DISTRIBUTED TARGET TRACKING UNDER COMMUNICATION CONSTRAINTS

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ABSTRACT

In distributed tracking, communication bandwidth is one of the most expensive resources when we require to send measurements to other locations for processing. Furthermore, bandwidth requirement increases when tracking in clutter is considered due to transmission of target as well as clutter measurements. This paper describes the tracking in clutter under bandwidth constraints. The main idea is that instead of sending all target and clutter measurements we combine them into a weighted sum and transmit the resultant measurement. A novel Bayesian filter is proposed utilising the received measurement information. We observe some loss of performance as compared to local tracker, however it is considerably small.

***Index Terms*—** Distributed Tracking, Compression, clutter , Communication constraints

1. INTRODUCTION

Target tracking with spatially distributed sensors and with constraints on communication resources such as bandwidth, is widely discussed in the literature. In a traditional spatially distributed sensor network, sensors collect target measurements in the surveillance area and transmit them to the fusion center where tracking is performed. The fusion center fuses the received measurements and updates the track of the target being followed. In presence of clutter, sensor collects target as well as clutter measurements making communication more onerous. Under constraint on bandwidth, instead of sending target and clutter measurements, we combine target and clutter measurements into weighted sum and transmit this resultant measurement information.

The primary objective is tracking performance in the mean square sense, the optimal architecture for tracking target using spatially distributed sensors is a centralized architecture, where each node sends its measurements to the fusion center [1]. However, the centralized architecture comes with several drawbacks, consisting of high bandwidth requirements, high vulnerability to attack, delay in transmission and reception, information received out of order etc [2].

Distributed or decentralized tracking overcomes some problems of the centralized architecture. In distributed tracking each local sensor has the capability to perform local tracking using its own measurement data and sends local state estimates to the fusion center. Nonetheless problem becomes complex when received estimates of a target from various sensors are correlated with each other [3].

Transmitting local estimates in a decentralized architecture requires less bandwidth when compared to a centralized structure. However, bandwidth requirements can be further reduced by transmitting equivalent measurements and/or equivalent innovations as discussed in [2] and [4]. However equivalent innovations transmission leads to random walk phenomenon as discussed in [4] due to accumulation of encoding errors at the fusion center. Transmitting equivalent measurements effectively saves bandwidth and proves to be a better approach as discussed in [5], [6], [7] and [8]. In a decentralized architecture, degradations of tracking performance have been discussed in [9] and [10]. In a centralized architecture, problems of bandwidth allocation are discussed in [11] and [12].

We address tracking of target under communication constraints in clutter environment where we need to send all acquired measurements to another location. We combine received measurements at local node using weighted sum of target and clutter measurements. The weights are calculated based on the likelihood of each measurement. This resultant compressed measurement contains information of clutter and target measurements received. We transmit this compressed measurement to the fusion centre (FC). We propose a novel Bayesian filter which extracts useful information from compressed measurement at the FC. The proposed filter requires the computation of intractable integrals which are solved with help of Monte Carlo simulations.

The major contribution of this work consists of the derivation of novel Bayesian filter which operates on weighted sum of target and clutter measurements. By adopting this approach, we save communication bandwidth and are able to send target and clutter measurement information to other end as well. This is a preliminary work to understand tracking filter which operates on combined measurement. As we observe, the loss of tracking performance is almost negligible for our proposed filter when compared to optimal local Probabilistic data association filter (PDAF).

The structure of the remainder of this paper is as follows. Section II, formulates the problem of target tracking in a decentralized architecture. The novel compression filter

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is derived in Section III. Moving forward, Section IV outlines the numerical and simulation results. Finally, conclusions are drawn in Section V.

2. PROBLEM FORMULATION

We consider distributed tracking where we have local processing of measurements to maintain local tracks and also global track is maintained by receiving measurement information from local processing unit. We consider tracking of a single target moving on straight line in one dimension surveillance space in cluttered environment and following below trajectory model.

$$x_{k+1} = Fx_k + \nu_k \tag{1}$$

where k represents sensor scan time, F is the target state transition matrix, and process noise ν_k is a zero mean white Gaussian noise sequence with covariance matrix Q. The sensor measurement model is

$$z_k = Hx_k + \omega_k \tag{2}$$

where H denotes the measurement matrix and measurement noise ω_k is a zero mean white Gaussian noise sequence with covariance matrix R uncorrelated with process noise ν_k. The target under observation is detectable with probability of detection is one. The clutter is uniformly distributed in surveillance space. Due to clutter in surveillance, we receive M_k measurements with at least one target measurement at each scan. The number of clutter measurements per scan follows poisson distribution with clutter measurement density ρ. We use classical probabilistic data association filter proposed in [13] to maintain local track. The set of validated measurements using gating procedure is represented in below equation.

$$Z_k = \{z_{k,i}\}_{i=1}^{m_k} \tag{3}$$

We need larger bandwidth to transmit above set of measurements to global processing unit and situation becomes more onerous in case of high dimensions. The idea is to combine above measurements into one measurement using some scalar coefficients:

$$y_k = \sum_i^{m_k} \alpha_i z_{k,i} \tag{4}$$

where α_i are scalars and values are calculated based on likelihood of each measurement falling inside gate. We transmit y_k alongwith associated weights α_i every scan to the FC.

