

Distributed Bayesian Filters for Multi-Robot Network by Using Latest-In-and-Full-Out Exchange Strategy of Observations

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Abstract—This paper presents a local exchange strategy of observations, i.e., Latest-In-and-Full-Out (LIFO), for distributed Bayesian filters (DBF) in a multi-robot network. Different from statistics dissemination approaches that transmit posterior distributions or likelihood functions, each robot under LIFO only receives the latest available measurements and then broadcasts full communication buffer to its neighborhood, which significantly reduces the transmission burden of each pair from the order of environmental size to that of robot number. Under the condition of fixed and undirected topology, LIFO can guarantee non-intermittent dissemination of all observations over the network within finite time. Two types of LIFO-based DBF algorithms are proposed to estimate individual posterior density function (PDF) for static and moving target, respectively. For the static target, each robot locally fuses the newly received observations while for the moving target, a triangular matrix of historical observations is stored and updated. The consistency of LIFO-based DBF is proved that individual PDF of each robot converges to the true target position when the number of observations tends to infinity. The effectiveness of this method is demonstrated by simulations. **(TODO: find out what convergence is)**

I. INTRODUCTION

Distributed filtering that focuses on using a group of networked robots to collectively infer environment status has been used for various applications, such as intruder detection [1], pedestrian tracking [2] and micro-environmental monitoring [3]. Several techniques have been developed for distributed filtering. For example, Olfati-Saber (2005) proposed a distributed Kalman filter (DKF) for estimating states of linear systems with Gaussian process and measurement noise [4]. Each DKF used low-pass and band-pass consensus filters for the average-consensus of weighted measurements and inverse-covariance matrices. Madhavan et al. (2004) presented a distributed Extended Kalman Filter (DEKF) for outdoor localization and mapping. DEKF was used to generate local maps by using pose estimates to combine elevation gradient and vision-based depth with environmental features. Gu (2007) proposed a distributed particle filter for

target tracking over sensor networks [5]. Gaussian mixture model (GMM) was adopted to approximate the posterior distribution from weighted particles and the parameters of GMM was exchanged via average consensus filter. As a generic filtering scheme for nonlinear systems and arbitrary noise distributions, distributed Bayesian filter (DBF) has received increasing interest during past years [6], [7], which is the focus of this study.

The design of distributed filtering algorithms is closely related to communication topology of multi-robot network, which can be classified into two types: fusion center-based and neighborhood-based. In fusion center (FC)-based approaches, each robot uses a local filter to convert its own measurement into estimation of environment status, which is then transmitted (possibly via multi-hopping) to a FC. At each filtering cycle, fusion center calculates the global state estimate only after receiving latest local estimates of all robots [8], [9]. In neighborhood (NB)-based approaches, all robots execute local filters and only communication between neighboring agents is allowed. NB-based methods have become popular in recent years since such approaches do not require routing protocols or global knowledge about the network and therefore are robust to changes in the network topology and to link failures.

So far, most studies on NB-based DBF have mainly focused on the so-called *statistics dissemination* strategy that each robot actually exchanges statistics, including posterior distributions and likelihood functions, with neighboring robots for distributed estimation. **(TODO: concern: this categorization is based on Hlinka's survey. Will this cause trouble? Besides, the name statistics dissemination and measurement dissemination are also from this survey. Any issues?)** DBFs using statistics dissemination strategy can be categorized into two types: leader-based and consensus-based. **????** In leader-based DBFs, environment status is sequentially passed and updated along a path formed by active robots, called leaders. Only leaders perform DBF based on its own measurement and received measurements from local neighbors. For example, Sheng et al. (2005) proposed a multiple leader-based distributed particle filter (DPF) with Gaussian Mixer for target tracking [10]. DPFs were run on a set of leader agents in uncorrelated sensor cliques and the particles were approximated as GMMs, the parameters of which were then exchanged among leaders for global estimation. In consensus-based DBFs, all robots locally execute filters simultaneously and diffuse the statistics among neighbors. Global agreement of statistics among robots is achieved by using consensus algorithms,

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as proposed in [11]–[13]. For example, Saptarshi et al. (2014) presented a Bayesian consensus filter (BCF) that uses logarithmic opinion pool for fusing posterior distributions of the tracked target among neighboring robots [6]. Julian et al. (2012) proposed a consensus-based distributed particle filter (DPF) that uses linear average consensus approach for fusing posterior functions of environment status. [14].

Despite the popularity of statistics dissemination strategy for NB-based DBFs, exchanging statistics can consume high communication resources, which can be infeasible in vast area or complex environment. Because of this, measurement dissemination strategy has been developed for NB-based DBFs, by which raw or quantized observations are exchanged among robots. Some pioneering studies have been done on this topic. For example, Coates et al. (2004) used adaptive encoding of observations to minimize communication overhead for tracking a maneuvering object [15]. Ribeiro et al. (2006) presented distributed estimation based on quantized (binary) observations along with error-variance limits for several pragmatic signal models. In a recent work, Djuric et al. (2011) proposed a distributed particle filtering for target tracking. At each time, all robots broadcast their measurements to other agents, therefore each robot has a complete set of measurements of other robots for estimating target states [16]. In aforementioned works, communication topology is assumed fully connected that each robot can broadcast observations to all other robots in single transmission step.

