SPACE-TIME INTEGRATION APPROACH TO TRACKING WEAK TARGETS USING SPATIALLY DISTRIBUTED SENSORS

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ABSTRACT

This paper investigates the performance and robustness of the space-time integration technique by applying it to two different scenarios; a target moving in a straight line through a sonobuoy field; and a target undertaking a major course change. Although most techniques will track a target moving in a straight line quite successfully many have difficulty tracking the target as it manoeuvres through a slow turn. The performance of this approach is compared with the more traditional extended Kalman Filter algorithm where the advantages and dis-advantages of each technique is highlighted. Results are presented for scenarios using both simulated and sea trial data.

1. INTRODUCTION

Acoustic target tracking algorithms based on grid-search techniques offer the potential for robust tracking performance when compared to standard recursive tracking techniques. The latter can suffer from instabilities due to the inherent non-linearity of the tracking problem. Furthermore, target environmental constraint information can be more easily and naturally incorporated in grid-search techniques than in recursive techniques. With the advent of very fast processors to deal with the computational load inherent in grid search techniques, they have become a viable alternative for practical sonobuoy target tracking applications.

Localising a potential target quickly and accurately is particularly important for airborne sonar applications, since one of the main roles of an aircraft is to track a target in a rapidly evolving tactical scenario. Historically the localisation of an underwater target has been performed manually using closest point of approach (CPA) events. The focus of the present work is to develop robust techniques to automate the process of localising and tracking weak (low signal to noise ratio) targets transiting through a field of spatially distributed sonobuoys.

The current work is an extension of the space-time integration technique initially proposed by Fawcett and Maranda (see [1] and [2]) which used line arrays of sensors. This approach is extended to deal with the problem of spatially distributed sonobuoy fields, for which the technique is well suited. Conventional recursive tracking techniques require the operator to first detect the presence of a target using traditional sonar displays. Once detected, the position and velocity of the target is estimated from the bearing information. These estimated parameters provide the necessary inputs to the tracking algorithm. By contrast, the space-time integration approach follows a track before detect philosophy. With this approach all possible target tracks are compared with the measured data. The track that provides the best correlation with the data is assumed to be the correct target track. The major advantage of this technique, particularly for weak targets, is that the instantaneous frequency and/or bearing of the target is not estimated. In low signal to noise ratio conditions the frequency and bearing estimation procedure can introduce large errors into the tracking process.

2. SPACE TIME INTEGRATION ALGORITHM

The Space Time Integration (STI) algorithm uses a track before detect philosophy. In this approach information about low level targets can be built up without having to run a signal follower. The processing stream used in the STI algorithm is outlined in Figure 1. The acoustic data is first segmented into batches each of a constant duration. Each batch is input into the estimator at the batch update rate. The rationale behind this approach is that a dynamic model of the target is needed to handle the time varying data, the simplest model being one of constant velocity. By making the batch time sufficiently short the need for a time varying dynamic model is therefore not too restrictive.

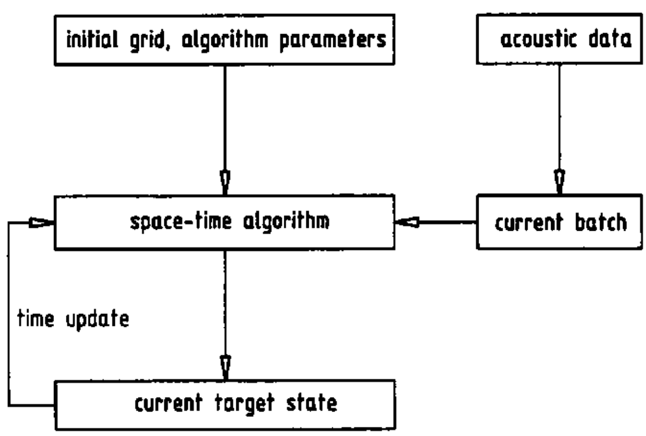

Figure 1 *Processing flow for the STI algorithm*

The operator selects the initial choice of parameters for the track such as grid centres and sizes and batch length. The data is divided into segments of constant time which are the inputs to the tracking algorithm. The algorithm determines the best estimate of the target position and

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velocity which matches the input data. The algorithm acts essentially as a batch estimator initialised at the predicted position. It generates an estimate of the current target position and velocity at the end of each batch time. This estimate is then propagated to the next update time using the estimate of the target velocity.

