A Hybrid System for Information Fusion with Application to Passive Ranging

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We propose a nonlinear filtering scheme that combines different measurement models in an interacting multiple models – particle filter framework. The technique is applied to the passive ranging problem by using two particle filters with different measurement models – one relating bearing angle with target kinematics, and the other relating target size from image to the same. The range at each time instant is estimated by designing an adaptive function that can intelligently combine the output of the two filters. No prior knowledge of the true size, shape or any feature of the target is assumed. The algorithm is successfully implemented at real time on video acquired from an unmanned aerial system.

1. Introduction

A number of techniques for estimating the range and bearings from image/video sequence have been developed over the years. One such method is based on triangulation and requires a minimum of two space (stereo-based) or time (motion-based) sequential images [AN88, DA89]. Systems relying on stereo methods (require two or more cameras) may be impractical for certain applications because they are bulky, expensive and consume more power. In motion-based methods, the same camera is moved from one position to another to capture two or more images of the scene.

Certain single sensor based techniques use linear models and Gaussian noise approximations and hence the Kalman filter can be applied [AM79]. High dimension state vector need to be used to limit the approximations to solve this inherently nonlinear problem. In contrast to this, methods which use nonlinear filters like particle filter [RA03, AMR04] give an approximate solution based on a physical model, rather than optimal solution to the approximate model. These filtering schemes rely on the bearing angle measurement for estimating the state vector. The main drawback of these methods is that it requires the sensor platform to make deliberate maneuver which can be disruptive to the application and cause inconvenience to both operators and regulators [NLG84]. Target size in image has also been considered as a potential measurement to resolve the problem at hand [V99].

The paper describes a general interacting multiple models - particle filter (IMM – PF) framework that combines different measurement models. The approach is evaluated using real time implementation for the passive ranging application. To overcome the abovementioned problems in the current systems, we propose to tackle the issue by fusing information obtained from particle filters using bearing angle measurements, and a general model of the variation of target size with observer - target kinematics. It is worth noting that we do not make any assumption about the size, shape, type or any other features of the target. The approach fully exploits the advantages of bearings-only method while complementing it with the additional size model information. Hence, it eliminates the limitation of the former which requires the sensor platform to perform deliberate maneuvers when the target is heading directly towards it or the change in the bearing angle is not significant.

The paper is organized as follows: Section 2 describes the basic framework and then describes its use in range estimation using monocular video. Section 3 compares the performance of this approach with bearings-only method using real data. The conclusions are presented in section 4.

2. Interacting Multiple Models – Particle Filter framework

In dynamic systems, nonlinear estimation using single state transition model is often error prone and there is a need for modeling multiple behavioral modes. Interacting Multiple Models (IMM) provide a simple and effective estimator that can "switch" between various behavioral modes for each estimation. IMMs assume that the switching of behavioral modes is Markovian and allow intelligent interaction between them [Den01, BD03]. The complexity of the system varies linearly with the number of behavioral modes while the performance compares with systems of quadratic complexity. The proposed algorithm has a similar framework, but uses multiple measurement sources and fuses the state estimates in a robust manner.

Consider the nonlinear system

$$s(k+1) = f(s(k), t(k), m(k)) + g(s(k), t(k), m(k))w(k, m(k)), k \in \mathbf{N}$$

$$z(k) = h(s(k), t(k), m(k)) + v(k, m(k)), k \in \mathbf{N}$$

where $s(k) \in \Re^{n(m(k))}$ is the dynamical state of the system in mode *m(k)* and $m(k) \in M \subset \mathbf{N}$ is the modal state of the system. The process noise and the measurement noise are possibly mode-dependent. Their densities are denoted by $d_{w(k,m(k))}(w)$ and $d_{v(k,m(k))}(v)$. $z(k) \in \Re^{p(m(k))}$ are the measurements in mode *m(k)*. For simplicity, the IMM filtering has been outlined for just one measurement. The exact process is repeated for each measurement.

The state probabilities are computed as

$$\mu_{i|j}(k-1 \mid k-1) = \frac{1}{c_j} p_{ij} \mu_i (k-1),$$

where $c_j = \sum_{i \in M} p_{ij} \mu_i (k-1)$ and μ_i is the initial state probability of state *i*.