This paper proposes a Latest-In-and-Full-Out (LIFO) strategy for distributed Bayesian filters (DBF) for undirected and connected communication topology. Each robot only broadcasts observations to its neighbors and implements Bayesian filter locally after receiving observations transmitted from neighboring robots. The main benefit of LIFO is the reduction of communication burden, with the transmission data volume scaling linearly with the robot number, while statistics dissemination-based strategies suffer from the data volume on the order of environmental size. The proposed LIFO-based DBF has following properties: (1) For an undirected and connected network with fixed topology, LIFO guarantees the global dissemination of all robots' observations among the network via multi-hopping, with each robot non-intermittently receiving (delayed) observations of all other robots via local communication. (2) The corresponding DBF ensures consistency of the estimation of states, which refers to the agreement between robots' estimates of target position and the true position of the target. Moreover, consistency implies the consensus of robots' target PDFs. In this study, the consistency and consensus using LIFO-DBF is formally proved.

The rest of this paper is organized as follows: The problem of distributed Bayesian filtering is formulated in Section II. The LIFO-based DBF algorithm is described in Section III, followed by the proof of consistency and consensus in Section IV. Simulation results are presented in Section V and Section VI concludes the paper.

II. PROBLEM FORMULATION

Consider a network of N robots in a bounded two-dimensional space S . Each robot is equipped with a binary sensor for environmental perception. Due to the limit of communication range, each robot can only exchange observations with its neighbors. The Bayesian filter is run locally on each robot based on its own and received observations.

A. Probabilistic Model of Binary Sensor

The goal of distributed Bayesian filter is to estimate the true target position by using a network of binary sensors. The binary sensor only gives two types of observation: 1 if the target is detected, and 0 if no target is detected. The observation of i^{th} sensor at k^{th} time step is denoted as z_k^i . The likelihood function that the target is detected is:

$$P(z_k^i = 1 | x_k^T; x_k^R) \in [0, 1], x_k^T \in S \quad (1)$$

where x_k^T denotes the target positions; x_k^R is the robot position. Correspondingly, the likelihood function that no target is detected is:

$$P(z_k^i = 0 | x_k^T; x_k^R) = 1 - P(z_k^i = 1 | x_k^T; x_k^R) \quad (2)$$

The combination of Eq. (1) and Eq. (2) becomes a binary sensor model parameterized by x_k^T and x_k^R . For the purpose of simplicity, we will not explicitly write x_k^R for the rest of the paper. The commonly used likelihood functions for binary sensor include Gaussian function [19], [20] and step function [21].

Remark 1: Given the knowledge of current target position, current observation of each robot is conditionally independent from both its own past observations and those of other robots.

Remark 2: This study is applicable for both homogeneous and heterogeneous binary sensors. A homogeneous model can simplify the analysis of completeness, while the heterogeneous model is more close to real sensing characteristics. In addition, it also works for other types of sensors, such as laser scanners [22] and cameras [23].

B. Graphical model of communication topology

The robot network is always assumed to be connected. Under this assumption, consider an undirected and fixed graph $G = (V, E)$, where $V = \{1, \dots, N\}$ represents the index set of robots and $E = V \times V$ denotes the edge set. The adjacency matrix $M = [m_{i,j}]$ describes the communication topology of G :

$$m_{i,j} = \begin{cases} 1 & \text{if } (i, j) \in E \\ 0 & \text{if } (i, j) \notin E \end{cases},$$

where $m_{i,j}$ denotes the entity of adjacency matrix. The notation $m_{i,j} = 1$ indicates that a communication link exists between i^{th} and j^{th} robot and $m_{i,j} = 0$ indicates no communication between them.

The *direct neighborhood* of i^{th} robot is defined as $\mathcal{N}_i = \{j | m_{i,j} = 1, \forall j \in \{1, \dots, N\}\}$. All the robots in \mathcal{N}_i can directly exchange information with i^{th} robot. In addition to direct neighborhood, another set called *available neighborhood*

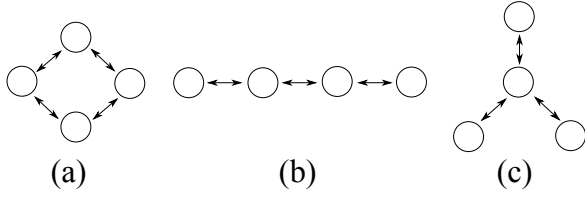


Fig. 1: Three types of topologies: (a)circular topology; (b)serial topology; (c)star topology

is defined as \mathcal{Q}_i , which contains indices of robots whose observations are received by the i^{th} robot given a specific observation exchange algorithm. Note that in general $\mathcal{N}_i \subseteq \mathcal{Q}_i$, but when only single-hopping is allowed, $\mathcal{N}_i = \mathcal{Q}_i$. Fig. 1 illustrates three types of typical topologies: circular [24], serial [25], and star [10]. All of them are undirected and connected topologies.

C. Distributed Bayesian Filter for Multiple Robots

The generic distributed Bayesian filter (DBF) is introduced in this section, which was also stated in [26] and [27]. Each robot has its individual estimation of posterior density function (PDF) of target position, called *individual PDF*. The i^{th} individual PDF at time k is defined as $P_{pdf}^i(x_k^T | z_{1:k}^i, z_{1:k}^{\mathcal{Q}_i})$. The individual PDF is initialized by the prior function $P_{pdf}^i(x_0^T | z_0^i, z_0^{\mathcal{Q}_i}) = P(x_0^T)$, given all available prior information including past experience and environmental knowledge. Under the framework of DBF, the individual PDF is recursively estimated by two steps, i.e., prediction step and updating step, based on the observations of i^{th} robot and robots in \mathcal{Q}_i .

