Bayesian Multiple Target Tracking in Forward Scan Sonar Images Using the PHD Filter

Daniel Edward Clark and Judith Bell

Ocean Systems Laboratory,

School of Engineering & Physical Sciences,

Heriot-Watt University,

Edinburgh, Scotland. EH14 4AS UK

dec1@hw.ac.uk, j.bell@hw.ac.uk

Abstract

A multiple target tracking algorithm for forward-looking sonar images is presented. The algorithm will track a variable number of targets estimating both the number of targets and their locations. Targets are tracked from range and bearing measurements by estimating the first-order statistical moment of the multitarget probability distribution called the Probability Hypothesis Density (PHD). The recursive estimation of the PHD is much less computationally expensive than estimating the joint multitarget probability distribution. Results are presented showing a variable number of targets being tracked with targets entering and leaving the Field of View. An initial implementation is shown to work on a simulated sonar trajectory and an example is shown working on real data with clutter.

I. Introduction

One of the goals of the sonar research community is to develop Autonomous Underwater Vehicles (AUVs), self-navigating robots which operate underwater. Such vehicles can be equipped with a range of sensors including

Published with kind permission of QinetiQ.

forward-look sonar, sidescan sonar and video to enable them to navigate autonomously and undertake a range of missions, for example mine countermeasures, pipeline inspection or seabed habitat mapping. To enable AUVs to do this successfully, methods for detecting and tracking objects on the seabed are required to aid path planning and navigation as well as using these techniques as an integral part of the mission. The obvious initial application is to enable the vehicle to sense its environment and prevent collision with any object. Although AUVs are typically equipped with inertial navigation systems, they are prone to drifting and errors in the measured vehicle position increase during the mission.

Presented in this paper is a method of tracking a variable number of targets in forward-looking sonar data. The objects of interest to be tracked will either be stationary on the seabed or moving through the water. The stationary objects will be moving with respect to the AUV's frame of reference image plane as it is the vehicle which is moving. Tracking the stationary objects can aid registration of the sequence of images generated by the forward-look sonar which could be useful for concurrent mapping and localisation of the underwater terrain [1], AUV path planning [2] and navigation [3].

The purpose of the application here is image registration for a sequence of forward-looking sonar images. Features in the images will be tracked to align the images as a preliminary step to providing a reconstructed 3D elevation map of the area surveyed by the sonar.

Traditional multi-target tracking is based on coupling trackers such as Kalman filters, extended Kalman filters or particle filters with a data association technique (Bar-Shalom [4] provides a comprehensive treatment). The aim of the data association process is to interpret which measurements are due to the targets and which are due to false alarms. An example of this used on forward-looking sonar data is shown in [5]. Another technique which has been applied to sonar imagery uses Optical Flow calculations to estimate direction motion [6].

Particle filter approaches to multiple target tracking have continued to use data association techniques [7] [8]. This can be partly attributed to well established techniques for tracking and partly due to a lack of efficient techniques for modelling multiple targets with particle filters. Recent developments include a Bayesian multiple-blob tracker [9] and independent partitioning and a representation of the joint multi target density [10].

Schulz et al[11] used a sample-based JPDAF (Joint Probabilistic Data Association Filter) for people tracking with mobile robots using laser range data. This technique is similar to the Kalman Filter technique with JPDAF commonly used except that the Kalman filter for each target is replaced by a particle filter. It works by running a particle filter for each object to be tracked in parallel and using the data association filter to associate the measurements between frames. In contrast, the PHD Filter is a method of propagating a multi-modal measure within a unified framework without associating the measurements and has the ability to estimate the number and position of targets in data with clutter. The data used in this paper is forward scan data which is much is much noisier than laser range data leading to high clutter rates.

The theory for the multiple target tracking approach used in this paper was derived by Mahler [12] from Finite Set Statistics, a reformulation of point process theory, which provided a mathematical framework for multitarget multisensor data fusion. For practical purposes, the use of Finite Set Statistics is unnecessary and can obscure the details although Mahler argues that other methods are just reformulations of this. A recursive Bayesian approach for approximating the first order statistical moment of the joint multitarget probability distribution or Probability Hypothesis Density (PHD) was proposed as an efficient means of tracking a variable number of targets, this was defined as the PHD Filter. Data association techniques are avoided as the identities of the targets are not kept. This is a drawback of the PHD Filter tracker as often continuity of identity is needed.

Particle filter approaches for the PHD-filter have been developed by Sidenbladh [13], for tracking vehicles observed by humans in different terrains, Vo et al [14] presented a 1D position and velocity PHD tracker with clutter on simulated data, Zajic et al [15] gave an implementation of a particle PHD Filter and Tobias [16] used it on passive radar for tracking targets located on an ellipse.

This paper demonstrates an application of the Particle PHD Filter to tracking a variable number of targets in a sequence of sonar images in the presence of clutter. One of the advantages of the PHD Filter is its ability to track objects in heavy clutter, which is often the case in sonar data where there are many spurious measurements due to the noisy data. The measurements are taken in the sonar reference plane so that stationary object in the global or world reference plane will be moving with respect to the underwater vehicle. Whilst many of the object to be tracked will be in the world reference plane, there could also be moving objects which it may be necessary to track such as fish. Thus the ability to track a variable number of targets in the presence of missed detections and spurious measurements is advantageous in this application. The PHD Filter works best when the objects to be tracked are moving independently and so this is a potential disadvantage when tracking a set of stationary targets.

II. Multiple Target Bayesian Filtering

This section describes the method for multiple target tracking which has been implemented for forward-looking sonar data. An explanation of recursive Bayesian estimation is given showing first how this works in the single target case and then how this is extended to a time varying number of targets where the target states are represented by Random Finite Sets. The Probability Hypothesis Density Filter (PHD Filter) is described as the first order moment statistic of the multitarget probability distribution and it is shown how this can be used for recursively estimating the multitarget states. A description of how a particle filtering technique can be extended from a single target case to a time varying number of targets using the PHD filter equations is given for the application of tracking targets in forward-looking sonar images.

A. Recursive Bayesian Estimation

To make inference about a dynamic system, two models are needed: the system model which describes the evolution of state with time i.e. the motion of the underwater vehicle and the measurement model which relates the measurements to the state i.e. the objects on the seabed.

In the case where an estimate is required every time a measurement is received, a recursive filtering approach is taken where these two models correspond to a prediction stage and a data update stage respectively. The prediction stage uses the system model to predict the state probability density function in the next time step and the update stage uses the measurement model to modify this density function using Bayes' Law.

