Collaborative Data Fusion Tracking in Sensor Networks using Monte Carlo Methods

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Abstract

The multi-modality nature of sensor networks and their potentially large-scale deployment have generated highly dimensional network data. This paper proposes a hierarchical collaborative data fusion scheme based on Particle Filters for cross-sensor fusion and cross-modality fusion for target tracking applications.

1 Introduction

Multi-modality information from sensor networks may be classified into two categories:

- Multi-modality information from the different sensing modes of the same sensor.
- Collaborative information of the same sensing modality from different sensors.

There is limited research in effectively utilizing and fusing information from these different dimensions in a consistent and efficient manner. Most previous works [1] over-simplified the problem by already assuming the existence of data-fusioning techniques. Others do not provide a comprehensive solution to this highly complex data fusion problem by only considering information from the second category [2].

2 Data Fusion Tracking

2.1 Cross-Sensor Fusion

$$q^{Mod}\left(x_n \mid x_{n-1}, z_n^{Mod}\right) = \left(\sum_{k=1}^{N_c} \omega_n^k \, p\left(x_n^k \mid x_{n-1}^k\right)\right) \Bigg/ \sum_{k=1}^{N_c} \omega_n^k \tag{1}$$

$$\omega_n^k = \log\left(T_h(z_n^{Mod}) \left. \frac{d\varphi^{Mod}(r)}{dr} \right|_{r = x_{n-1}} \right) \tag{2}$$

$$T_h(p) = \frac{1}{1 + e^{-\alpha(p - \beta_T)}} \tag{3}$$

Suppose a group of N_c sensors collaborate with each other by exchanging information between them, where $N_c \geq 3$. Let x_n be the coordinate of a target of interest (unknown state), z_n^{Mod} be the sensor measurement in the modality *Mod*, ω_n^k be denoted the quality weight assigned to the k^{th} sensor, and n be a discrete time index. We propose the importance density for the modality *Mod* in eqn (1). Here, the importance density is the weighted sum of the contributions from all the N_c sensors in collaboration, $\varphi^{Mod}(r)$ is the governing equation for the sensor modality signal strength for varying target distances r obtained through empirical studies or datasheets, and T_h is a soft threshold function where α is a constant, β_T is a threshold value and $0 < T_h(p) < 1$, $p \in \Re$. The threshold function reduces the number of participating sensors in the computation of the importance density function so that sensors lying too far away from the target of interest will not be included in the computation. There is therefore, an energy-efficient active region around the target that follows the target as it traverses in the sensor field. The quality weights ω_n^k are also used to determine the degree of urgency the information needs to be sent for the processing of the importance density.

2.2 Cross-Modality Fusion

The fundamentals of Particle Filters (PF) are well known. Uunfamiliar readers may wish to refer to [3]. Data from the different modalities may be fused by a layered sampling particle filtering approach. Let $\left\{x_{n-1}^{(i)}, w_{n-1}^{(i)}\right\}_{i=1}^{N}$ be the particle set at the time step (n-1). Then at time n, for the next modality *Mod*,

Simulate: $x_n^{Mod(i)} \sim q^{Mod}\left(x_n^{Mod} \mid x_{n-1}^{(i)}, z_n^{Mod}\right)$ (4)

Update weights by:

$$w_n^{Mod(i)} \propto w_{n-1}^{(i)} \frac{p\left(z_n^{Mod} \mid x_n^{Mod(i)}\right) p\left(x_n^{Mod(i)} \mid x_{n-1}^{(i)}\right)}{q^{Mod}\left(x_n^{Mod(i)} \mid x_{n-1}^{(i)}, z_n^{Mod}\right)} \tag{5}$$

where $\sum_{i=1}^{N} w_n^{Mod(i)} = 1$. (6)

Update the particle set at the next time step using:

$$\left\{x_n^{(i)}, w_n^{(i)}\right\}_{i=1}^{N} \leftarrow \left\{x_n^{Mod(i)}, w_n^{Mod(i)}\right\}_{i=1}^{N} \tag{7}$$

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If re-sampling, simulate $a_n^{(i)} \sim \left\{w_n^{(k)}\right\}_{k=1}^{N}$ and replace

$$\left\{x_n^{(i)}, w_n^{(i)}\right\} \leftarrow \left\{x_n^{a(i)}, \frac{1}{N}\right\}. \tag{8}$$

This layered approach is extremely effective in guiding the search in the state space, with each stage refining the result from the previous stage.