1) *Prediction*: At time k , the prior individual PDF $P_{pdf}^i(x_{k-1}^T | z_{1:k-1}^i, z_{1:k-1}^{\mathcal{Q}_i})$ is first predicted forward by using the Chapman-Kolmogorov equation:

$$P_{pdf}^i(x_k^T | z_{1:k-1}^i, z_{1:k-1}^{\mathcal{Q}_i}) = \int P(x_k^T | x_{k-1}^T) P_{pdf}^i(x_{k-1}^T | z_{1:k-1}^i, z_{1:k-1}^{\mathcal{Q}_i}) dx_{k-1}^T \quad (3)$$

where $P(x_k^T | x_{k-1}^T)$ is a Markov motion model of the target, independent of robot states. This model describes the state transition probability of the target from a prior state x_{k-1}^T to posterior state x_k^T . Note that the target is static in many search applications, such as the indoor search for stationary objects [28]. For a static target, its Markov motion model is simplified to be

$$P(x_k^T | x_{k-1}^T) = \begin{cases} 1 & \text{if } x_k^T = x_{k-1}^T \\ 0 & \text{if } x_k^T \neq x_{k-1}^T \end{cases}.$$

2) *Updating*: At time k , the i^{th} individual PDF is then updated by Bayes' formula using the latest available observations at time k :

$$P_{pdf}^i(x_k^T | z_{1:k}^i, z_{1:k}^{\mathcal{Q}_i}) = K_i P_{pdf}^i(x_k^T | z_{1:k-1}^i, z_{1:k-1}^{\mathcal{Q}_i}) P(z_k^i | x_k^T) \prod_{j \in \mathcal{Q}_i} P(z_k^j | x_k^T) \quad (4)$$

where K_i is a normalization factor, given by:

$$K_i = 1 / \int P_{pdf}^i(x_k^T | z_{1:k-1}^i, z_{1:k-1}^{\mathcal{Q}_i}) P(z_k^i | x_k^T) \prod_{j \in \mathcal{Q}_i} P(z_k^j | x_k^T) dx_k^T$$

where $P_{pdf}^i(x_k^T | z_{1:k}^i, z_{1:k}^{\mathcal{Q}_i})$ is called posterior individual PDF; $P(z_k^i | x_k^T)$ is the likelihood function of observation z_k^i , described in Eq. (1) and Eq. (2).

III. DISTRIBUTED BAYESIAN FILTER VIA LOCAL EXCHANGE OF OBSERVATIONS

This study proposes a Latest-In-and-Full-Out (LIFO) strategy for observation exchange and derives two corresponding distributed Bayesian filtering (DBF) algorithms, shorted as LIFO-DBF. The data communication in LIFO uses synchronized step as the execution of DBF. In each step, LIFO only allows single-hopping communication within the neighborhood, but is able to broadcast observations of each robot to any other agents after a finite number of steps. The individual PDF is forward predicted and updated in DBF after each LIFO cycle. The theoretical analysis show that LIFO-DBF can ensure the consistency and consensus of distributed estimation while requiring much less communication burden than any statistics dissemination-based methods.

A. Strategy for Latest-In-and-Full-Out (LIFO)

Under LIFO, each robot contains a communication buffer (CB) to store its latest knowledge of the observations of all robots:

$$\mathbf{z}_k^i = [z_{k_1^i}^1, \dots, z_{k_N^i}^N]$$

where $z_{k_j^i}^j$ represents the observation made by j^{th} robot at time k_j^i . Note that under LIFO, $\mathcal{Q}_i = \{1, \dots, N\}$, which will be proved in Corollary 1. At time k , $z_{k_j^i}^j$ is received and stored in i^{th} robot CB, in which k_j^i is the latest observation time of j^{th} robot available to i^{th} robot. Due to the communication delay, $k_j^i < k, \forall j \neq i$ always holds in practice.

The **LIFO strategy** is stated as follows:

(1) Initialization: The buffer of i^{th} robot is initialized when $k = 0$:

$$z_{k_j^i}^j = \emptyset, k_j^i = 0, j = 1 : N$$

(2) At k^{th} step for i^{th} robot :

(2.1) Receiving Step:

The i^{th} robot receives all CBs of its neighboring robots. The received CBs are totally $|\mathcal{N}_i|$ groups, each of which corresponding to the $(k-1)$ -step CB of a robot in \mathcal{N}_i . The received CB from l^{th} ($l \in \mathcal{N}_i$) robot is denoted as

$$\mathbf{z}_{k-1}^l = [z_{(k-1)_1^l}^1, \dots, z_{(k-1)_N^l}^N], l \in \mathcal{N}_i$$

(2.2) Observation Step:

The i^{th} robot updates $z_{k_j^i}^j$ ($j = i$) by its own observation at current step:

$$z_{k_j^i}^j = z_k^i, k_j^i = k, \text{ if } j = i.$$

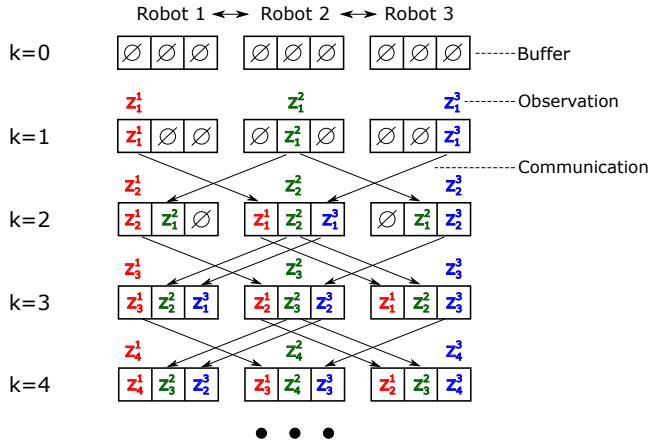


Fig. 2: Example of LIFO with three robots using serial communication topology

(2.3) Comparison Step:

The i^{th} robot updates other elements of its own CB, i.e., $z_{k_j}^j$ ($j \neq i$), by selecting the latest information among all received CBs from \mathcal{N}_i . For all $j \neq i$,

$$l_{\text{latest}} = \operatorname{argmax}_{l \in \mathcal{N}_{i,i}} \left\{ (k-1)_j^i, (k-1)_j^l \right\}$$

$$z_{k_j}^j = z_{(k-1)_j^i}^j, \quad k_j^i = (k-1)_j^l$$

(2.4) Sending Step:

The i^{th} robot broadcasts its updated CB to all of its neighbors defined in \mathcal{N}_i .

(3) $k \leftarrow k + 1$ until stop

Fig. 2 illustrates the LIFO cycles with 3 robots using a serial topology. Two facts can be noticed in Fig. 2: (1) all robot CBs are filled within 3 steps, which means under LIFO each robot has a maximum delay of 2 steps for receiving observations from other robots; (2) after filled, the updating of CBs are non-intermittent, which means each robot continuously receives new observations of other robots. Extending the two facts to a network of N robots, we have the following proposition:

Proposition 1: For a fixed and undirected network of N robots, LIFO uses the shortest path(s) between i^{th} and j^{th} robot to exchange observation, the length of which equals the delay $\tau_{i,j}$ between them.

Proof: Without loss of generality, assume that there is a unique shortest path between i and j , denoted by $T_{n^*}^{j,i} = (v_1, \dots, v_{n^*})$, with $v_1 = j$, $v_{n^*} = i$, $v_{m+1} \in \mathcal{N}_{v_m}$. Then, the distance between i and j is $d(j,i) = n^* - 1$. The following mathematical induction will prove Proposition 1.

Step (1): When $d(j,i) = 1$, $j \in \mathcal{N}_i$ and j can directly send z_k^j to i . Then z_k^j is stored in i^{th} CB at time $k+1$, i.e. $\tau_{i,j} = 1$. Proposition 1 holds for $d(j,i) = 1$, $i, j \in \{1, \dots, N\}$.

Step (2): Suppose that Proposition 1 holds for $d(j,i) = s$, $s \geq 2$. Then for $d(j,i) = s+1$, i.e., $n^* = s+2$, by the Bellman's principle of optimality, the path $T_{n^*-1}^{j,l} = (v_1, \dots, v_{n^*-1})$ is a shortest path between j and l , where

$v_{n^*-1} = l$ and $i \in \mathcal{N}_l$. The assumption that Proposition 1 holds for $d(j,i) = s$ implies that z_k^j is received and stored in l^{th} robot's CB at time $k+s$. Since $i \in \mathcal{N}_l$, i^{th} robot receives z_k^j at $k+s+1$. For any other path $T_n^{j,i} = (v_1, \dots, v_n)$ with $n > n^*$, z_k^j cannot be received by i earlier than $k+s+1$. Therefore $\tau_{i,j} = s+1$. This proves the Proposition 1 for $d(j,i) = s+1$. ■

Corollary 1: For the same topology in Proposition 1, all elements in z_k^i under LIFO become filled when $k \geq N$.

Proof: In a network of N robots, the maximal length of shortest paths is no greater than $N-1$. Based on Proposition 1, $\tau_{i,j} \leq N-1$ and thus all elements of z_k^i become filled when $k \geq N$. ■

Corollary 2: For the same topology in Proposition 1, once all elements in z_k^i are filled, the updating of each element is non-intermittent.

Proof: For a network with fixed topology, shortest path(s) between any nodes are fixed. Therefore, based on Proposition 1, $\tau_{i,j}$ is constant and the updating of each element in z_k^i is non-intermittent. ■

Remark 3: Compared to statistics dissemination, LIFO is more communication-efficient for distributed filtering. To be specific, consider an $M \times M$ grid environment with a network of N robots, the transmitted data of LIFO between each pair of robots are only the CB of each robot, the length of which is $O(N)$. On the contrary, the length of transmitted data for a statistics dissemination approach is $O(M^2)$, which is the size of the environment. Since M is generally much larger than N in target search and tracking, LIFO requires much less communication resources.

B. Algorithm of LIFO-DBF for Static Target

This section derives the LIFO-DBF algorithm for localizing a static target. Each robot stores last-step individual PDF, i.e., $P_{pdf}^i(x^T | \mathbf{z}_{1:k-1}^i)$. The assumption of static target can simplify the Bayesian filter as the prediction step becomes unnecessary. Therefore, the i^{th} individual PDF is only updated by

$$P_{pdf}^i(x^T | \mathbf{z}_{1:k}^i) = K_i P_{pdf}^i(x^T | \mathbf{z}_{1:k-1}^i) \prod_{j=1}^N P(z_{k_j}^j | x^T) \quad (5)$$

where

$$K_i = 1 / \int P_{pdf}^i(x^T | \mathbf{z}_{1:k-1}^i) \prod_{j=1}^N P(z_{k_j}^j | x^T) dx^T$$

C. Algorithm of LIFO-DBF for Moving target

This section derives the LIFO-DBF for localizing a moving target. Instead of storing last-step PDF, each robot maintains an individual PDF of time $(k-N)$ and a triangular matrix of historical observations from time $(k-N+1)$ to current time k . The i^{th} individual PDF is then alternatively predicted and updated by using aforementioned Bayesian filter (Eq. (3) and Eq. (4)) from $(k-N)$ to k . Fig. 3 illustrates the LIFO-DBF procedure for the 1st robot as an example. The