1) Single Target Inference: Let $x_{0..t}$ be the state sequence (x_t is a random vector representing the target state at time t) and $z_{1..t}$ be the sequence of measurements obtained. The tracking problem is governed by two functions:

$$x_t = F_t(x_{t-1}, v_{t-1}) \tag{1}$$

$$z_t = H_t(x_t, n_t) \tag{2}$$

where $v_{1..t}$ is the process noise sequence from the system model and $n_{1..t}$ is the measurement noise sequence. The process noise reflects the unknown target motion and the measurement noise reflects the sensor errors. The process and measurement noises are uncorrelated. Function F_t is a Markov Process on the state of the system and H_t is a function related to observing x_t. In Bayesian terms, the problem is to recursively calculate the belief of state x_t at time t given observations $z_{1..t}$.

The prior distribution $p_{t|t-1}(x_t|z_{1:t-1})$ of the target being in state x_t based on previous observations is:

$$p_{t|t-1}(x_t|z_{1:t-1}) = \int f_{t|t-1}(x_t|x_{t-1}) p_{t-1|t-1}(x_{t-1}|z_{1:t-1}) dx_{t-1}, \tag{3}$$

where $f_{t|t-1}(x_t|x_{t-1})$ represents the motion of the target and $p_{t-1|t-1}(x_{t-1}|z_{1:t-1})$ is the posterior distribution at time $t-1$.

When z_t has been observed, the posterior distribution at time t is obtained by Bayes' Law:

$$p_{t|t}(x_t|z_{1..t}) \propto g_t(z_t|x_t) p_{t|t-1}(x_t|z_{1..t-1}), \tag{4}$$

where $g_t(z_t|x_t)$ is the likelihood of observing z_t given target state x_t.

2) Multiple Target Inference: The multiple target inference model adopted here uses Finite Set Statistics as a means of directly extending the single target Bayesian recursive state estimation to a multiple target scenario. Instead of using a random vector to represent a target state, a random finite set of vectors is used representing a variable number of target states.

The set of objects tracked at time t, Γ_t, is modelled by the Random Finite Set (RFS):

$$\Gamma_t = S_t(X_{t-1}) \cup Y_t, \tag{5}$$

where X_{t-1} is the outcome of random set Γ_{t-1}, $S_t(X_{t-1})$ is the set of targets survived at time t from the previous time step and Y_t is the set of targets that appear spontaneously at time t.

The measurements at time t, Σ_t, are modelled by RFS:

$$\Sigma_t = E_t(X_t) \cup C_t(X_t), \tag{6}$$

where $E_t(X_t)$ are measurements from target states in X_t and $C_t(X_t)$ are the measurements due to clutter.

The Bayesian recursion for the multiple target model is determined from the following prior and posterior calculations:

$$p_{t|t-1}(X_t|Z_{1:t-1}) = \int f_{t|t-1}(X_t|X_{t-1}, Z_{1:t-1}) p_{t-1|t-1}(X_{t-1}|Z_{1:t-1}) \delta X_{t-1} \tag{7}$$

$$p_{t|t}(X_t|Z_{1:t}) \propto g_t(Z_t|X_t) p_{t|t-1}(X_t|Z_{1:t-1}) \tag{8}$$

where Z_t is the outcome of measurement RFS Σ_t at time t and

$p_{t|t-1}(X_t|Z_{1:t-1}), g_t(Z_t|X_t), p_{t|t}(X_t|Z_{1:t})$ represent the multitarget prior, likelihood and posterior respectively. The integral in the equation for the prior is the set integral from Finite Set Statistics.

B. PHD Filter

The Probability Hypothesis Density (PHD) is the first moment of the multiple target posterior distribution. This property represents the expectation, the integral of which in any region of the state space S is the expected number of objects in S. The reason for estimating this property instead of the multiple target posterior distribution (equation (8)) is that it is much less computationally expensive. The time required for calculating joint multi-target likelihoods grows exponentially with the number of targets and is thus not very practical for sequential target estimation as this may need to be undertaken in real time. The model used here only calculates single target likelihoods and so is a great improvement on explicitly calculating joint multi-target likelihoods[17]. The PHD is defined as the density, $D_{t|t}(x_t|Z_{1:t})$, whose integral:

$$\int_S D_{t|t}(x_t|Z_{1:t}) \delta x_t = \int |X_t \cap S| f_{t|t}(X_t|Z_{1:t}) \delta X_t \tag{9}$$

on any region S of the state space is the expected number of targets in S. The estimated object states can be detected as peaks of this distribution.

The derivation for the PHD prediction equation is obtained by considering the multitarget prior distribution (equation (7)), calculating the probability generating functional for this and then subsequently obtaining the PHD. A full derivation of this process is provided by Mahler [12]. The prior PHD is given by:

$$D_{t|t-1}(x_t|Z_{1:t-1}) = b_t(x_t) + \int P_S(x_{t-1}) f_{t|t-1}(x_t|x_{t-1}) D_{t-1|t-1}(x_{t-1}|Z_{1:t-1}) \delta x_{t-1} \tag{10}$$

where b_t is the PHD for spontaneous birth of a new target in the image at time t, P_S is the probability of target survival and $f_{t|t-1}(x_t|x_{t-1})$ is the single target motion distribution.

A similar derivation is repeated for the PHD data update equation by considering the multitarget posterior distribution (equation (8)). The calculation of the posterior PHD is given by:

$$D_{t|t}(x_t|Z_{1:t}) \approx F_t(Z_t|x_t) D_{t|t-1}(x_t|Z_{1:t-1}), \tag{11}$$

$$F_t(Z_t|x_t) = (1 - P_D) + \sum_{z_t^i \in Z_t} \frac{P_D g_t(z_t^i|x_t)}{\lambda_t c_t(z_t) + P_D \langle D_{t|t}, g_t \rangle}, \tag{12}$$

where g is the single target likelihood function and $\langle ., . \rangle$ is the usual integral inner product. λ is the Poisson parameter specifying the expected number of false alarms, c_t is the probability distribution over the state space of clutter points and P_D is the probability of detection.

C. Particle Filter Algorithm

Particle filters were designed for implementing sequential Bayesian estimation by representing probability distributions by random samples or particles rather than in their functional forms. This stochastic simulation is done by sequential Monte Carlo methods. The technique has the advantage over Kalman filtering of having non-linear state estimation and non-Gaussian system and measurement noises. The first particle filter, called the Bootstrap filter, was implemented by Gordon [18] in 1993 and since then there has been a lot of research into particle filtering techniques and a thorough review of Sequential Monte Carlo Methods with applications is given in the compilation of papers [19].

The PHD-Filter is an extension of the single target particle filter with the ability to track multiple targets without data association. A version of the basic particle filter is presented initially before extending this to the PHD-Filter which has been applied in section 3.

1) Single Target Filter: The posterior probability distribution of the target state at time $t-1$ is represented by N particles where each particle has a state vector comprising of 2D position and velocities and each particle represents a hypothesis about the state of the actual target. An estimation of the target location is obtained by taking a mean of these positions. The particles are propagated in time by the system model which estimates their position before the next observation, after which weights are assigned to the particles based on their likelihood. N Particles are then resampled from this set according to their weights, giving the representation of the posterior distribution at time t. As the samples are representing a probability distribution, the weights of the particles sum to 1.