Priori probability density in mode *j* is

$$\hat{p}_0^j (s_{0j}(k-1) \mid Z(k-1)) = \sum \hat{p}^i (s_i (k-1) \mid Z(k-1)) \times \mu_{i|j}(k-1 \mid k-1)$$

Then, $\forall j \in M$ draw N samples $\bar{s}_1^j (k-1)$ according to $\hat{p}_0^j (s_{0j}(k-1) \mid Z(k-1))$.

Compute predicted samples as

$$\hat{s}_j^l (k) = f(\bar{s}_j^l (k-1, t(k-1), j)) + g(\bar{s}_j^l (k-1, t(k-1), j))w^l (k-1, j)$$

where $w^l (k-1, j)$ are samples from $d_{w(k-1,j)}(w)$.

The predicted output will be

$$\hat{z}_j^l(k \mid k-1) = h\left(\hat{s}_j^l(k), t(k), j\right),$$

and the weights are

$$\bar{q}_j^l(k) = d_{v(k,j)}\left(z(k) - \hat{z}_j^l(k \mid k-1)\right), \text{ with } \bar{q}_j(k) = \sum_{l=1}^{N} \bar{q}_j^l(k) \text{ and } q_j^l = \frac{\bar{q}_j^l(k)}{\bar{q}_j(k)}.$$

Mean and covariance of the state vectors are given by

$$\bar{s}_j(k) = \sum_{l=1}^{N} q_j^l \, \hat{s}_j^l(k) \text{ and } \hat{P}_j(k) = \sum q_j^l \left(\hat{s}_j^l(k) - \bar{s}_j(k)\right)\left(\hat{s}_j^l(k) - \bar{s}_j(k)\right)'.$$

Then, the probability density function is computed as mixture of Gaussians as

$$\tilde{p}_N^j(s_j(k)/Z(k)) = \sum_{l=1}^{N} q_j^l N(\hat{s}_j^l(k), \upsilon_j \tilde{P}_j(k))$$

where $\upsilon_j = 0.5N^{-2/d_j}$ and d_j is the state dimension.

Similarly, the mean $\overline{h_j}(k)$ and covariance $\hat{S}_j(k)$ of the output are computed. The innovation will be

$$r_j^l(k) = z(k) - h(\hat{s}_j^l(k), k, j),$$

and the probability density function is

$$\tilde{p}^j(r_j(k)/Z(k)) = \sum_{l=1}^{N} q_j^l N(0, \hat{S}_j(k)).$$

The state likelihoods may be computed as

$$\mu_j(k) = \frac{1}{c} L_j(k) c_j,$$

where $L_j^l(k) = N(r_j^l(k); 0, \hat{S}_j(k))$ and $c = \sum_{j \in M} L_j(k) c_j$.

Similarly, the state likelihoods for each measurement are computed. Using these likelihoods and the properties of the application, a fusion function that computes the *a posteriori* conditional probability density function for the system may be designed. For example, for the ranging application, if the bearing angle is seen as a reliable measurement compared to the size data, the fusion function can be defined such that the probability density functions corresponding to the size measurement are used only when the estimate from the bearing angle model is erroneous. On the other hand, if both the measurements are determined to be equally reliable, then fusion function that combines the most likely probability density functions from each measurement is designed. Such an approach gives a generic solution to information fusion and allows high flexibility in application specific design.

To construct a particle filter using object size as a measurement, a model relating it to the state vector of the system needs to be established, i.e.,

$size = g(\mathbf{x})$, where $\mathbf{x}$ is the state vector.

The function g depends on the target kinematics and hence its design is application dependent. The derivation of the target size model for passive range estimation is explained in the following section.

Target size model

For the passive ranging application, a simple target size model can be designed using the concept of projective geometry. Figure 1 shows the perspective geometry of the camera. Here, H, h and R are true size of the target, target size on the image and range respectively.