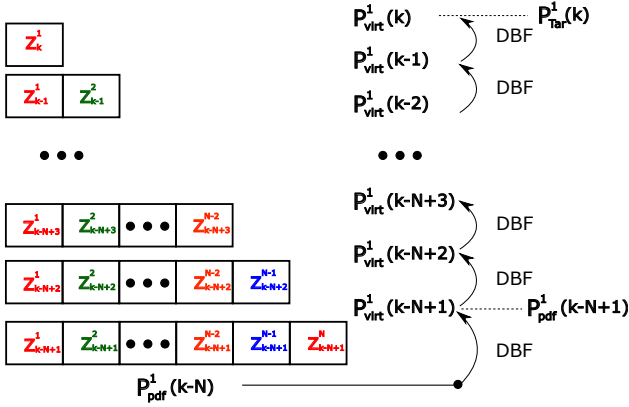


Fig. 3: Example of LIFO-DBF for 1st robot at time k . The current individual PDF is $P_{pdf}^1(x_{k-N}^T | z_{1:k-N}^1, \dots, z_{1:k-N}^N)$, denoted as $P_{pdf}^1(k-N)$ in the figure. The robot first calculates $P_{virt}^1(k-N+1)$ using DBF and stores it as $P_{pdf}^1(k-N+1)$. Repeating DBF until obtaining $P_{pdf}^1(k)$, which is then used as the target PDF estimation of 1st robot at time k .

generic **LIFO-DBF algorithm** for moving target is stated as follows:

For i^{th} robot at k^{th} step:

(1) The stored individual PDF for time $(k-N)$ is:

$$P_{pdf}^i(x_{k-N}^T | z_{1:k-N}^1, \dots, z_{1:k-N}^N)$$

(2) Initialize a virtual PDF by assigning the individual PDF to it:

$$P_{virt}^i(x_{k-N}^T) = P_{pdf}^i(x_{k-N}^T | z_{1:k-N}^1, \dots, z_{1:k-N}^N)$$

(3) From $\xi = 1$ to N , repeat two steps of Bayesian filtering:

(3.1) Prediction

$$P_{virt}^{pre}(x_{k-N+\xi}^T) = \int P(x_{k-N+\xi}^T | x_{k-N+\xi-1}^T) P_{virt}^i(x_{k-N+\xi-1}^T) dx_{k-N+\xi-1}^T$$

(3.2) Updating

$$P_{virt}^i(x_{k-N+\xi}^T) = K_\xi P_{virt}^{pre}(x_{k-N+\xi}^T) \prod_{j \in \Omega_\xi^i} P(z_{k-N+\xi}^j | x_{k-N+\xi}^T)$$

$$K_\xi = 1 / \int P_{virt}^{pre}(x_{k-N+\xi}^T) \prod_{j \in \Omega_\xi^i} P(z_{k-N+\xi}^j | x_{k-N+\xi}^T) dx_{k-N+\xi}^T$$

(4) Store the first-step virtual PDF as the individual PDF for time $(k-N+1)$

$$P_{pdf}^i(x_{k-N+1}^T | z_{1:k-N+1}^1, \dots, z_{1:k-N+1}^N) = P_{virt}^i(x_{k-N+1}^T).$$

Note that Ω_ξ^i denotes the index set of robots whose observation at time $(k-N+\xi)$ is stored in i^{th} robot's CB. The individual PDF of i^{th} robot at time k is $P_{virt}^i(x_k^T)$.

Remark 4: For the static target, each robot only needs current step CB to update individual PDFs. Therefore, except storing individual PDFs, all historical CBs can be discarded

and only current-step CB is stored in robot memory, the length of which is $O(N)$. On the contrary, for the moving target, each robot needs to store a triangular matrix of history observation (except current step CB) with size of $O(N^2)$ and an individual PDF with size $O(M^2)$, which means that the size of occupied memory in each robot is $O(M^2 + N^2)$.

IV. PROOF OF CONSISTENCY AND CONSENSUS

This section proves consistency and consensus of LIFO-DBF. Only proofs for localizing static target using static robots and moving robots are presented. The proof of LIFO-DBF for moving target is similar to that of static target by considering the dynamic model of the target, but with more complicated algebraic manipulation.

Assume that S is finite and x^{T*} is the true location. Define an *equivalent-location* set $X_{eq}^T \subseteq S$ such that

$$X_{eq}^T = \{x^T \in S | P(z_k | x^T) = P(z_k | x^{T*}), \forall z_k \in \{0, 1\}\},$$

i.e., x^T gives the same the observation likelihood as x^{T*} for given robot positions. Since X^T is finite, X_{eq}^T is also finite.

The reason to introduce equivalent-location set is that ghost target might exist in some special robot arrangement and sensor types. For example, for undirected binary sensors that are linearly arranged, a ghost target can exist at the mirror position of the true target. When sensors are overlapped at a single point, ghost targets can exist on a circle that contains the true target. In theory, DBF cannot rule out ghost targets in such cases and prior knowledge is needed for further clarification. This study only proves the convergence to the equivalent-location set rather to the true location.