The Field of View (FoV) in the case here is the sector scanned ahead of the sonar and the system model is determined by the motion of the sonar across the seabed. Initially, it is assumed that there is no knowledge of the target location and a uniform prior has been chosen to reflect this.

The procedure for the algorithm is given by the following five steps:

Step 1: Initialisation.

At the start of the procedure, N particles are distributed uniformly across the FoV.

Step 2: Data Update. (cf eqn (4))

Weights are assigned according to the likelihoods for the particles: $\omega^s_{t|t} = g_t(z^i_t|\xi^s_t)$. The particle set is a weighted representation of the posterior.

Step 3: Resampling.

An unweighted particle set is obtained by resampling from the weighted set.

Step 4: Estimation of Target Location.

The location of the target is found by calculating the mean position of the particles.

If there are no more incoming measurements then exit, otherwise proceed.

Step 5: Prediction. (cf eqn (3))

The posterior at time t is represented by N unweighted particles $\{\xi_t^1, ..., \xi_t^N\}$. These are propagated by the motion model for predicting the location at time $t+1$: $f_{t+1|t}(x_{t+1}|\xi_t^s)$, for all $s = 1..N$.

Go to Step 2

This description, based on the original particle filter in Gordon et al [20], was given for simplicity to compare with the multi-target model as when extending to the multiple target model the weight update equation becomes much more complex. Better techniques for the single target case can be implemented based on using the optimal importance function by minimising the variance of the importance weights instead of sampling form the prior and reweighting by the likelihood. The resampling step can also be chosen more carefully by only resampling when necessary to avoid sample impoverishment [19].

2) Multiple Target Filter: The PHD Particle Filter extends the basic particle filter to allow for a variable number of targets. In this case the number of particles is proportional to the number of targets with N per target and the sum of the particle weights here gives the number of targets at time t, σ_t.

New targets are introduced into the model by the birth model which assigns M uniformly distributed particles at the end of the sector for incoming objects into the FoV according to the rate in which the sonar moves across the seabed (the new targets are assumed to come at the end of the sector as this is the new section of seabed surveyed). Again, the particles represent a hypothesis about speed and position of a target although they are not specifically attached to any particular target.

In the target location estimation stage the number of targets is estimated by taking the sum of all particle weights, the nearest integer value is taken to be the number of targets. A Gaussian mixture model is fitted to the data, to determine the target locations.

The procedure is given by the following:

Step 1: Initialisation.

At the start, N unweighted particles are distributed uniformly across the FoV.

Step 2: Data Update. (cf eqn (11))

Let $Z_t = \{z_t^1, ..., z_t^n\}$ be the observations obtained at time step t. For each observation, the likelihoods are computed for the particles, $g_t(z_t^i|\xi_t^s)$, and new weights are assigned:

$$\omega_{t|t}^s = \left[(1 - P_D) + \sum_{z_t^i \in Z_t} \frac{P_D g_t(z_t^i|\xi_t^s)}{\lambda_t c_t(z_t) + P_D \langle \omega_{t|t-1}, g_t \rangle}\right] \omega_{t|t-1}^s, \tag{13}$$

where $\langle ., . \rangle$ is the summation inner product (this is the discrete version of equation (12)). The particle set is a weighted representation of the posterior.

Step 3: Estimation of Target Location.

The locations of the targets are found by fitting a Gaussian mixture model to the particles where the number of components in the mixture is the expected number of targets at time t, $\sigma_t = \sum_s \omega_{t|t}^s$. (The nearest integer to the sum of weights is taken as the estimated number of targets).

If there are no more incoming measurements then exit, otherwise proceed.

Step 4: Resampling.

An unweighted representation of the posterior is the obtained by resampling N particles from the weighted set.

Step 5: Prediction. (cf eqn (10))

The posterior function at time t is represented by unweighted particles $\{\xi_t^1, ..., \xi_t^N\}$. These are propagated by the motion model for predicting the locations in time step $t+1$: $f_{t+1|t}(x_{t+1}|\xi_t^s) \forall s = 1..N$ and assigned weight $\omega_{t+1|t}^s = P_S/N$ according to their probability of survival P_S which is dependent on the position in the FoV. In addition, M particles are distributed at the end of the FoV for the birth model and assigned weight $\omega_{t+1|t}^s = P_B/M$ where P_B is the probability of birth.

Go to Step 2

III. Forward-Looking Sonar Implementation

This section presents the implementation of the algorithm described in the previous section. The algorithm is shown working on a simulated target trajectory where the accuracy of the tracker can be determined. It is then demonstrated using real data to show that this technique is applicable in a real scenario.

The sonar data returns from objects on the seabed have a much higher intensity than the surrounding region of seabed due to a combination of higher reflectivity properties and the geometry of the sonar imaging process which will result in multiple returns at the same time. The measurements for the tracker have been obtained by thresholding the images and finding the centroid of the regions above the threshold. The signal to noise ratio for objects is high so this simple technique is effective for finding the target locations although there is often a large number of spurious measurements. However, as will be demonstrated in section 3.2, the estimated positions converge to the actual target locations despite the false alarms.

The forward-looking sonar can be considered as having k beams, where the angular distance between their central axes is $\delta\theta$ degrees. The data for each of the beams is in the form of acoustic intensity against time. The time values are related to the slant range to the object. If isovelocity conditions are assumed then they can be translated into range measurements. The measurements taken from the sonar are in polar co-ordinates and so the tracker implemented for forward-scan sonar will track range and bearing measurements obtained from thresholded sonar images.

The following state space model is used :

$$\mathbf{x_t} = \begin{pmatrix} 1 & 1 & 0 & 0 \\ 0 & 1 & 0 & 0 \\ 0 & 0 & 1 & 1 \\ 0 & 0 & 0 & 1 \end{pmatrix} \mathbf{x_{t-1}} + \begin{pmatrix} 0.5 & 0 \\ 1 & 0 \\ 0 & 0.5 \\ 0 & 1 \end{pmatrix} \mathbf{v_{t-1}}, \tag{14}$$

$$\mathbf{o_t} = \begin{pmatrix} \arctan\left(y_t/x_t\right) \\ \sqrt{(x_t)^2 + (y_t)^2} \end{pmatrix} + \mathbf{n_t}. \tag{15}$$

$\mathbf{v_t}$ and $\mathbf{n_t}$ are the process and measurement noises respectively, which are uncorrelated.

The state vector is defined as the 2D position and velocity vector of the target, relative to a fixed external reference frame:

$$\mathbf{x_t} = \begin{pmatrix} x_t \\ \dot{x}_t \\ y_t \\ \dot{y}_t \end{pmatrix}. \tag{16}$$

The observation at time t ($\mathbf{o_t}$) is the bearing angle and range from the fixed observer towards the target.