3. THE COMPRESSED FILTER

In this section, we derive a filter which uses combined measurement y_k defined in equation (4) as measurement information. We use standard Bayesian procedures to derive this filter as procedure outlined in [14] and name it the Compressed Filter (CF).

The conditional density of x_k given measurements (in our case combined measurement) up to time k is denoted as $p(x_k|y^k)$ and defined in below equation:

$$p(x_k|y^k) \propto p(y_k|x_k)p(x_k|y^{k-1}) \tag{5}$$

From equation (4), y_k is combination of m_k number of measurements, We assume that each measurement i is target measurement with $p(\theta_k(i))$. Now the conditional density can be written as

$$p(x_k|y^k, m^k) \propto p(y_k, m_k|x_k)p(x_k|y^{k-1}, m^{k-1}) \tag{6}$$

The prediction density in above equation is given by Chapman Kolmogorove equation as below

$$p(x_k|y^{k-1}, m^{k-1}) = \int p(x_k|x_{k-1})p(x_{k-1}|y^{k-1}, m^{k-1})dx_{k-1} \tag{7}$$

The dynamical equation (1) is linear and we assume Gaussian prior pdf, we can write $p(x_k|y^{k-1}, m^{k-1}) = N(x_k; \hat{x}_{k|k-1}, P_{k|k-1})$ where

$$\hat{x}_{k|k-1} = F\hat{x}_{k-1|k-1}$$
$$P_{k|k-1} = FP_{k-1|k-1}F^T + Q$$

Now, we need to derive likelihood part of Bayesian formula in equation (6). At time k, we receive m_k number of validated measurements and assume only one measurement being target measurement while rest of them are clutter measurements. We define association events $\theta_k(i)$ in way that measurement i is target originated measurement with some probability value of $p(\theta_k(i))$ where $i = 1, 2..., m_k$. All these association events are mutually exclusive and exhaustive events for each time k.

Therefore likelihood function is define as

$$p(y_k|x_k) = \sum_{i=1}^{m_k} p(y_k|x_k, \theta_k(i))p(\theta_k(i))$$
$$p(y_k|x_k, \theta_k(i)) = \int ... \int p(y_k, z_k(j)|x_k, \theta_k(i))dz_j...dz_{m_{k-1}} \tag{8}$$

where j is all from set of m_k validated measurements except i^{th} measurement. The above integral evaluates likelihood of y_k considering i^{th} measurement in equation (4) to be target originated while considering all other measurements as clutter measurements. According to measurement equation and considering Gaussian measurement noise assumption, above equation can be written as

$$p(y_k|x_k, \theta_k(i)) = \int ... \int N(y_k; \alpha_i Hx_k + \sum_{j=1, j\neq i}^{m-k} \alpha_j z_j, \alpha_i^2 R)$$
$$dz_j...dz_{m_{k-1}} \tag{9}$$

Now likelihood function can be written by combining above equations as below

$$p(y_k|x_k) = \sum_{i=0}^{m_k} \int ... \int N(y_k; \alpha_i H x_k + \sum_{j=1, j\neq i}^{m_k} \alpha_j z_j, \alpha_i^2 R) \\ dz_j ... dz_{m_{k-1}} p(\theta_k(i)) \tag{10}$$

The Bayesian formula established in equation (6) can be written below after putting $p(y_k|x_k)$ and we solve further.

$$p(x_k|y_k) \propto \sum_{i=1}^{m_k} \int ... \int N(y_k; \alpha_i H x_k + \sum_{j=1, j\neq i}^{m_k} \alpha_j z_j, \alpha_i^2 R) \\ dz_j ... dz_{m_{k-1}} p(\theta_k(i)) N(x_k; \hat{x}_{k|k-1}, P_{k|k-1}) \\ p(x_k|y_k) \propto \sum_{i=1}^{m_k} \int ... \int N(y_k; \alpha_i H x_k + \sum_{j=1, j\neq i}^{m_k} \alpha_j z_j, \alpha_i^2 R) \\ \times N(x_k; \hat{x}_{k|k-1}, P_{k|k-1}) p(\theta_k(i)) dz_j ... dz_{m_{k-1}} \tag{11}$$