The STI algorithm accepts power spectra containing a narrowband signal as its input data. The algorithm is modified from the original approach used in [1] to make use of sonobuoy information. The current implementation of the STI algorithm uses the Doppler shift information from a narrowband tonal.

The STI algorithm requires a grid of candidate target positions at the start of the batch of data and a grid of candidate target positions at the end of the batch. The grids may overlap and must be large enough to allow for target motion during the batch time. This is schematically shown in Figure 2. Each pair of points, r_0 in the initial grid and r_1 in the final grid defines a candidate constant velocity track which is given by,

$$v = \frac{r_1 - r_0}{\tau}$$
$$r(t) = r_0 + vt$$

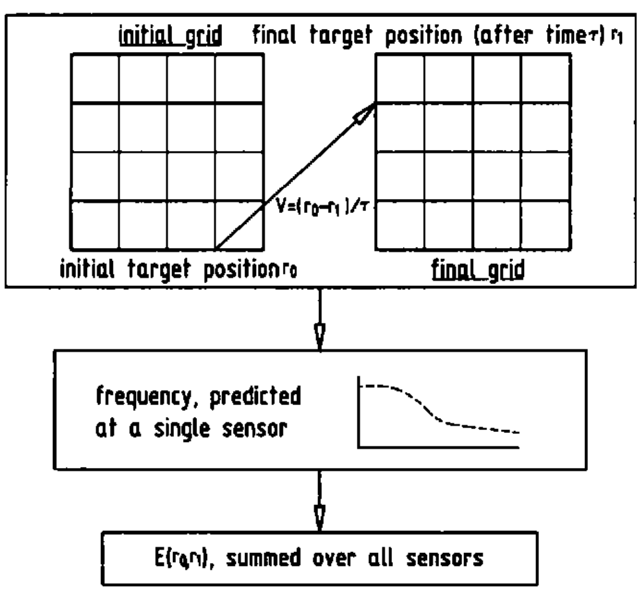

Figure 2 Schematic diagram of STI algorithm

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where τ is the batch duration and t the current time. At each new record the Doppler shifted frequency observed at sensor i is calculated from the rest frequency f_r, the assumed target state and the sensor position R_i and is given by

$$f(t) = f_r\left[1+\frac{v}{c}\frac{r_o + vt - R_i}{\left|r_o + vt - R_i\right|}\right]^{-1}$$

This is based on the assumption of a constant velocity profile with sound speed c and direct path propagation. The energy associated with a choice of r_0 and r_1 is obtained by summing over all sensors, the power $p(b)$ in each calculated bin $b = f/_{df}$, where df is the bin width. This energy is given by

$$E(r_o,r_1) = \sum_{sensors\, i}\sum_{time\, t} p\left(\frac{f(t)}{df}\right)$$

The STI algorithm selects the values of r_0 and r_1 which maximise this energy function.

3. EXTENDED KALMAN FILTER ALGORITHM

When linear Kalman Filter [4] equations for local calculations are taken over to the non-linear problem by linearisation, the result is the Extended Kalman Filter (EKF) algorithm [5]. The only theoretical justification for the procedure is the assertion of a sufficiently small and unspecified amount of non-linearity in the problem which follows from numerical simulation. When applied to non-linear problems, the EKF algorithms cannot be expected to be completely reliable or robust due to this property. However, this can be improved by seeking suitable non-linear transformations of the parameters to be estimated.

The EKF algorithm implemented in this paper uses the bearing information obtained from the sensor data to estimate x, y and their velocities. The model underlying the EKF algorithm is that of a target moving at a constant velocity. The measurements are assumed to be the true values compounded with a random error drawn from a multi-variate Normal distribution, thus the solution is an estimate of the mean and covariance of this distribution. These covariances give an indication of the likely error in an estimated position or motion variable. The EKF tracking solution at time t_n is an estimate of the state vector

$$S_n = \begin{bmatrix}\dot{x}\\ \dot{y}\\ x\\ y\end{bmatrix}$$

The state vector at time t_{n+1} is predicted, in the absence of observations to be

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$$S'_{n+1} = S_n + vdt \ , \quad dt = t_{n+1} + t_n \ , \quad v = \begin{bmatrix} 0 \\ 0 \\ \dot{x} \\ \dot{y} \end{bmatrix}$$