Although more complex noise models can be used, Gaussian observation and state noise distributions have been used for initial investigation with the filter. (The model was taken from Gordon et al. [20])

The motion of the sonar is assumed to be linear for the particle filter and so the objects are moving towards the sonar. The FoV is a sector of 10 degrees with range 20m to 60m. Due to the linear motion of the sonar and the FoV, new objects are most likely to appear at the end of the sector and disappear at the beginning with the objects moving towards the sonar and so the probabilities of birth P_B and survival P_S have been defined to reflect this. The birth model will allow for new targets entering the FoV by distributing particles uniformly at the end of the sector.

A. Tracker on Simulated Data

To demonstrate the efficacy of the technique the tracker is firstly tested on simulated data. The advantage of using simulated data is that it allows various different realistic scenarios and trajectories to be created easily. The exact locations of the vehicle and objects are known and thus the accuracy of the tracker can be determined.

A sequence of forward-looking sonar images is simulated using the Sonar Simulator developed by Bell [21] which has the capability of modelling sonar in complex underwater terrain. The artificial seabed is modelled by a $100 \times 100m^2$ textured image. Spherical shaped objects of radius $0.5m$ have been placed on the seabed.

Figure 1 shows the sequence of simulated sonar images from the above scenario, where the highlights are created by the objects. The sonar has followed an approximately linear trajectory with a small amount of deviation from this. For ease of display, the images are shown on a rectangular grid although the data is in polar form. Blank lines separate the images in the sequence.

The results of the tracking for the simulated sonar run have been displayed in the sonar image reference frame and the global reference frame. In the sonar image reference frame the objects are moving towards the sonar, figure 2 shows the measurements and estimated positions with respect to the sonar. In the global reference frame, figure 3, the sonar positions are marked on a global co-ordinate map and the objects are stationary. The actual positions are shown along with the measurements and estimated positions. The tracker estimates well the number of targets in each image which is between 1 and 4 targets. There are a few outliers where the position has wrongly estimated a target location, this can often happen in the initialisation stage where the particles have been uniformly spread and the distribution of particles are not sufficiently localised onto the target.

Obtaining accurate navigation information can be a significant problem during AUV missions. However, this technique is still robust when no navigation information is present. The same scenario as above has been repeated but the sequence of sonar images have been simulated with the AUV following a sinusoidal trajectory. The tracking was then repeated with the system having no knowledge of the actual motion, and the results in the global reference frame have been displayed in figure 4. The measurements taken were not as accurate as the linear path (figure 3) but the tracker seems to perform well tracking the measurements with only a few false estimates.

B. Tracker on Real Data

The tracker was then applied to a sequence of real forward-look sonar images. The data was obtained from a forward-looking sonar device fitted to an underwater vehicle where the sonar scans a sector of seabed in the direction of the vehicle motion. The sequence of 18 images (figure 5) was obtained as the vehicle was flown towards a cylindrical object lying on the seabed. The images are very noisy but the object can be seen in the sequence as the small bright highlight moving from top right to bottom left in the sequence. The seabed over which the sonar traverses appears to be composed of two different sediment types, one of which provided higher intensity returns. This can be seen in the region before the target in the first 10 images of the sequence.

The results of the tracking is illustrated in figure 6. The measurements and tracked positions are in the sonar reference frame, the global positions are unknown since no navigation information was provided with the data and no accurate ground truth of the object's location was available. The location of the cylinder is given by the sequence of points from the lower right hand region of figure 6, moving towards the centre of the figure, as the vehicle moves closer to the object. In the first few images, there were a lot of false targets, or clutter points, due to bad observations of the cylinder as a result of high intensity returns from a region of seabed. These are the group of measurements in the top half of figure 6.

To show how well the implementation works with clutter, the tracker has been run on the data forward in time (where there are a lot of clutter points initially and fewer in the later images) and backward in time (where there are few clutter points initially and more in the later images). This demonstration is to show how the initial conditions affect the performance of the algorithm and the convergence as the clutter density at the start is different in this sequence of images when run backward and forward. Running the algorithm in the forward direction results in poor estimation initially but afterwards converges onto the correct target location (see figure 6). When the algorithm is run on the data backwards, the algorithm quickly converges onto the correct target and manages to predict the correct location through the clutter (see figure 7).

These results show that there is a sequence of images where there are few false alarms and then encounter a cluttered region then the algorithm can predict the correct target but it works poorer if the cluttered region is at the start. This can be expected as the distribution of the particles is propagated from one frame to the next and so if the particles are predominantly located in the region of the true target they are more likely to track it well.

IV. Discussion

An application of the particle PHD filter has been implemented for tracking a variable number of objects in a sequence of forward-looking sonar images for the purpose of aligning data from a sequence of images to aid fusing the data onto a global co-ordinate system where it will be reconstructed into a 3D map of the seabed.

The tracker was shown working on simulated data where the results could be displayed on a global map and then on real sonar data with clutter for tracking a cylindrical object on the seabed. The simulated data provided a test case scenario where accurate ground truth was available, but the simulated sonar images contain significantly less noise and clutter than real data.

The current implementation tracks the objects in 2-dimensions, although it is currently being extended to 3D forward looking sonar data.

This technique also has the capacity to incorporate measurements obtained from other sensing equipment such as video data although the implementation here is restricted to sonar.

The identities of the objects are not determined in this implementation and so data association techniques are not used. In many applications, knowledge of which target in the current frame relates to which target in the previous frame is important and so the data association problem would need to be addressed. One of the advantages of the PHD Filter is its ability to filter clutter and so the number of spurious measurements is reduced. Sonar data is very noisy which gives rise to many spurious measurements and the PHD Filter copes well with this. If the identities of the targets are needed then the data association problem is reduced although this needs to be addressed.

Future work will include addressing the data association issue for continuity of target identity and a comparison of the PHD filter with the sample based JPDAF technique in cluttered data.

V. Acknowledgements

This work has been funded by QinetiQ through an MoD funded programme. The authors wish to express their thanks to Dr. Douglas Carmichael and Dr. Samantha Dugelay from QinetiQ Bincleaves for their support and for provision of sonar data. The authors would also like to thank Yvan Petillot and Yves de Saint-Pern in the Oceans Lab at Heriot-Watt University for their help and useful comments.

References

[1] S. Reed, I. Tena Ruiz, Y. Petillot, D. M. Lane, and J. M. Bell. Concurrent mapping and localisation using side-scan sonar for autonomous navigation. *Oceanic Engineering, IEEE Journal of*, 29, Issue 2:442–456, 2004.

[2] Y. Petillot, I. Tena Ruiz, D. M. Lane, Y. Wang, E. Trucco, and N. Pican. Underwater vehicle path planning using a multi-beam forward looking sonar. *IEEE/OES OCEANS'98 conference*, 1998.

[3] I. Tena Ruiz, Y. Petillot, and D. M. Lane. AUV navigation using a forward looking sonar. *Unmanned Underwater Vehicle Symposium. Rhode Island, USA.*, 2000.