We can solve product of two Gaussian $N(y_k; \alpha_i H x_k + \sum_{j=1, j\neq i}^{m_k} \alpha_j z_j, \alpha_i^2 R) N(x_k; \hat{x}_{k|k-1}, P_{k|k-1})$ in above equations using Gaussian product formula given in [14]

$$N(y_k; \hat{y_k} + \sum_{j=1, j\neq i}^{m_k} \alpha_j z_j, \hat{S_k}) N(x_k; \hat{x}_{k|k}, P_{k|k})$$

The parameters of the above Gaussians are calculated using following equations:

$$\begin{aligned} \hat{y_k} &= \alpha_i H \hat{x}_{k|k-1} \\ \hat{S_k} &= \alpha_i^2 (H P_{k|k-1} H' + R) \\ \hat{x}_{k|k} &= \hat{x}_{k|k-1} + K(y_k - \alpha_i H \hat{x}_{k|k} - \sum_{j=1, j\neq i}^{m_k} \alpha_j z_j) \\ P_{k|k} &= P_{k|k-1} - \alpha_i K H P_{k|k-1} \end{aligned}$$

Where $K = \alpha_i P_{k|k-1} H' \hat{S_k}^{-1}$ is the gain of the filter.

The posterior probability density function can be written as

$$p(x_k|y_k) \propto \sum_{i=1}^{m_k} \int ... \int N(y_k; \hat{y_k} + \sum_{j=1, j\neq i}^{m_k} \alpha_j z_j, \hat{S_k}) \\ \times N(x_k; \hat{x}_{k|k}, P_{k|k}) p(\theta_k(i)) dz_j ... dz_{m_{k-1}} \tag{12}$$

3.1. Compressed Filter Algorithm

Finding the closed form solution of equation (12) is intractable. However, in literature there exist techniques to solve complex integrals using either numerically or Monte Carlo simulations. We adopt Monte Carlo simulation method to solve equation (12). By adopting Monte Carlo simulation procedure to find approximate solution of equation (12), we require simulating m_{k-1} variables for each i. Although, this procedure works however when m_{k-1} becomes bigger, the growing computations makes this procedure less attractive. We propose another simple approach to handle this computation problem. The summation term $\sum_{j=1, j\neq i}^{m_k} \alpha_j z_j$ is sum of $m_k - 1$ clutter measurements. From the distribution of clutter, we know that clutter is uniformly distributed in surveillance. This summation term is actually sum of uniformly but non-identically distributed random variable. The distribution of sum of n uniformly distributed random variables over intervals $[a_i, b_i]$ can be found in [15].

$$S_n = \sum_{j=1}^{n} \alpha_j z_j = \sum_{j=1}^{n} X_j \tag{13}$$

Equation (12) can be re-written by replacing $\sum_{j=1, j\neq i}^{m_k} \alpha_j z_j$ with another random variable S_n defined above. Now resultant equation contains one integral and can be easily solved in Monte Carlo integration framework.

$$p(x_k|y_k) \propto \sum_{i=1}^{m_k} \int N(y_k; \hat{y_k} + S_n, \hat{S_k}) p(S_n) \\ \times N(x_k; \hat{x}_{k|k}, P_{k|k}) p(\theta_k(i)) dS_n \tag{14}$$

The parameters of $N(y_k; \hat{y_k} + S_n, \hat{S_k}) N(x_k; \hat{x}_{k|k}, P_{k|k})$ are given in below set of equations:

$$\begin{aligned} \hat{y_k} &= \alpha_i H \hat{x}_{k|k-1} \\ \hat{S_k} &= \alpha_i^2 (H P_{k|k-1} H' + R) \\ \hat{x}_{k|k} &= \hat{x}_{k|k-1} + K(y_k - \alpha_i H \hat{x}_{k|k} - S_n) \\ P_{k|k} &= P_{k|k-1} - \alpha_i K H P_{k|k-1} \end{aligned}$$

Where K is the gain of the filter similar as defined earlier.

The simulation of algorithm is based on mixture of Gaussian propagating and updating. We initialize with nG number of Gaussian and its weight and predict each Gaussian using standard prediction as described in Equation (3). To update each predicted Gaussian and its associated weight, we need to implement Equation (14). The integral in Equation (14) is solved by simulating S_n as defined in Equation (13). Each predicted Gaussian is updated with every sample of S_n and for all data association hypothesis and we update weight of each resultant Gaussian. The number of Gaussians in this mixture grows exponentially with time, however we maintain a high weighted Gaussians and discard low weighted Gaussians in mixture. The summary of implementation is given in Algorithm 1.

