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DETECTION AND TRACKING OF PIPES IN SONAR DATA

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Abstract: *This paper outlines a technique used for detecting and tracking pipes in multibeam echo-sounder data. Pipes are detected using a model of their geometry to generate a distribution of their possible positions. A particle filter is used to track the position of the pipe in the scan by observing the detections. This technique can be applied in pipe inspection using AUVs and tracking laid pipes in real-time as other pipes are being laid in the same area.*

Keywords: *Pipe, Detection, Tracking, Sonar, Model, Particle, Filter*

1. INTRODUCTION

The offshore industry regularly inspects thousands of kilometres of underwater pipes. With the advent of Autonomous Underwater Vehicles (AUVs) a new generation of automatic pipe detection and tracking technologies are required in order to automate the pipe inspection process. This paper introduces a novel technique that can be used to aid an AUV inspection task or to aid operators. This technique automatically tracks pipes using multibeam echo sounder data during inspection and pipe laying tasks. The outcome is an automatically produced distribution of the possible pipe positions along a swath, as shown in section 2. Then, an adapted particle filter is used to track the most likely pipe position in the sequence of swaths, as shown in section 3. Results with three different swath sequences, obtained using two different types of sonars, demonstrate the validity of the system, as shown in section 4.

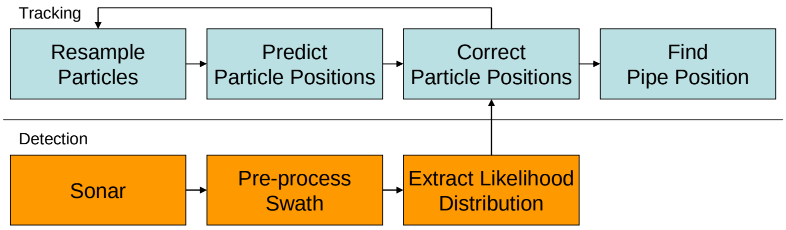

Fig.1: System overview.

2. DETECTION OF PIPES

This paper uses the model in [1] to detect the pipes in a multibeam echo-sounder scan. That model has the following set Θ of parameters:

- Centre of Pipe: $\lfloor C_x, C_y \rfloor$
- Depth of Pipe: D
- Burial Depth of Pipe: B
- Major and Minor axis of Pipe Cross Section: $[M_a, M_i]$

A pipe cross section is created using two consecutive points and the known dimensions of the pipe ($[M_a, M_i]$).The rest of the parameters from the set Θ can be extracted once the cross section of the pipe is drawn on the scan. Circles are created for every two consecutive points in the scan. Thus, the number of circles N_C created for each scan is $N_C = N_p - 1$, where the number of pings per scan is N_p.

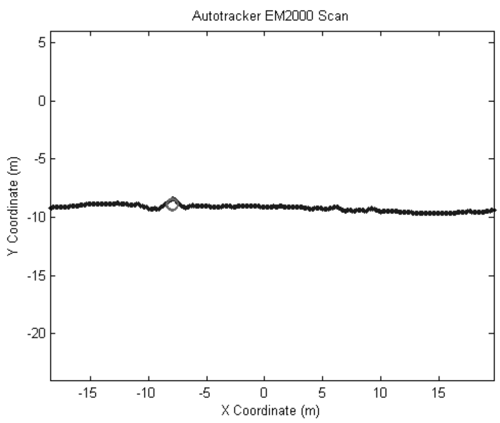

Fig.1: Sample scan with most likely pipe position superimposed.

The system works out a likelihood figure for each possible pipe cross-section created using the model. The likelihood figure is:

$$L(\Theta) = L_1(\Theta) + L_2(\Theta) \tag{1}$$

Where $L_1(\Theta)$ is the likelihood term that tests how close the model is to the observed data. This term is calculated using the sum of squared differences between the data and the ellipse. The second term $L_2(\Theta)$ tests whether the pipe sits proud on the seabed and measures the distance between the centre coordinates of the model and the local seafloor returns. The system has been tuned with a constant weight on $L_2(\Theta)$. Re-sampling of the data is required as the data sampling rate is not constant. Fig. 2 below shows a sample output $L(\Theta)$ obtained by processing the scan shown in Fig. 1.

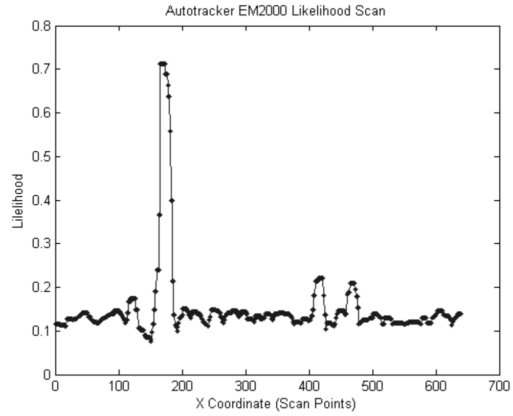

Fig.2: Sample likelihood plot for scan in Fig. 1.

3. TRACKING THE PIPES

The proposed system does not use the common Kalman filter solution [2], but it uses instead an adapted particle filter to track the pipes. The key idea of the particle filter is to represent the posterior density by a set of random samples with associated weights and to compute estimated states using these samples and weights. As the number of samples becomes very large, this Monte-Carlo characterisation becomes an equivalent representation to the usual functional description of the posterior.