[4] Y. Bar-Shalom and T.E. Fortmann. *Tracking and Data Association*. Academic Press, 1988.

[5] E. Trucco, Y. Petillot, I. Tena Ruiz, C. Plakas, and D. M. Lane. Feature tracking in video and sonar subsea sequences with applications. *Computer Vision and Image Understanding, No.79*, pages 92–122.

[6] I. Tena Ruiz, D. M. Lane, and M. J. Chantler. A comparison of inter-frame feature measures for robust object classification in sector scan sonar image sequences. *IEEE Journal of Oceanic Engineering*, 24, No.4:458–469, 1999.

[7] C. Hue, J.P. Le Cadre, and P. Perez. Tracking multiple objects with particle filtering. *IEEE Trans. on Aerospace and Electronic Systems*, 38(3):791–812, 2002.

[8] R. Karlsson and F. Gustafsson. Monte Carlo data association for multiple target tracking. *Target Tracking: Algorithms and Applications (Ref. No. 2001/174), IEE*, 1:13/1– 13/5, 2001.

[9] M. Isard and J. MacCormick. Bramble: a Bayesian multiple-blob tracker. *Computer Vision, 2001. ICCV 2001. Proceedings. Eighth IEEE International Conference on*, 2:34 – 41, 2001.

[10] C. Kreucher, K. Kastella, and A.O. Hero. A Bayesian method for integrated multitarget tracking and sensor management. *Information Fusion, 2003. Proceedings of the Sixth International Conference of ,Volume: 1 , July 8-11 2003*, pages 704 – 711.

[11] People tracking with a mobile robot using sample-based Joint Probabilistic Data Association Filters. *International Journal of Robotics Research*, pages 99–116, 2003.

[12] R. Mahler. Multitarget Bayes filtering via first-order multitarget moments. *IEEE Transactions on Aerospace and Electronic Systems*, 2003.

[13] H. Sidenbladh. Multi-target particle filtering for the Probability Hypothesis Density. *International Conference on Information Fusion*, pages 800–806, 2003.

[14] B.N. Vo, S. Singh, and A. Doucet. Sequential Monte Carlo Implementation of the PHD filter for Multi-target Tracking. *Proc. FUSION 2003*, pages 792–799, 2003.

[15] T. Zajic and R. Mahler. A particle-systems implementation of the PHD multitarget tracking filter. *SPIE Vol. 5096 Signal Processing, Sensor Fusion and Target Recognition*, pages 291–299, 2003.

[16] M. Tobias and A.D. Lanterman. A Probability Hypothesis Density-based multitarget tracker using multiple bistatic range and velocity measurements. *System Theory, 2004. Proceedings of the Thirty-Sixth Southeastern Symposium on , March 14-16, 2004*, pages 205 – 209.

[17] D.L. Hall and J. Llinas, editors. *Handbook of Multisensor Data Fusion*, chapter 7. CRC Press, 2001.

[18] N.J. Gordon, D.J. Salmond, and A.F.M. Smith. Novel approach to nonlinear/non-Gaussian Bayesian state estimation. *IEE Proceedings on Radar and Signal Processing*, 140:107–113, 1993.

[19] A. Doucet, N. de Freitas, and N. Gordon. Sequential Monte Carlo Methods in Practice. 2001.

[20] N. Gordon, D. Salmond, and C. Ewing. Bayesian State Estimation for Tracking and Guidance using the Bootstrap Filter. *Journal of Guidance, Control and Dynamics*, 1995.

[21] J.M. Bell. *A model for the Simulation of Side Scan Sonar*. PhD thesis, Heriot-Watt University, 1995.