If an observation S^o_{n+1} of the state vector existed at time t_{n+1}, then the updated state vector would be

$$S_{n+1} = S'_{n+1} + g_{n+1}(S^o{}_{n+1} - S'_{n+1}) \ , \ g_{n+1} \in [0,1]$$

where g_{n+1} is the gain of the filter. Generally, measurement errors are unknown so it is necessary to use a probabilistic model of the observations. The prediction for the model is given by

$$\hat{S}'_{n+1} = U(t_{n+1}, t_n)\hat{S}_n + W(t_{n+1}, t_n) \qquad (1)$$

$$P'(t_{n+1}) = U(t_{n+1}, t_n)P(t_n)U^+(t_{n+1}, t_n) + Q(t_{n+1}, t_n)$$

where $W(t_{n+1}, t_n)$ is the white gaussian sequence and $Q(t_{n+1}, t_n)$ is a noise term.

The correction model with bearing only observations expected is

$$\hat{S}_{n+1} = \hat{S}'_{n+1} + G_{n+1}(b^o - b)$$

where b^o is the observed value at t_{n+1} and b' is the value that would be predicted from the expected state vector S'_{n+1} projected ahead of time using equation (1).

The updated covariance matrix P_{n+1} is

$$P_{n+1} = P'_{n+1} - G_{n+1}G^+{}_{n+1}(mP'_{n+1}m^+ + \mathrm{var}(b^o))$$

and using the gain

$$G_{n+1} = \frac{P'_{n+1}m^+}{mP'_{n+1}m^+ + \mathrm{var}(b^o)}$$

$$\text{and } m = \left(\frac{\partial b}{\partial v_x}, \frac{\partial b}{\partial v_y}, \frac{\partial b}{\partial x}, \frac{\partial b}{\partial y}\right)$$

An example of how well the EKF can track a target is given in Figure 3. In this scenario the target is moving at constant velocity in a straight line across the sonobuoy which provides variation in the bearing information available to the tracker. The EKF algorithm provides a very good estimate of the target position and velocity in this case. However, when the target exhibits behaviour which varies from the ideal the performance of the EKF algorithm starts to degrade. This is illustrated in the next section.

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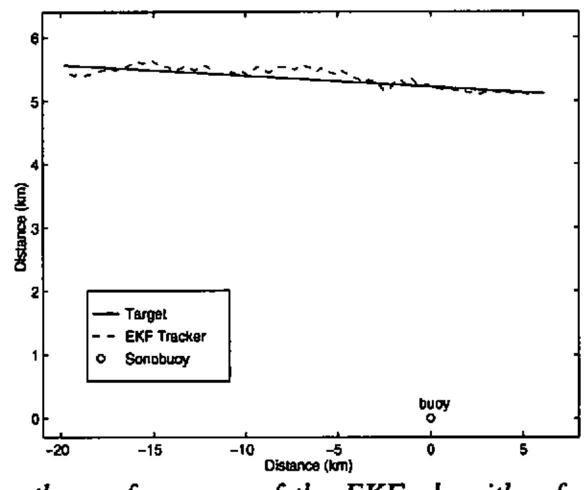

Figure 3 Example showing the performance of the EKF algorithm for a target moving in a straight line at a constant speed.

4. RESULTS

In this section results are presented comparing the performance of the EKF and STI algorithms using two simulated data examples. In addition, the performance of the STI algorithm is examined using data obtained from a recent sea trial.

4.1. Simulated Data

The simulated data was created using a target travelling in a realistic fashion eg. non-constant speed and trajectory. The signal strength of the narrowband line projected by the target was 145 dB and the bearing estimates used in the EKF algorithm had a standard deviation of 5^0.

4.1.1. Example A: Target Motion in a Straight Line

In this scenario a target is moving with an approximate speed of 5 knots. Initially the target moves easterly and then reverses direction and continues to move west for the remainder of the 90 minute scenario. Four stationary sonobuoys were deployed as shown in Figure 4. The STI algorithm uses information from all four sonobuoys and estimates the target position at 5 minutes intervals along the track. The results depicted in Figure 4 indicate that the STI algorithm follows the target closely as it moves easterly and then follows it west. In contrast the EKF algorithm uses bearing estimates from sonobuoy 2 and initially diverges from the true track. Eventually the algorithm arrives at an accurate solution near the end of the scenario, about an hour later. When data from sonobuoy 4 is used the EKF algorithm follows the true track closely from the start but as the target moves further away from the sonobuoy it cannot see enough of a bearing change and so has difficulty estimating the target velocity. By the end of the 90 minute period the track is approximately 6 km behind the actual target position.