3 Agent-Based Hierarchical Scheme

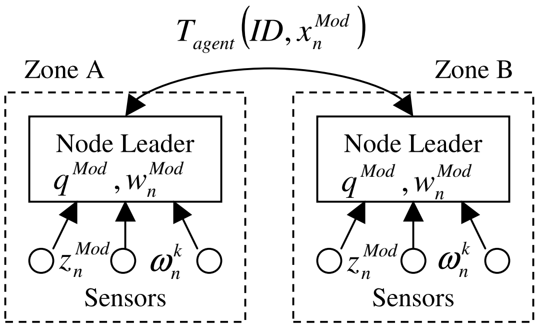

Fig. 1 - Hierarchical Collaborative Tracking Schematics

Eqn (1) suggests that it is unnecessary to compute the importance density in all sensors. Fig. 1 illustrates our hierarchical distributed tracking scheme where sensors are tasked to only compute quality weights ω_n^k according to eqn (2). This information, together with sensor measurements z_n^{Mod} are then communicated back to the group leader that the sensor belongs to, where the leader is in charge of the more computationally intensive calculations of q^{Mod} , the particle filtering states x_n^{Mod} and weights w_n^{Mod} update operations. Each group leader is also in charge of a geographical zone on the topological space. Whenever a target of interest enters a zone and is being detected, the node leader for that zone launches a tracking agent T_{agent} for that target with a unique ID. When the target moves from one zone to a neighboring zone, T_{agent} is communicated to the node leader of that new zone for continual tracking of that same target in the sensor field. Hence, agents propagate in the sensor network according to the trajectory of its targets. Computational requirements are distributed in the sensor networks, with node leaders handling computationally intensive operations while the individual sensors calculate quality weights.

4 Preliminary Results

Real raw data from two modalities acoustic and seismic obtained from the Sensor Networks Research Group, University of Wisconsin-Madison [4] are used for our simulation. The measurements are obtained from a "live" testbed with real environmental disturbances measurement errors and communication delays. Fig. 2 shows our results.

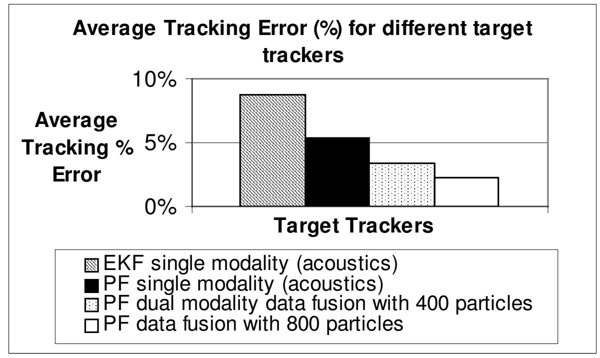

Fig. 2 - Tracking accuracy for different trackers

Preliminary results indicate that Extended Kalman Filter (EKF) fails in comparison to our PF implementation because real-world noise and target dynamics are non-linear and not necessarily always Gaussian. EKF is merely a local linearization to describe non-linearity and always approximates $p(x_k \mid z_{1:k})$ to be Gaussian and thus does not work well with skewed-distributions. Further, Our data fusion technique using N = 400 particles improves tracking accuracy by almost 40%, compared to regular PFs with no data fusion capabilities. PF with 800 particles outperforms that with only 400 particles with a resulting tracking accuracy of almost 98%.

5 Conclusion

We have provided a realistic solution for data fusion of multi-sensor, multi-modalities information for tracking applications based on a Monte Carlo filtering technique.

6 References

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