4. SIMULATION RESULTS

Each experiment discussed in this section assumes an identical simulation environment. One target is moving in a straight

Algorithm 1 The Compressed Filter one Iteration

Initialize $\leftarrow [w^l_{k-1|k-1}, N(x; \hat{x}^l_{k-1|k-1}, P^l_{k-1|k-1})]^{nG}_{l=1}$
Recursion Starts
for $l \leftarrow 1, nG$ **do**
  Prediction $\leftarrow N(x; \hat{x}^l_{k|k-1}, P^l_{k|k-1})$
  for $i \leftarrow 1, m_k$ **do**
    Draw nS *Samples of* S_n *as in (13)*
    for $j \leftarrow 1, nS$ **do**
      Update $\leftarrow N(x; \hat{x}^{l,i,j}_{k|k}(S_n(j)), P^{l,j,i}_{k|k})$
      $w^{l,i,j}_{k|k} = w^l_{k-1|k-1} N(y_k; \alpha_i H \hat{x}^l_{k|k-1} + S_n(j), \alpha_i^2 S^l_{k|k-1})$
end for
end for
end for
Discard Gaussians with low weights
Weighted Sum $\leftarrow \hat{x}_{k|k} = \sum^G_{i=1} w^G_{k|k} \hat{x}^G_{k|k}$
Recursion Ends

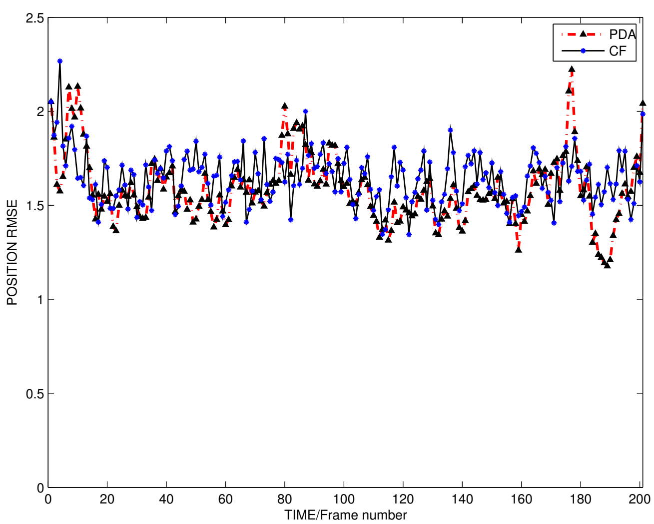

Fig. 1. The simulations comparison of RMSE of local PDAF filter and proposed global Compressed filter with very high clutter measurement density of $\rho = 0.1$.

line in a one dimensional surveillance space. The target is moving with uniform velocity of 2 m/s parallel to the Cartesian x axis. This surveillance space is observed with one sensor with scan interval of $T = 1s$. Sensor measurement noise is assumed to be Gaussian, white and independent of process noise, with covariance matrix $R = 4$. The clutter measurement is $0.1/scan/m^2$. A local filter used is classical probabilistic data association filter (PDAF) [13]. The sensor node is connected to the fusion center via a digital communication channel with assumption that the network is ideal with no transmission errors and no out of sequence records. The measurements falling inside PDAF gate are combined into one measurement and weights are calculated based on likelihood of each measurement. The resultant measurement along with associated scaling factors is sent to global processing facility. The proposed Compressed Filter utilizes received information to track the target in surveillance space. Figure 1, shows the root mean square error comparison of local PDA filter and our proposed compressed filter. The time averaged RMSE values for local PDA and our proposed CF are 1.6044 and 1.7236 respectively. Based on this statistics, we can say that tracking performance of our proposed filter is slightly decreased while just sending one combined measurement.

5. CONCLUSION

In this paper, we proposed a scheme for measurement information transmission in a distributed tracking architecture. This scheme proved to be helpful in transmitting information with low data rates. We combined received measurements at local node into single measurement with associated weights, calculated based on likelihood of each measurement. The resultant combined measurement is transmitted to global processing unit. We proposed Bayesian recursive filter which operate on combined measurement. We implemented Monte carol simulation based method to update predicted conditional densities. The implementation is based on Gaussian mixture with associated weights. To limit the number of Gaussians in mixture, we keep high weighted Gaussians and discard negligible weighted Gaussians. The simulation results show that tracking performance is reduced a bit but we can still track the object without being lost. Our proposed approach requires lower communication bandwidth and maintains the track and its quality. This is preliminary work and need extension to study practical tracking limitations such as missing measurements, probability of detection is less than 1 and high dimension cases.

6. REFERENCES

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