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Collaborative Multiple UAVs Navigation With GPS/INS/UWB Jammers Using Sigma Point Belief Propagation

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ABSTRACT Location awareness and navigation promote varieties of emerging applications of mobile collaborative multiple uncrewed aerial vehicles (UAVs). Cooperative UAVs fuse the global position system (GPS), inertial navigation systems (INS), peer to peer ranging radios derived from relative navigation of ultra-wideband (UWB) under complicated environments. Those information sources can be incorporated into spatiotemporal cooperation posited by the intra-user measurement of INS and GPS, and the inter-user measurement of the relative navigation of swarm UAVs. This paper considers the localization and navigation of multiple collaborative UAVs in networks with GPS/INS/UWB jammers in the case that the measurements are missed or randomly delayed by a sampling period. In a navigation situation with a partially denied navigation signals (e.g.GPS Jammers for some UAVs, UWB jammers for others, etc.), we propose an improved method of cooperation location for the swarm, allowing measurement jammers concerning the normal sigma point belief propagation (SPBP). This algorithm integrates message passing based on the Bayesian framework, a sigma point belief propagation of random packet loss (SPBP-RPL) to exploit spatiotemporal cooperation and measurement knowledge. Compared with existing general sigma point belief propagation, the advantages of the novel method are validated through a simulation of swarm UAVs with GPS/INS/UWB. Results show that the algorithm of combining spatiotemporal cooperation with measurement knowledge reduces the location uncertainty of swarm UAVs agents and improves location accuracy remarkably.

INDEX TERMS Collaborative networks belief propagation, location awareness and navigation for swarm UAVs, randomly delayed measurements, message-passing, sigma point belief propagation.

I. INTRODUCTION

Collaborative location awareness and navigation of assembled agents promote emerging applications of mobile multiple uncrewed aerial vehicles (UAVs) in scientific research [1], autonomous driving [2], [3], maritime situational awareness [4], communication relay [5] and battlefield surveillance [6]. Collaborative swarm UAVs can ensure the agents work collectively toward a common goal safely and reliably [4]. The Collaborative UAVs fuse GPS, inertial navigation systems (INS) [7], and peer to peer ranging-measurements derived from relative navigation of ultra-wideband (UWB) under complicated environments. Those information sources can be incorporated into spatiotemporal cooperation posited by the intra-user measurement of INS and GPS, and the inter-user measurement of the relative navigation of swarm UAVs. Especially in GPS-denied environments, the tightly coupled technology of UWB and INS are substantially efficient for short and intermediate-range localization [8]. The IoT techniques are essential for enabling those agents to share the mentioned measurements and messages amongst themselves [9].

The powerful collaborative localization algorithms have been mapped on graphical models by extensive measures, developing various message passing and sequential estimation strategies on Bayesian strategy.

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A net message-passing schedule algorithm, in particular, the sum-product algorithm over a wireless network (SPAWN), is a general Bayesian framework of the collaborative location. The accuracy of the algorithm was determined by the belief propagation of message-passing [10]. Various belief propagations exhibit superior empirical results in different scenarios. The sigma point belief propagation (SPBP) message passing scheme was proposed to approximate Bayesian estimation's marginalization corresponds to loopy factor graphs. SPBP requires significantly fewer computations and communications compared with existing nonparametric (particle-based) BP [11].

Meanwhile, Sigma point belief propagation (SPBP) was introduced into a scalable algorithm for network localization and synchronization [12]. Unfortunately, due to the network congestion of communication, message transmission misadventure may come along measurements transmission delays, packet dropouts and missing in an application environment. Message passing algorithms have been enabled by multitarget tracking, which can cope with missed, clutter detections [13]. Self-tuning algorithms were developed using belief propagation for multi-sensor and multitarget tracking for unknown model parameters, which dealt with the unknown association measurements affected by false alarms and missed-detections [14].

Due to an unknown number of objects and agents, Multitarget tracking (MTT) has to infer the states of these agents obligatorily from measurements, which is different from collaborative navigation. Those swarm UAVs serve as the Communication and Navigation Networks (CNN), and navigation autonomously is an exact understanding number of static and moving cooperative agents. The fusion algorithm used for jammers measurement plays a critical role in the state-of-the-art swarm UAVs. A large number of scholars in UAVs have conducted relevant research in recent years, including GPS with distance measuring sensors [15], [16], machine learning [10], and filtering techniques [17]. The researchers have proposed an algorithm of re-localizing UAV with a malfunction in its GPS receiver, which equipped the most of any other healthy UAVs [10]. However, the algorithm did not mine additional information about the jammer measurements for the scenario.