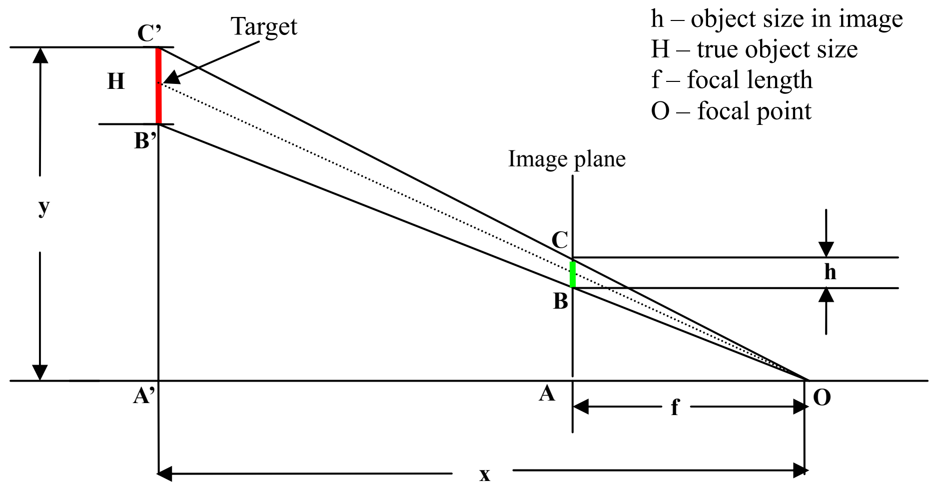


Figure 1: Projective geometry of the camera

Using the properties of similar triangles,

$$\frac{h}{H} = \frac{OB}{OB'} \text{ and } \frac{OB}{OB'} = \frac{f}{x}.$$

Equating the two, we get

$$h = H.\frac{f}{x}$$

For a given target, the true size H is fixed. Also, since the camera specifications are known, f is a constant. Thus, the model is simply a relation between the size of the target on the image and the x coordinate in world space. The model parameters are obtained by investigating the size trend in a number of image sequences. Such a model will enable accurate range estimation when the image geometry is exactly projective. However, as ideal projective geometry cannot be assumed in most real scenarios and the measurements are noisy, the size model is used in a nonlinear filtering framework. The target size model is a valuable add-on to the framework that complements the bearings-only range estimator.

3. Results

In this section, the feasibility of the proposed algorithm on real Sense-and-Avoid recorded data captured on an unmanned aerial system is demonstrated. The image sequences and the target detections were provided by Defense Research Associates Inc. (DRA) and Air Force Research Lab (AFRL). The bearing angle and size measurements were made for each frame and the range was estimated using our IMM-PF algorithm. Figure 2 shows the first frame of a sequence of 200 images which was used for experimentation. The true range at this frame is 3.5 nautical miles (NM).

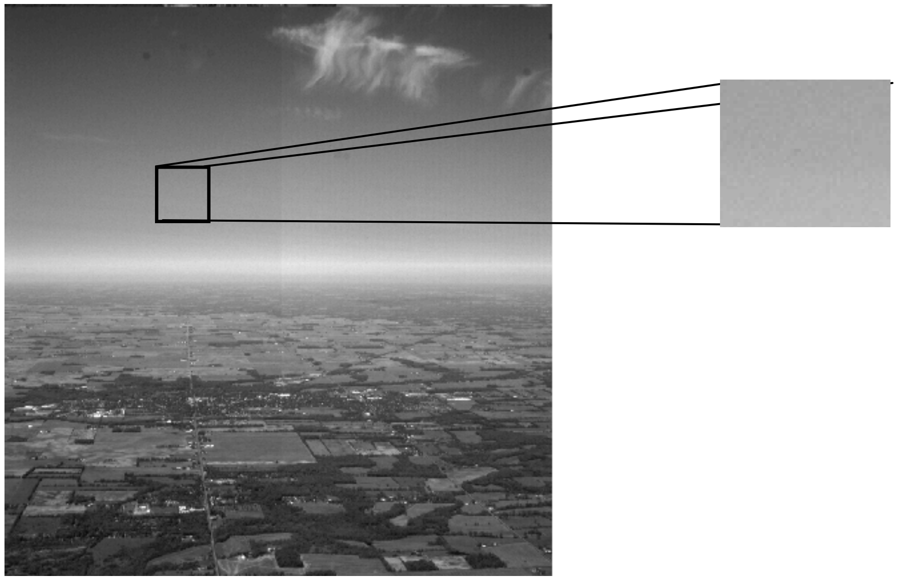
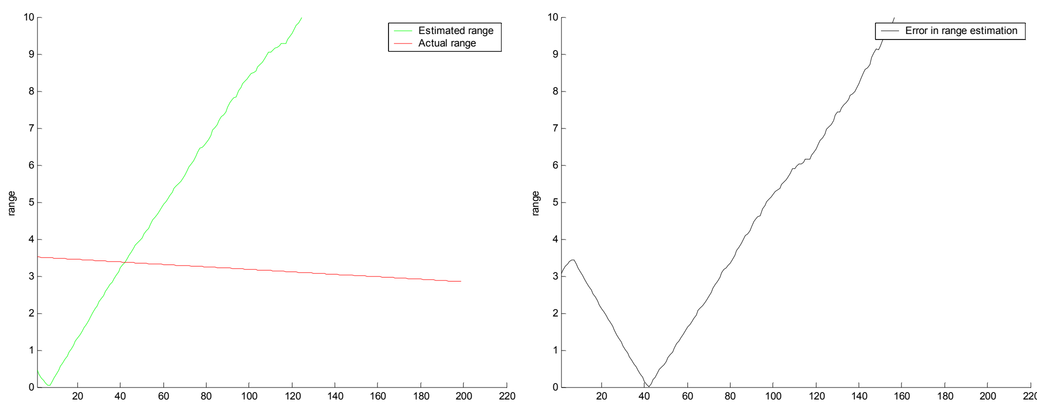