List of Figures

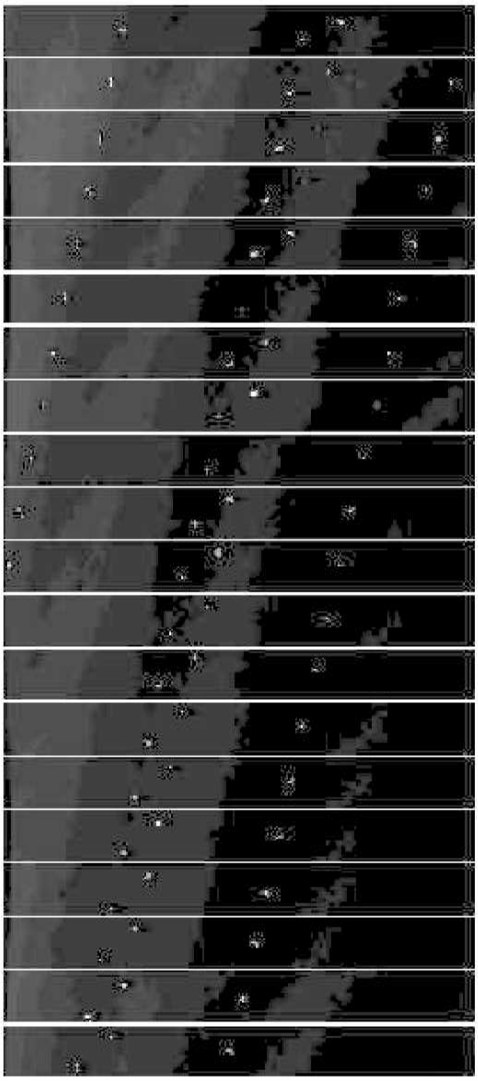

Fig. 1. Sequence of Simulated Forward Scan Sonar Images with Objects

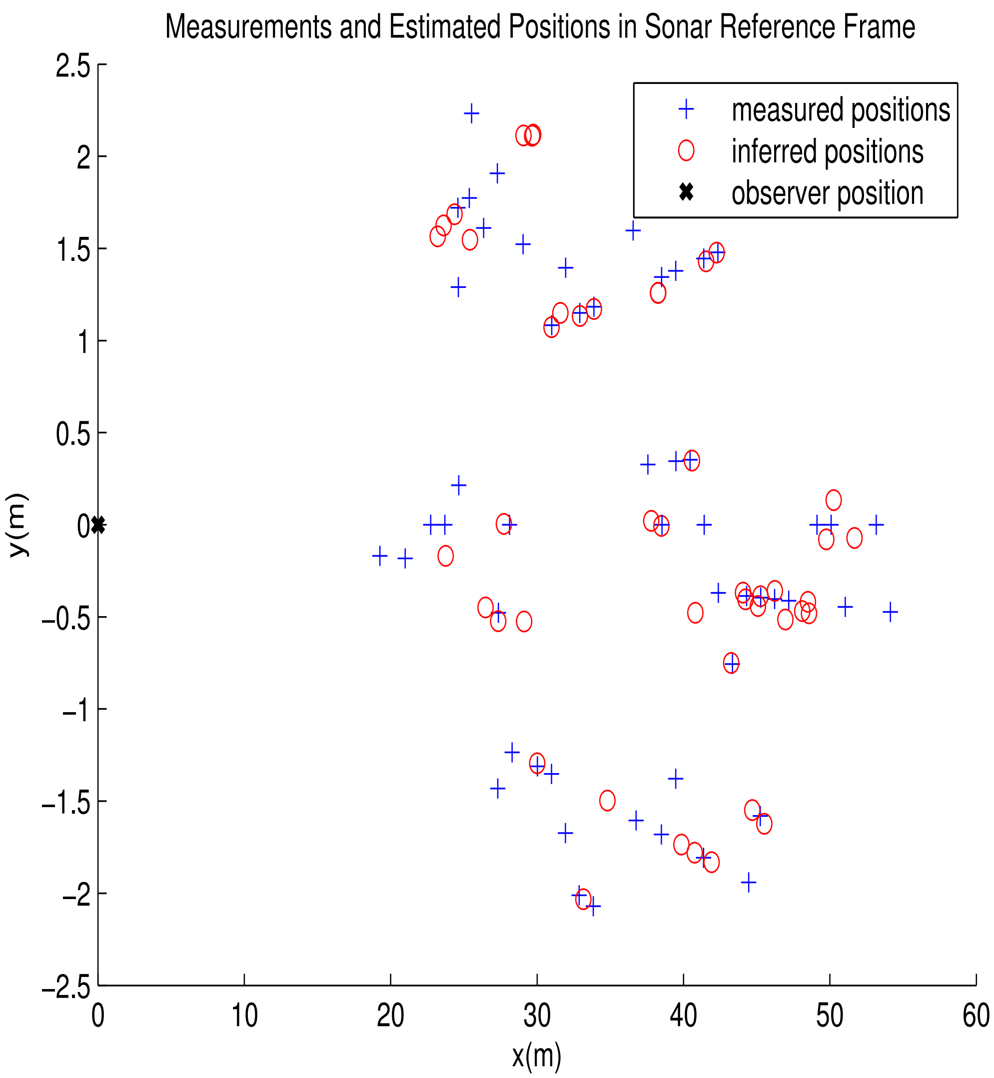

Fig. 2. Linear Tracking in Sonar Image Reference Frame