A Variational Bayesian (VB) based adaptive Kalman filter was designed with unknown the Bernoulli random variable and probabilities measurement noise [18]. However, the algorithm-established a master-slave cooperative localization framework, which was unpractical for network localization and navigation (NLN) due to decentralized network topology and the limited wide-scale in parallel. Moreover, UAVs are interestingly foresighted as an essential element of the Internet of Things, aiming at enabling measuring anything anytime and anywhere. The body of swarm UAVs should be considered a virtual entity, or UAVs -IoT [15]. Generally, collaborative multiple UAVs location and navigation in-network with jammers are planned for physical applications. Bayesian algorithms dealing with the localization of GPS jammers and a receiver's network were proposed in [19], [20]. The proposed algorithms for multiple GPS jammers formulated a bipartite graph to the weighted Gaussian probability hypothesis density based on particle belief propagation, required from the computational and communication resources. To our knowledge, in general, real-time must be compulsory. There is still short of a unified framework to fully simultaneously collaborate, localize, and measure intermittently for swarm UAVs. To solve the mentioned matter above, we propose a sigma point belief propagation of random packet loss (SPBP-RPL) to exploit spatiotemporal cooperation and measurement knowledge.

In our prior work [21], the Gaussian filter framework with intermittent measurements [22] was established, and the sequence of conditional error covariance was proved to be stochastically bounded. In this paper, the techniques address the message passing scheme on belief propagation with measurement jammers. In a navigation situation with partially denied navigation signals (e.g., GPS Jammers for some UAVs, UWB jammers for others, etc.), we propose an improved cooperation location for the swarm, allowing measurement jammers concerning the expected sigma point belief propagation (SPBP) [23]. We developed a graphical framework swarm UAVs with multiple measurement jammers intermittently based on spatiotemporal cooperation and measurement knowledge. We derived an SPBP-RPL filter, which formulates a measurement-estimation resolution involving all the UAVs augmented agent states.

Our contributions are presented as follows.

1. SPBP-RPL calculates the posterior probability distribution of the measurement jammer process. The noise state of multiple measurement jammers is expanded as association variables. A further principle is a definition of "UAVs augmented agent states," which involves all the UAVs agent states and multiple measurement jammer variables.

2. SPBP-RPL approximates the localization precision of SPBP when measurement vectors arrive on time and in orderly. SPBP-RPL with measurement jammers can degrade to the standard SPBP without measurement jammers while the probability of delay is zero.

The novel method's advantages are validated through a simulation of swarm UAVs with GPS/INS/UWB compared with that of existing general sigma point belief propagation. The paper is organized in the following. In Section II, we develop the system model of swarm UAVs and formulate the problem. In Section III, we elaborate on the SPBP-RPL message-passing scheme, including a graphical model of measurement jammers, collaborative relative navigation using belief propagation algorithm, and SPBP-RPL correction operation. Section IV verifies the proposed theoretical proposal. We conclude in Section V with a discussion.

II. SYSTEM MODEL AND PROBLEM FORMULATION

UAVs' collaborative navigation and positioning systems are modeled as multiple mobile agent nodes and various anchor points. Each mobile node self localizes in scenarios. Its intra-user measurements are obtained from the acceleration and angular velocity of inertial navigation systems (INS) to perform strap-down calculations. GPS signals are fed to correct the accumulated errors by the INS. Besides, UWB systems, namely inter-user measurements, accomplish robust communication and precision relative measurements simultaneously. UAVs in IoT have the capability of self-location and relative measure independent of the intra-user measures.

A. SYSTEM MODEL

We use relative measurements to modify the following errors of INS. Consider a general Gaussian process, $X = \{x_1^{(t)}, \cdots, x_k^{(t)} \cdots, x_K^{(t)}\}$ is a stochastic variable, whose realization $\mathrm{x} = \{\mathrm{x}_1^{(t)}, \cdots, \mathrm{x}_k^{(t)} \cdots, \mathrm{x}_K^{(t)}\}$ is swarm UAVs variable labeled finite sets of agent state. The state of the k-th UAV in the agent network is indicated by the vector $\mathrm{x}_k^{(t)} \in N_k$ at continuous time t, $\mathrm{x}_k^{(n)}$ at discrete-time $n \in \{0, 1, 2, \ldots\}$, and its neighbor is $N_k = \{l_1, l_2, \ldots, l_{|N_k|}\}$. We denote PDFs as $f(\cdot)$ and $h(\cdot)$, which are error estimation state equations and measurement equations of integrated navigation, respectively. Swarm UAVs using GPS generates measurements subducted intra-user measurements of INS, which is denoted as $\mathrm{z}_{\mathrm{self}} = \{z_{\mathrm{self},1}^{(t)}, \cdots, \mathrm{z}_{\mathrm{self},k}^{(t)} \cdots, \mathrm{z}_{\mathrm{self},K}^{(t)}\}$. It $\mathrm{z}_{\mathrm{self},k}^{(t)}$ is the GPS measurement of goal UAV k at time t, which is a general positioning or velocity match in this paper.