A. Proof for static robots

The consistency of LIFO-DBF for static robots is stated as follows:

Theorem 1: For static robots, each individual PDF converges to X_{eq}^T using LIFO-DBF when the number of observations tends to infinity, i.e.

$$P_{pdf}^i(x^T \in X_{eq}^T | \mathbf{z}_{1:k}^i) \rightarrow 1, k \rightarrow \infty$$

where $\mathbf{z}_{1:k}^i = (z_{1:k}^1, \dots, z_{1:k}^N)$.

Proof: Considering the conditional independence of observations z_k^j for given $x^T \in S$, the batch form of DBF at k^{th} step is:

$$P_{pdf}^i(x^T | \mathbf{z}_{1:k}^i) = P_{pdf}^i(x^T | z_{1:k}^1, \dots, z_{1:k}^N)$$

$$= \frac{P_{pdf}^i(x^T) \prod_{j=1}^N \prod_{l=1}^{k_j} P(z_l^j | x^T)}{\sum_{x^T \in S} \prod_{j=1}^N \prod_{l=1}^{k_j} P(z_l^j | x^T)},$$

where P_{pdf}^i is i^{th} robot's initial individual PDF. It is known from Corollary 1 and Corollary 2 that $k-N < k_j \leq k$.

Compare $P_{pdf}^i(x^T | \mathbf{z}_{1:k}^i)$ with $P_{pdf}^i(x^{T*} | \mathbf{z}_{1:k}^i)$:

$$\frac{P_{pdf}^i(x^T | \mathbf{z}_{1:k}^i)}{P_{pdf}^i(x^{T*} | \mathbf{z}_{1:k}^i)} = \frac{P_{pdf}^i(x^T) \prod_{j=1}^N \prod_{l=1}^{k_j} P(z_l^j | x^T)}{P_{pdf}^i(x^{T*}) \prod_{j=1}^N \prod_{l=1}^{k_j} P(z_l^j | x^{T*})} \quad (6)$$

Take the logarithm of Eq. (6) and average it over k steps:

$$\frac{1}{k} \ln \frac{P_{pdf}^i(x^T | \mathbf{z}_{1:k}^i)}{P_{pdf}^i(x^{T*} | \mathbf{z}_{1:k}^i)} = \frac{1}{k} \ln \frac{P_{pdf}^i(x^T)}{P_{pdf}^i(x^{T*})} + \sum_{j=1}^N \frac{1}{k} \sum_{l=1}^{k_j} \ln \frac{P(z_l^j | x^T)}{P(z_l^j | x^{T*})} \quad (7)$$

Since $P_{pdf}^i(x^T)$ and $P_{pdf}^i(x^{T*})$ are bounded,

$$\lim_{k \rightarrow \infty} \frac{1}{k} \ln \frac{P_{pdf}^i(x^T)}{P_{pdf}^i(x^{T*})} \rightarrow 0 \quad (8)$$

The binary observations subject to Bernoulli distribution $B(1, p_j)$, yielding

$$P_{pdf}^i(z_k^j | x^T) = p_j^{z_k^j} (1 - p_j)^{1 - z_k^j}$$

where $p_j = P(z_k^j = 1 | x^T)$. Utilizing the facts: (1) z_l^j are conditionally independent samples from $B(1, p_j^*)$ and (2) $k - N < k_j \leq k$, the law of large numbers yields

$$\lim_{k \rightarrow \infty} \frac{1}{k} \sum_{l=1}^{k_j} z_l^j = p_j^*, \quad \lim_{k \rightarrow \infty} \frac{1}{k} (k_j - \sum_{l=1}^{k_j} z_l^j) = 1 - p_j^*$$

where $p_j^* = P(z_k^j = 1 | x^{T*})$. Then,

$$\lim_{k \rightarrow \infty} \frac{1}{k} \sum_{l=1}^{k_j} \ln \frac{P(z_l^j | x^T)}{P(z_l^j | x^{T*})} = p_j^* \ln \frac{p_j}{p_j^*} + (1 - p_j^*) \ln \frac{1 - p_j}{1 - p_j^*} \quad (9)$$

Note that the right-hand side of Eq. (9) achieves maximum if and only if $p_j = p_j^*$. Considering Eq. (8) and Eq. (9), the limit of Eq. (7) is:

$$\lim_{k \rightarrow \infty} \frac{1}{k} \ln \frac{P_{pdf}^i(x^T | \mathbf{z}_{1:k}^i)}{P_{pdf}^i(x^{T*} | \mathbf{z}_{1:k}^i)} = \sum_{j=1}^N p_j^* \ln \frac{p_j}{p_j^*} + (1 - p_j^*) \ln \frac{1 - p_j}{1 - p_j^*} \quad (10)$$

It is known from Eq. (10) that

1) When $p_j \neq p_j^*$, that is $x^T \notin X_{eq}^T$,

$$\lim_{k \rightarrow \infty} \frac{1}{k} \ln \frac{P_{pdf}^i(x^T | \mathbf{z}_{1:k}^i)}{P_{pdf}^i(x^{T*} | \mathbf{z}_{1:k}^i)} < 0, \text{ thus}$$

$$\lim_{k \rightarrow \infty} \frac{P_{pdf}^i(x^T | \mathbf{z}_{1:k}^i)}{P_{pdf}^i(x^{T*} | \mathbf{z}_{1:k}^i)} = 0$$

2) When $p_j = p_j^*$, that is $x^T \in X_{eq}^T$,

$$\lim_{k \rightarrow \infty} \frac{1}{k} \ln \frac{P_{pdf}^i(x^T | \mathbf{z}_{1:k}^i)}{P_{pdf}^i(x^{T*} | \mathbf{z}_{1:k}^i)} = 0, \text{ thus}$$

$$\lim_{k \rightarrow \infty} \frac{P_{pdf}^i(x^T | \mathbf{z}_{1:k}^i)}{P_{pdf}^i(x^{T*} | \mathbf{z}_{1:k}^i)} = 1$$

B. Proof for moving robots

The difficulty of consistency proof for moving robots lies in the fact that each robot observes at multiple positions. The main idea is to classify robot observation positions into two disjoint sets: *infinite-observation spots* that contains positions where a robot makes infinite observations, and *finite-observation spots* that contains positions where the robot makes finite observations. Before stating main theorem, the following lemma is introduced.