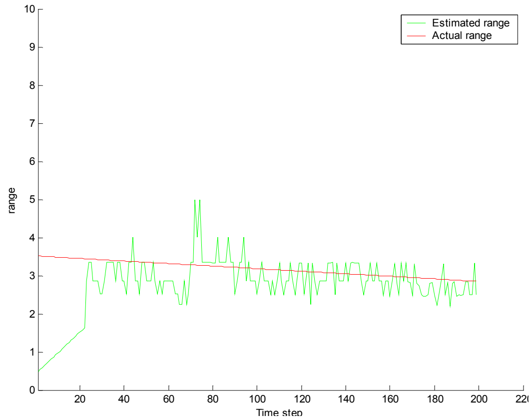
Figure 2: Frame 1 from test sequence. True range of target at this frame is approximately 3.5 NM

One of the fundamental drawbacks with non-linear filtering methods (such as extended Kalman filter, and particle filter) is that they rely heavily on the initial estimate of the state vector. In practical implementations, the initial estimate is often error prone. In our experiments, an initial error of 85% was introduced in order to evaluate the realistic performance of the approach. Figure 3 and Figure 4 compare the performance of our range estimation technique with the bearings-only method. Table 1 tabulates the error values for both the methods. Here, the particle filter using bearing angle does not converge and completely loses the target. The algorithm thus depends heavily on the size measurement model and the error drops from 3 NM (equivalent to an initial range estimation of 0.5 or 6.5 NM) to 0.3435 NM in just 200 iterations.

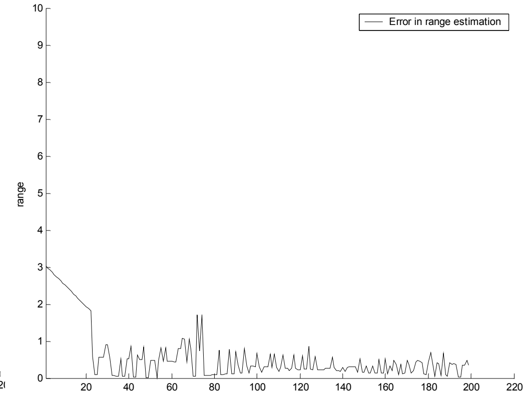


(a) (b)

Figure 3 : (a) Estimated range using bearings-only approach (initial error = 3 NM) (b) Mean absolute error



(a)



(b)

Figure 4 : (a) Estimated range using our approach (initial error = 3NM) (b) Mean absolute error

	With Bearing Angle Only	With Bearing Angle and Size
Initial range (NM)	3.5	3.5
Initial Error (NM)	-3	-3
Final Error (NM)	13.6030	0.3534
Mean Absolute Error (NM)	5.8863	0.4952

Table 1: Performance of UC's approach against Bearings only approach

4. Conclusion

We provide a novel technique for information fusion in the IMM-PF framework. The design of the fusion function is flexible and can be made application specific. For the ranging application, the approach completely exploits the advantages of the bearing angle measurement and uses size as an additional measurement to improve the accuracy of the range estimate. Therefore, the performance of our method is at least as good as range estimation using bearings-only and is significantly better when approximate size measurements are available. The approach (1) does not require the sensor platform to make deliberate maneuver, and (2) it estimates the target location with small error and number of iterations even when the bearing angle does not change significantly, thereby eliminating the major drawbacks with the existing passive ranging technology.

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