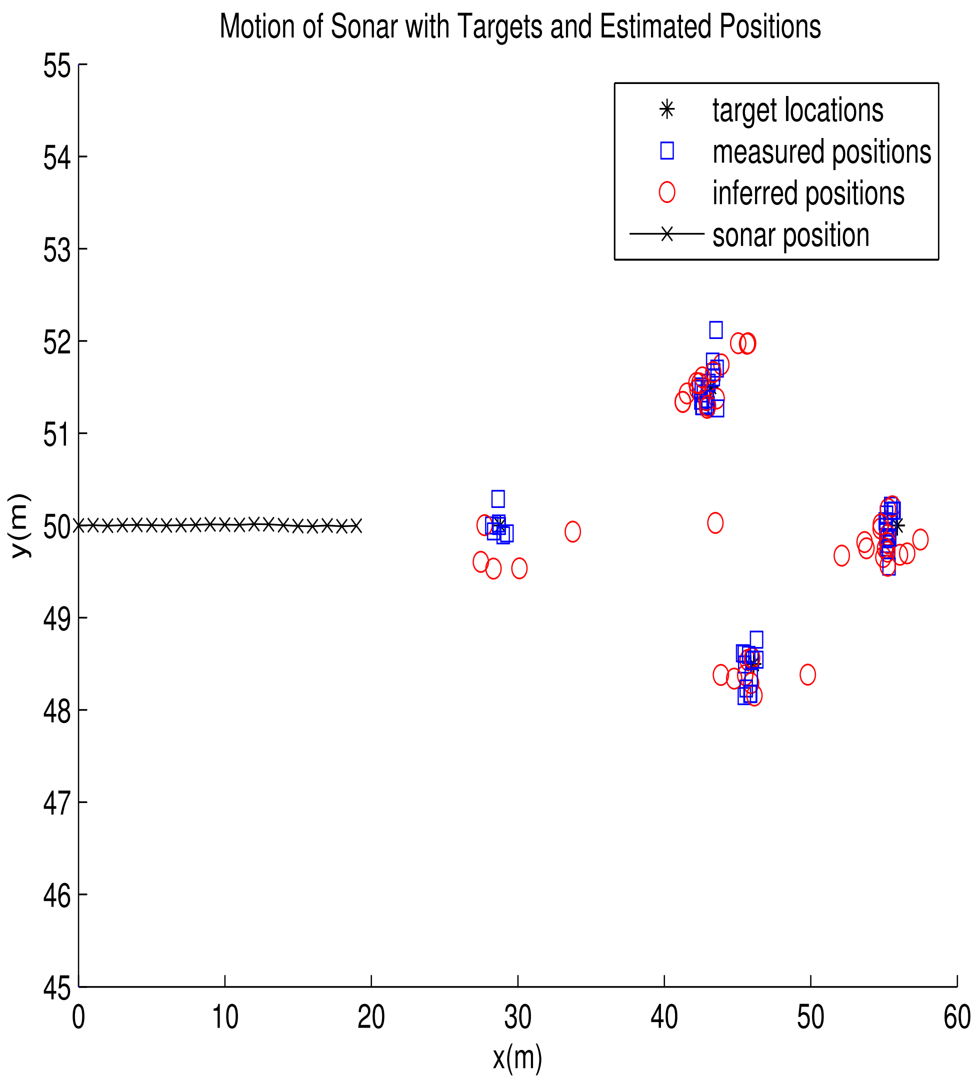

Fig. 3. Linear Tracking in Global Reference Frame

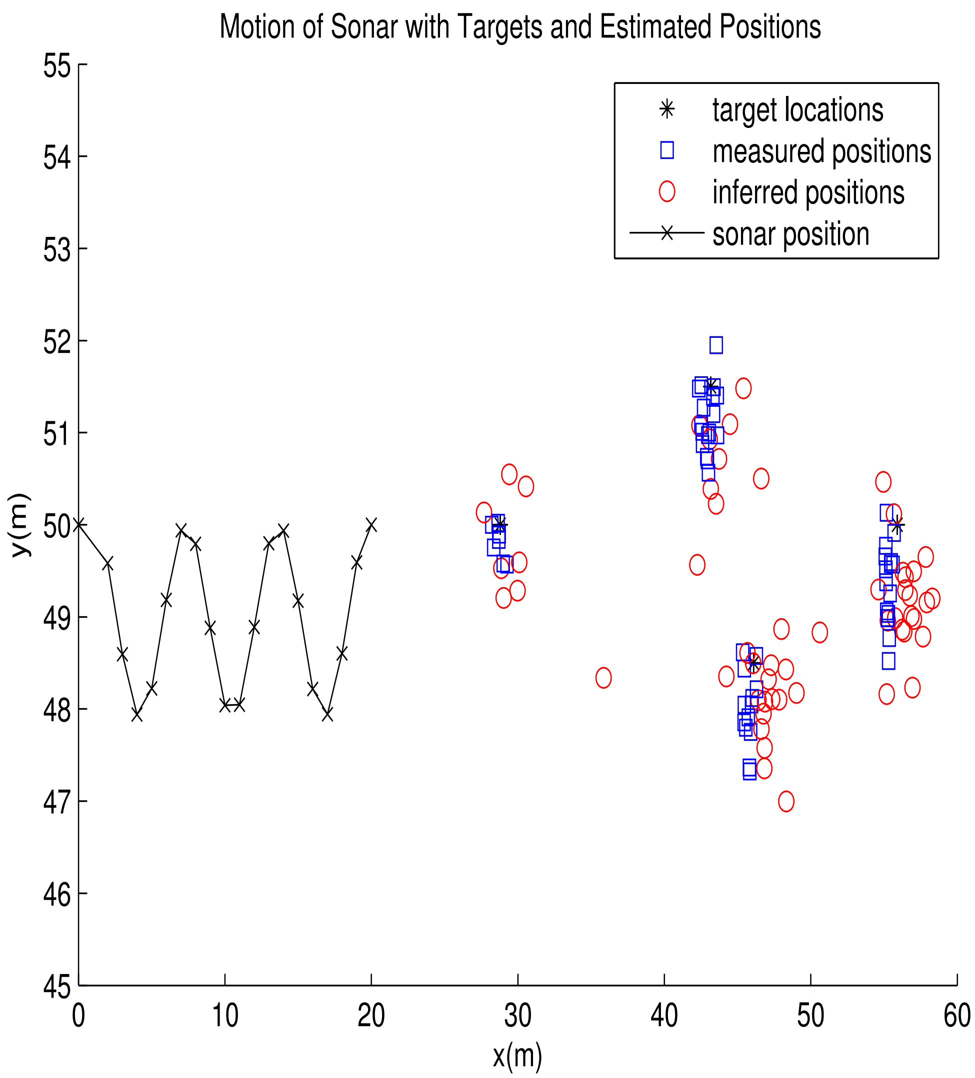

Fig. 4. Sinusoidal Sonar Tracking in Global Reference Frame

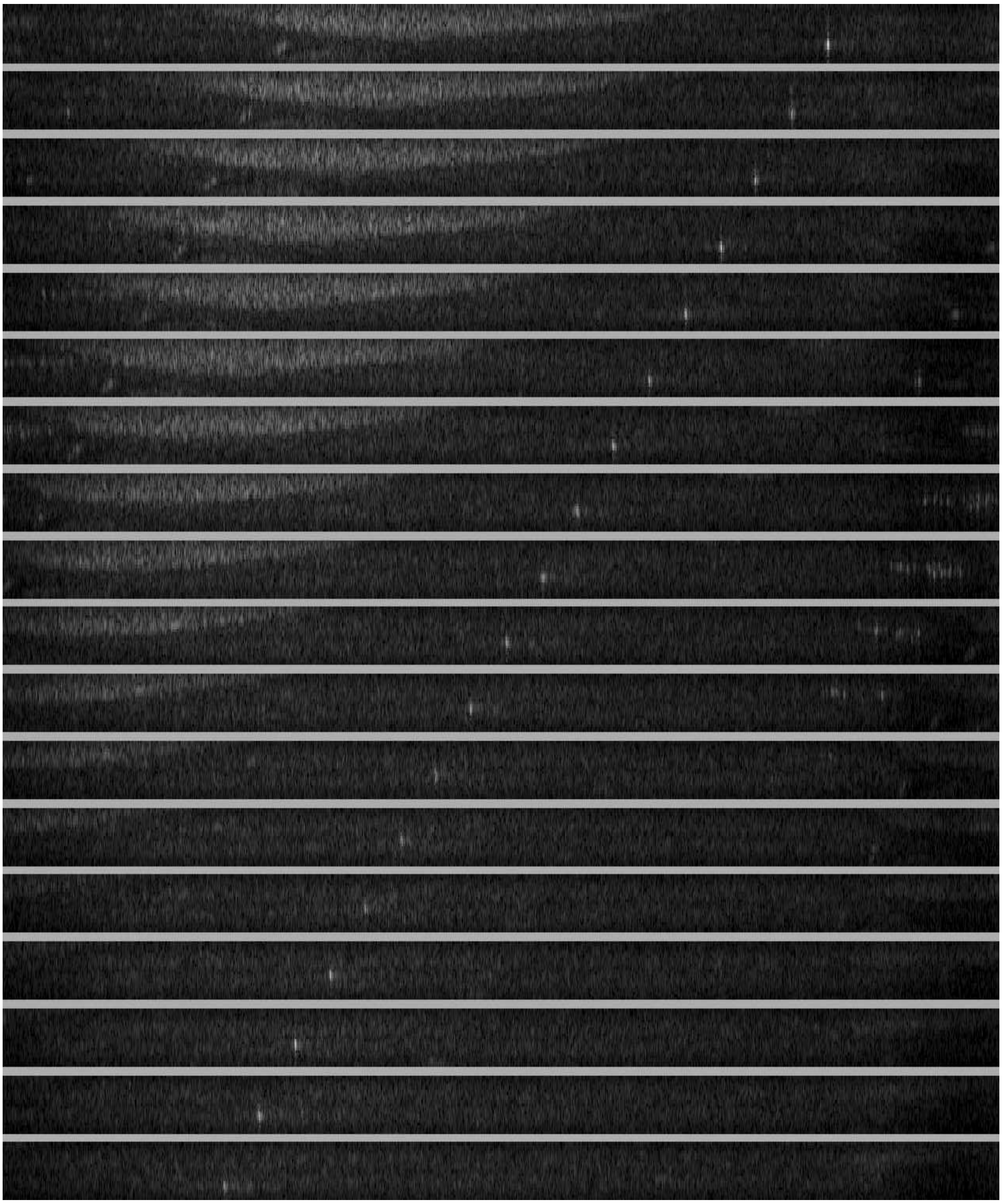