Lemma 1: For a set of robots with a collection of finite positions, each robot has at least one position where has infinite observations as k tends to infinity.

Proof: Let $n_j^{i,k}$ denote the times that i^{th} robot visits j^{th} position up to time k . Then, $\sum_j n_j^{i,k} = k$. It is straightforward to see that $\exists n_j^{i,k}$, such that $n_j^{i,k} \rightarrow \infty$, as $k \rightarrow \infty$. ■

Theorem 2: Under the condition of moving robots, each individual PDF by LIFO-DBF converges to X_{eq}^T when the number of observations tends to infinity, i.e.,

$$P_{pdf}^i(x^T \in X_{eq}^T | \mathbf{z}_{1:k}^i) \rightarrow 1, \quad k \rightarrow \infty$$

where $\mathbf{z}_{1:k}^i = (z_{1:k_1}^1, \dots, z_{1:k_N}^N)$.

Proof: Similar to Theorem 1, the batch form of DBF at k^{th} step is:

$$\frac{P_{pdf}^i(x^T | \mathbf{z}_{1:k}^i)}{P_{pdf}^i(x^{T*} | \mathbf{z}_{1:k}^i)} = \frac{P_{pdf}^i(x^T) \prod_{j=1}^N \prod_{l=1}^{k_j} P(z_l^j | x^T; x_l^R)}{P_{pdf}^i(x^{T*}) \prod_{j=1}^N \prod_{l=1}^{k_j} P(z_l^j | x^{T*}; x_l^R)} \quad (11)$$

The only difference from Eq. (6) is that $P(z_l^j | x^T; x_l^R)$ in Eq. (11) depends on x_l^R . For each robot, there exists at least one position from which infinite observations is made as $k \rightarrow \infty$, according to Lemma 1. All positions can be classified into finite-observation spots and infinite-observation spots. For the former, it is straightforward to know that their contribution to Eq. (10) is zero. Therefore, the proof of Eq. (11) can be reduced by only considering infinite-observation spots, which is similar to Theorem 1. ■

Remark 5: (TODO: what convergence is?) Under LIFO-DBF, consistency implies that all individual PDFs converge to the same X_{eq}^T , thus the consensus is guaranteed. It must be noted that traditional statistics dissemination-based methods only ensure consensus of individual PDFs. To the best knowledge of authors, there is no proof of consistency of individual PDFs?

V. SIMULATION

This section simulates three scenarios of target localization to demonstrate the effectiveness of LIFO-BDF. In all scenarios, six robots are utilized and each robot is equipped with a binary sensor. All sensors are modeled with identical Gaussian functions:

$$P(z = 1 | x^T; x^R) = \exp \left\{ -\frac{1}{2} (x^T - x^R)^T \Sigma^{-1} (x^T - x^R) \right\} \quad (12a)$$

$$P(z = 0 | x^T; x^R) = 1 - P(z = 1 | x^T; x^R). \quad (12b)$$

The first scenario consists of six static robots and single static target. The second scenario subsequently deals with six moving robots for localizing a single static target. Robot positions are randomly generated at each time step. The third scenario contains six moving sensors and one moving target. A single-integrator dynamics is used for the target motion model.

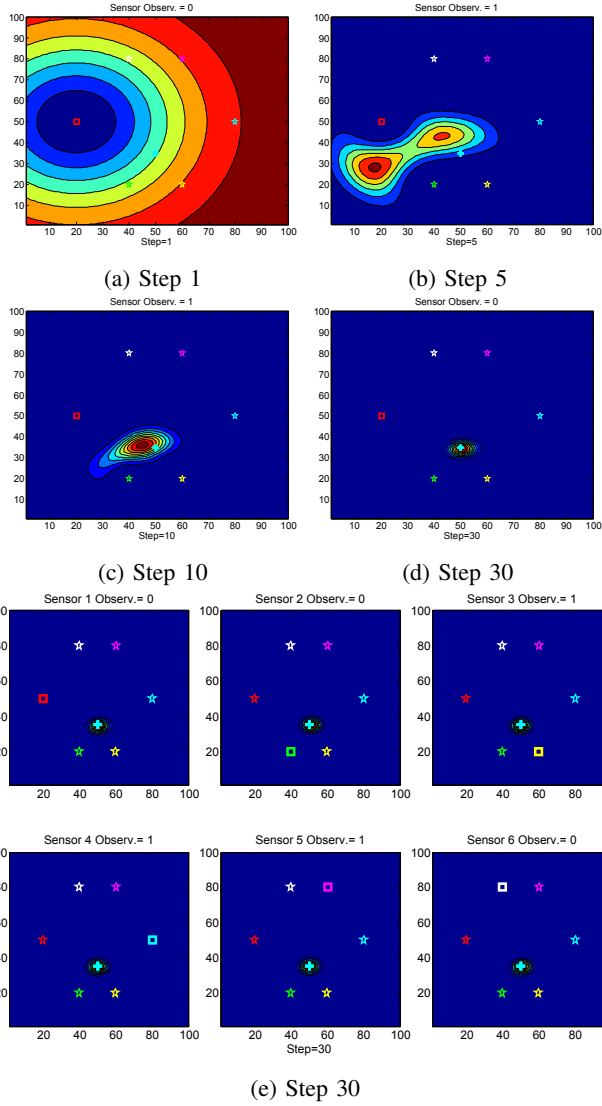


Fig. 4: (a)-(d): The 1st robot's individual PDFs at different time; (e) All robots' individual PDFs at time 30. The square denotes the current robot and stars represent other robots. The cross stands for the target.