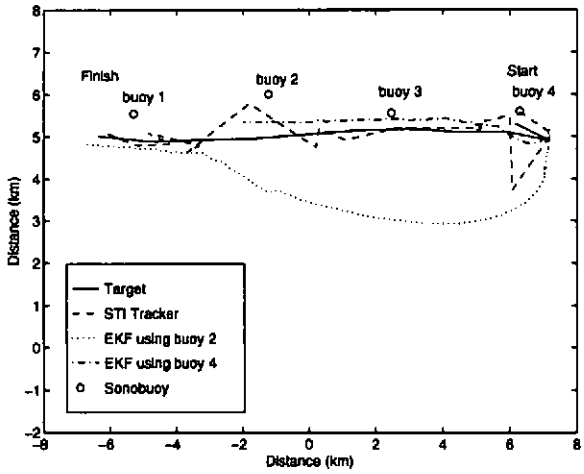

Figure 4 Simulated data for a target moving in a straight line

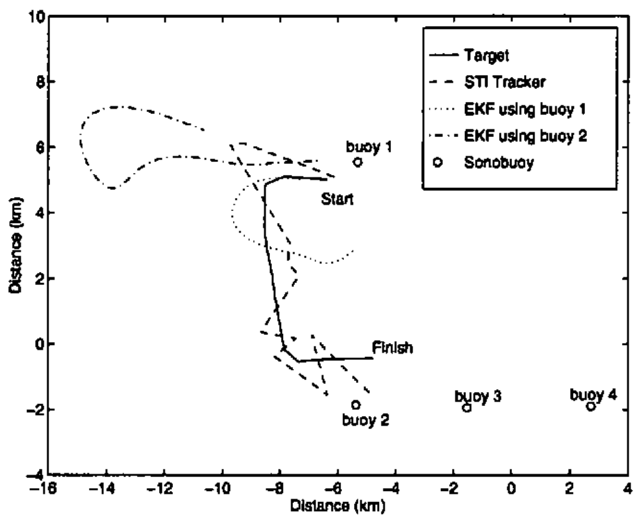

Figure 5 Simulated data for target manoeuvring around a turn

4.1.2. Example B: Target Manoeuvring Around a Turn

In this scenario the target characteristics are similar to those in the previous section. In this example the target is executing a turn. The EKF using data from buoy 2 executed the target turn in the opposite direction. The EKF using buoy 1 initially arrived at an accurate solution and executed the turn but was about 3 km away from the actual target position at the end of the scenario. However, the STI algorithm follows the trajectory of the target relatively well throughout the entire manoeuvre.

4.2. Sea Trial Data

The results presented in this section describe the performance of the STI algorithm using data obtained from a recent sea trial. The target positions and the sonobuoy positions are the same as the scenario described in section 4.1.1. Figure 6 shows the results obtained with the STI algorithm using the sea trial data. The STI algorithm provides a reasonably accurate estimate of the target track throughout the entire scenario.

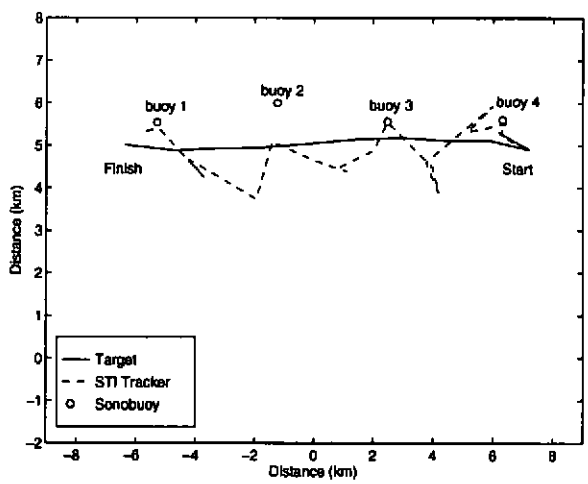

***Figure 6** Performance of the STI algorithm using sea trial data*

5. CONCLUSIONS

This paper has applied the STI algorithm to the case of spatially separated sonobuoy sensors and has compared its performance to a standard EKF approach. This comparison was undertaken using two different simulated scenarios. Problems with the model based EKF approach were highlighted in the results obtained. Departures from the assumed model eg. target speed or course variations caused a degradation in performance of the EKF algorithm. By contrast the STI algorithm performed well under these conditions. An example using sea trial data also highlighted the robustness of the STI approach.

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