Fig. 5. Sequence of Real Forward-Scan Images

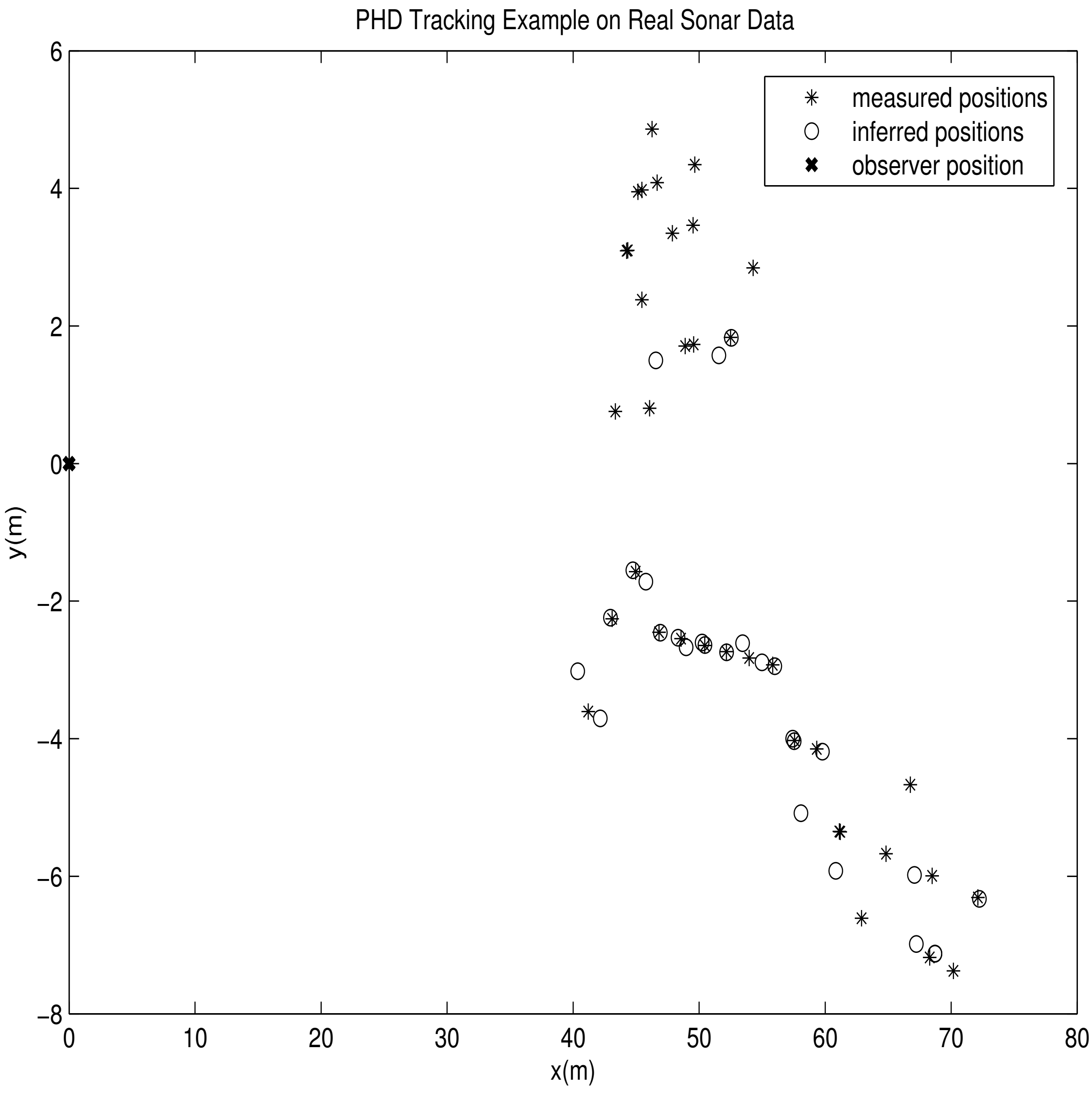

Fig. 6. Tracked Cylinder in Forward Direction

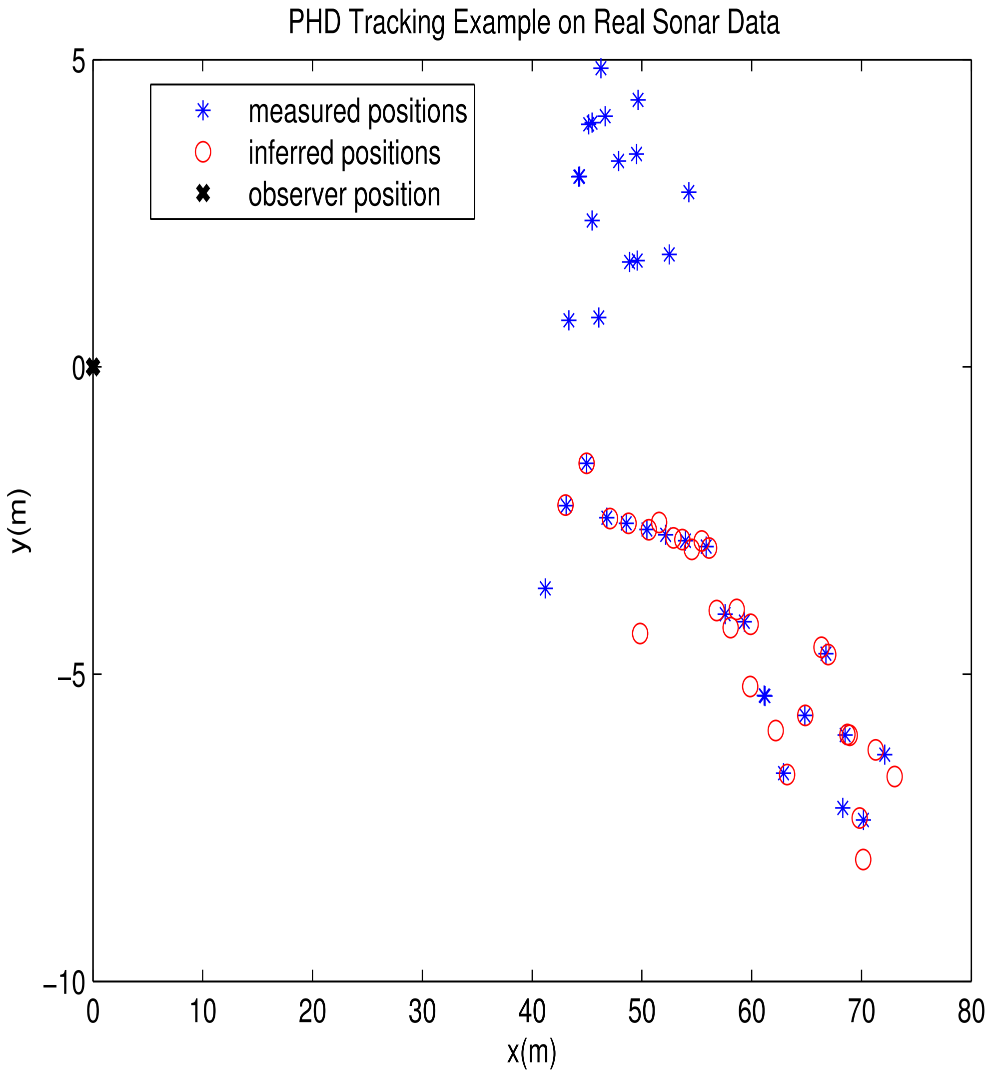

Fig. 7. Tracked Cylinder in Backward Direction