A. Static Robots, Static Target

The positions of six static robots are shown as stars in Fig. 4. The LIFO-DBF for static target is implemented on each robot for target position estimation. Fig. 4 shows the estimation results of the static target. After the initial observation, each robot forms a circular individual PDF, centered at its own position. The circular PDF happens because the Gaussian sensor model (Eq. (12)) only depends on the distance between robot and target. As more observations are received, the posterior individual PDF concentrates (TODO: concentrate or converge?) on the true location of the target (Fig. 4d), which accords with the consistency of LIFO-DBF.

B. Moving Robots, Moving Target

The six robots move within the field to estimate the target position. In this work, the robot positions are randomly gen-

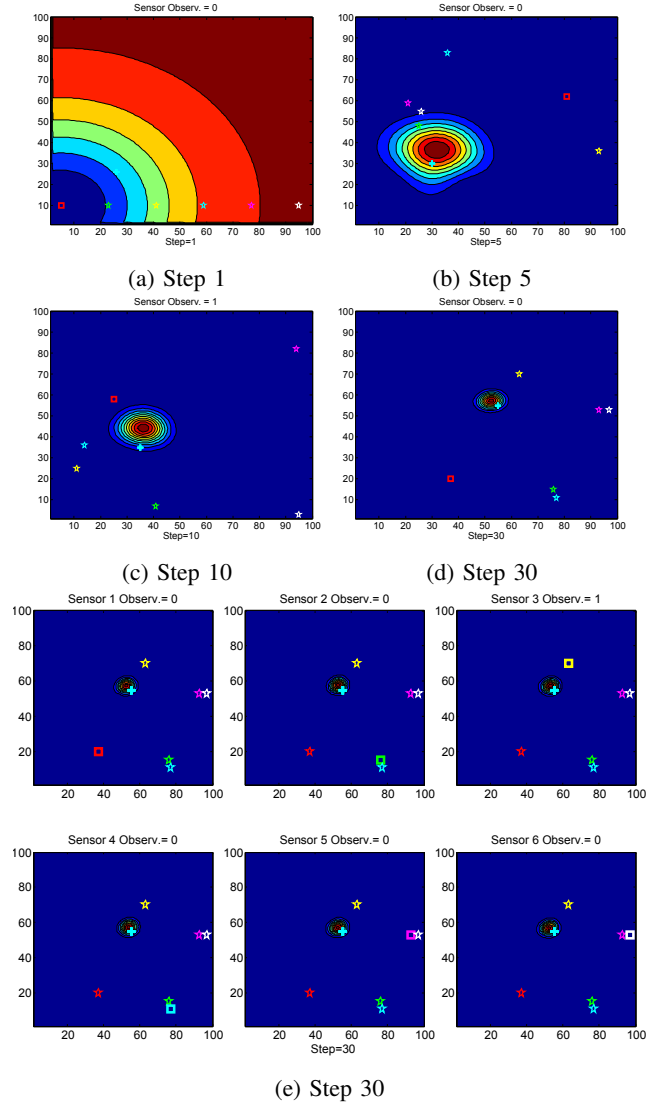


Fig. 5: (a)-(d): The 1st robot's individual PDFs at different time; (e) All robots' individual PDFs at time 30.

erated at each time in order to demonstrate the effectiveness of LIFO-DBF approach. The target dynamics is given by a single-integrator model:

$$x^T(k+1) = x^T(k) + v\Delta T$$

where v is the constant velocity of the target; ΔT is the sampling time.

The LIFO-DBF described in Section III-C is utilized for target localization. Fig. 5 shows the estimation results of the moving target. It is interesting to notice that the posterior individual PDFs concentrate to the true target location at each time, even when the target constantly moves.

VI. CONCLUSION

This paper presents the Latest-In-and-Full-Out (LIFO) strategy for measurement dissemination-based distributed Bayesian filters (DBF) in a multi-robot network. Different

from statistics dissemination approaches that transmit posterior distributions or likelihood functions, each robot under LIFO only receives the latest available measurements and then broadcasts full communication buffer to its neighborhood, which significantly reduces the transmission burden of each pair from the order of environmental size to that of robot number. Under the condition of fixed and undirected topology, LIFO can guarantee non-intermittent dissemination of all observations over the network within finite time via local communication among neighbors. Two types of LIFO-based DBF algorithms are proposed to estimate individual PDF for static and moving target, respectively. For the static target, each robot locally fuses the newly received observations while for the moving target, a triangular matrix of historical observations is stored and updated. The consistency of LIFO-based DBF is proved utilizing law of large numbers, which ensures that individual PDF of each robot converges to the true target position when the number of observations tends to infinity. (TODO: find out what convergence is)

Future work includes extensions to other types of sensors and switching topology. Other types of sensors may have biased observations and subject to non-Bernoulli distribution, which complicates the design and analysis of LIFO-based Bayesian filters. The switching topology, including package loss, can lead to unpredictable delay and intermittent transmission, which may affect the consistency and consensus of individual PDFs.

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