Let $\{x_k^i, \omega_k^i\}_{i=1}^N$ denote a set of samples at time k that characterises the posterior $p(x_k \mid z_{1:k})$, where N is the number of random samples x_k^i weighted by ω_k^i. These weights are normalised such that $\sum \omega_k^i = 1$. Then, the probability density function can be approximated as

$$p(x_k \mid z_{1:k}) \approx \sum_{i=1}^{N} \omega_k^i \delta(x_k - x_k^i) \tag{2}$$

Or a discrete weighted approximation to the true posterior whose convergence speed is independent on the dimension of x_k. In this paper the dimension of x_k is simply one. The state represents the across track position in the swath.

3.1. Prediction step:

Particles are sampled from a function $q(\cdot \mid x_{0:k-1}, z_{1:k})$, called “importance density”. This sampling propagates each particle using appropriate transition and observation models. If $q(\cdot \mid x_{0:k-1}, z_{1:k}) = q(\cdot \mid x_{k-1}, z_k)$ then the importance density only depends on the previous particle x_{k-1} and on the current measurement z_k.

$$\forall i = 1, \ldots, N \quad x_k^i \sim q(\cdot \mid x_{k-1}^i, z_k) \tag{3}$$

3.2. Update step:

The filter shown in this paper uses the likelihood scan produced in the previous section to weight the particles. In this step, unlike normal particle filters [3], the weights ω_k^i are assigned to each particle given their position in the scan and their previous weight. Then

$$\omega_k^i \propto \omega_{k-1}^i L_k^i(\Theta) \tag{4}$$

Where $L_k^i(\Theta)$ is the likelihood at time step k for particle i.

3.3. Peak extraction:

When all random samples are generated, the state at time k can be estimated as

$$\hat{x}_k \approx \sum_{i=1}^{N} \omega_k^i x_k^i \tag{5}$$

3.4. The degeneracy problem

A very common problem with the particle filter is the degeneracy phenomenon, where after several iterations all but a few particles have negligible weights. It implies that a large computational effort is devoted to updating particles whose contribution to the approximation of $p(x_k \mid z_{1:k})$ is almost zero. A method by which these effects can be reduced is to resample whenever a significant degeneracy is observed. The basic idea is to eliminate particles which have small weights and to focus on significant particles. The resampling step creates a new set $\{\bar{x}_k^i\}_{i=1}^N$ by resampling N times with replacement so that all the weights are reset to $1/N$.

Nevertheless, applying this resampling step systematically is in fact a loss of information because relevant particles are copied many times while the number of particles N is maintained constant. Thus it is important to keep some “noise” in the system by generating some rate J of new random samples as done in the initialization step. The authors have chosen the well known Sampling Importance Resampling (SIR) strategy [4] to resample the particles at every update of the particle filter.

4. RESULTS

This section provides results for the detection and tracking algorithms working on three different pipe sequences.

4.1. AUTOTRACKER Results

The first data set was obtained during the recent Autotracker trials by Subsea 7's GeoSub AUV. The data was obtained with a Simrad EM2000 multibeam echo-sounder. The Autotracker trials tracked a 0.9 m diameter pipe. The detector matched the actual position of the pipe with the most likely pipe position in over 75% of scans with the accuracy set by the sensor's resolution, an example scan is Fig.1. The tracking algorithm was able to use the outputs from the detector to successfully track the pipe and accurately estimate its position through the whole sequence of scans.

4.2. RESON Sonar Results

The detection was also tested with data obtained using a RESON multibeam echo-sounder. The algorithm was used in two sequences. In the first sequence the data showed a pipe as laid. In the second sequence the data showed a concrete pipe section. The algorithm for the as laid pipe correctly detected the most likely pipe position in over 75% of scans; Fig.3 is an example scan showing a correct detection in the first sequence. The algorithm for the concrete pipe section correctly detected the most likely pipe position over 90% of the time; Fig. 4 is an example scan showing the correct detection in the second sequence. The tracking algorithm was able to use the outputs from the detector to successfully track the pipe and accurately estimate its position through the whole sequence of scans.

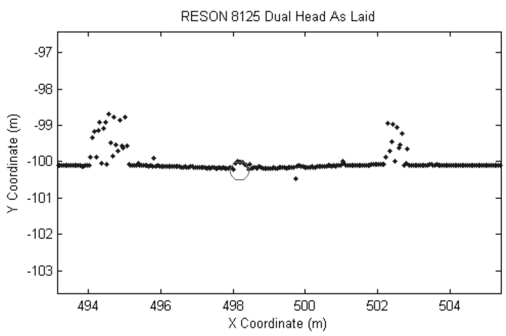

Fig.3: Sample scan with most likely pipe position superimposed (Reson sonar as laid example).

5. CONCLUSIONS

This paper has shown a novel algorithm capable of accurately detecting and tracking proud pipes on the seabed using the data from a multibeam echo sounder. The system has been tested with three different data sets obtained using SIMRAD 2000 and RESON 8125 sonars. The authors plan to extend the tracking filter in order to simultaneously track up to five pipes in a single scan. The PHD filter will be used to fulfil this purpose [5].

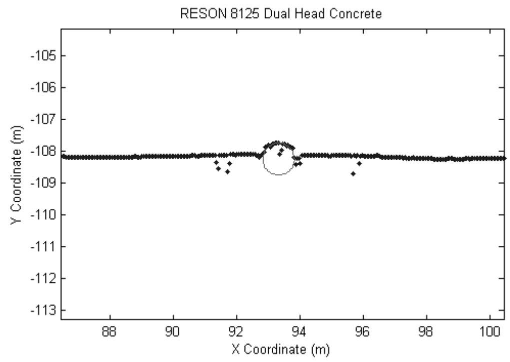

Fig.4: Sample scan with most likely pipe position superimposed (Reson sonar concrete section example).

6. ACKNOLEDGEMENTS

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