(f(X)/Y) = \frac{\int f(X)P(Y/X)P(X)dX}{\int P(Y/X)P(X)dX} \qquad (1)$$

B Optimization process

In practice, solving E(f(X),Y) is very difficult and requires the use of numerical techniques. Monte Carlo Markov Chains (MCMC) have been successfully used for efficiently sampling large parameters space to find an optimal estimate of E(f(X)/Y). The solution to equation 1 can be broken into two parts:

- Generate samples using a Markov Chain approach
- Use the samples to approximate the integral using the Monte Carlo integration.

More details on MCMC techniques can be found in [2]. We have used the Metropolis Hastings algorithm to generate the Markov Chain.

C Algorithm

Our algorithm looks for ellipses in the profile using the MCMC technique described above. The profile is first median filtered to remove outliers. The ellipse is then initialized as follows:

Position in x (cx) and y (cy): As previous detection in tracking mode. Center of the profile in detection mode.

Ellipses major and minor axes: Initialized as previous detection in tracking mode. Pipeline has known radius in detection mode. The other parameters (burial depth, bottom) are directly calculated from the data.

Parameter Estimation using Metropolis Hastings algorithm

Each parameter is then altered using a Gaussian random law, moving to a new position in the parameter space. The change is accepted if:

- The new likelihood is better than the older one.
- The ratio between the new and the old likelihood is bigger than a random number generated uniformly in the [0,1] range.

This process is iterated until the so-called "burn-in" period of the Markov Chain has been achieved (here typically 500 iterations) where the Markov Chain has reached its Invariant distribution [2]. Then the mean (Monte Carlo integration phase) of the next 500 iterations is taken has the final estimated model. The likelihood of this model directly relates to the probability of detection of the pipeline in the current profile.

Likelihood model

The likelihood model used is composed of 2 terms:

Model likelihood term integrating all the prior information. This likelihood term can be written as:

$$L(\Theta) = L_1(c_x, c_y) + L_2(a,b) + L_3(bo_d) + L_4(bu_d)$$

In our system, all the parameters are modeled as Gaussian laws around the initial value.

Data likelihood term testing how close the model is to the observed data. This term is simply calculating the SSD (Sum of Squared difference) between the data and the ellipse. Re-sampling of the data is required as the data sampling rate is not constant.

D Results

The system has been tested on large real data files. The data was generated by an ROV driven on top of the pipeline by an ROV pilot. Hence the pipe location is almost always centered on the center of the profile. This has been used to assess our algorithm for both detection and tracking modes. Table 3 and 4 show the result of this evaluation. In tracking mode, a better initialization of the model could be done using a Kalman filter to track the model parameters. This is part of an on-going work.

TABLE 3
MEAN AND STANDARD DEVIATION OF THE ERROR IN POSITION OF THE PIPE ESTIMATE IN METERS ON 100 PIPE PROFILES FOR EACH SCENARIO IN DETECTION MODE. PROBABILITY OF DETECTION IN %.

Pipe type	Half Buried	Trenched	Spanned
Mean Error in meters	0.0258	0.13	0.22
Standard deviation	0.03	0.12	0.36
PD (in %)	99.33	88.23	73

TABLE 4
MEAN AND STANDARD DEVIATION OF THE ERROR IN POSITION OF THE PIPE ESTIMATE IN METERS ON 100 PIPE PROFILES FOR EACH SCENARIO IN TRACKING MODE.

Pipe type	Half Buried	Trenched	Spanned
Mean Error in meters	0.0104	0.16	0.08
Standard deviation	0.0092	0.12	0.14
PD (in %)	100	91.18	96

An example of raw data and reconstructed pipeline can be seen on figure 3.2 and 3.3.

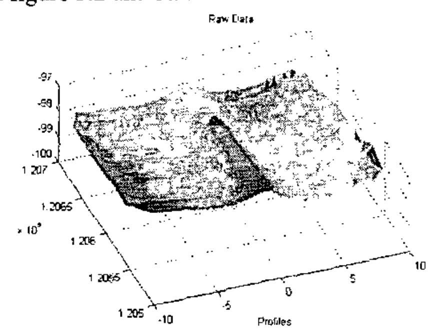


Figure 3.2: Raw data

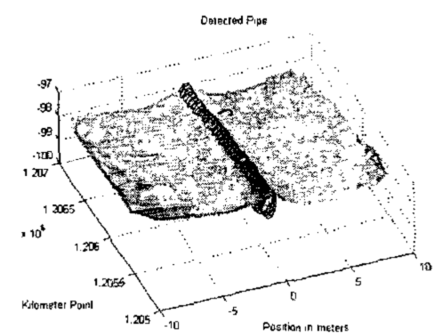


Figure 3.3: Reconstructed pipeline

IV. Conclusion and future work

We have presented two new techniques to perform pipeline detection and tracking using acoustic sensors. These techniques have been evaluated on real data sets and have produced promising results. The system will soon be tested on-board an AUV in real time within the AUTOTRACKER project. Complex scenarios such as pipe crossing and pipe splitting have not been integrated into our models yet but this will be done in the near future.

Acknowledgments

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