Inter-user measurements obtained via UWB ranges among users subducted intra-user measures of INS denotes $\mathrm{z}_{\mathrm{rel}} = \{z_{\mathrm{rel},1}^{(t)}, \cdots, \mathrm{z}_{\mathrm{rel},k}^{(t)} \cdots, \mathrm{z}_{\mathrm{rel},K}^{(t)}\}$. UAVs are distributed nutrition among its victims as well as to coordinate the operations of relief teams. For each agent $k \in \{1, 2, \ldots, K\}$ and its team, $l_i \in \{1, 2, \ldots, K\}\backslash\{k\}$ $k \in \{1, 2, \ldots, K\}\{k, l_i\} \in \varepsilon g(\cdot)$ is the UWB measurement PDF.

We consider pairwise measurements as two cases follow.

Case 1. Swarm UAVs may be mobile and pairwise measurements between UAV agents and anchors are given.

$$\begin{aligned} z &= g(\mathrm{x}_{k,l_i}) = g(\mathrm{x}_k, \mathrm{x}_{l_i}) + \mathrm{v}_{rel,k,l_i}^{(t)} \\ &= \mathrm{norm}(p_k^{\mathrm{INS}} - p_{l_i}^{\mathrm{anchor}}) - \mathrm{norm}(p_k^{\mathrm{agent\_UWB}} - p_{l_i}^{\mathrm{anchor}}) \\ &\quad + \mathrm{v}_{rel,k,l_i}^{(t)}(k, l_i) \in \varepsilon \end{aligned} \tag{1}$$

Those swarm UAVs are mobile agents labeled "agent_UWB," and those stationary UAVs are the anchors. These UAVs fitting in GPS/INS/UWB are unified mathematical coordinated frames as ENU. ENU=East, North, Up. $p_{k,j}^{\mathrm{INS}}$ is the position calculated by the intra-user measurement of INS and GPS, and that delta $\delta p_{k,j}$ is the position error of the state of INS integrated navigation. The physical ranges got from UWB here are labeled the norm $(p_k^{\mathrm{agent\_UWB}} - p_{l_i}^{\mathrm{anchor}})$. The navigation platform provides high-precision positioning via UWB, which can be obtained to compensate for the position calculated by INS or GPS / INS combined navigation

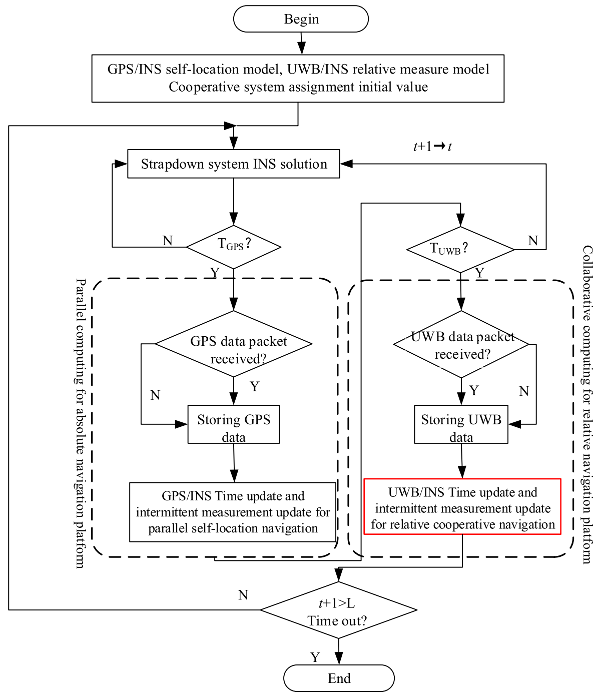

FIGURE 1. The system of multiple swarm UAVs using GPS/INS/UWB.

as follows.

$$\begin{aligned} &\mathrm{norm}(p_k^{\mathrm{agent\_UWB}} - p_{l_i}^{\mathrm{anchor}}) \\ &\quad = \sqrt{\sum_{j=E,N,U} (p_{k,j}^{\mathrm{UAV}} + \delta p_{k,j}) - p_{l_i,j}^{\mathrm{anchor}})^2} \end{aligned} \tag{2}$$

Case 2. Swarm UAVs may be mobile, and measurements in pairs between cooperative UAV agents are formulated during runtime as follows.

$$\begin{aligned} z &= g(\mathrm{x}_k, \mathrm{x}_{l_i}) + \mathrm{v}_{rel,k,l_i}^{(t)} \\ &= \mathrm{norm}(p_k^{\mathrm{INS}} - p_{l_i}^{\mathrm{INS}}) - \mathrm{norm}(p_k^{\mathrm{agent\_UWB}} - p_{l_i}^{\mathrm{agent\_UWB}}) \\ &\quad + \mathrm{v}_{rel,k,l_i}^{(t)}(k, l_i) \in \varepsilon \end{aligned} \tag{3}$$

$\mathrm{norm}(p_k^{\mathrm{INS}} - p_{l_i}^{\mathrm{INS}})$ is the relative ranging between the goal agent navigation platform and its team. $\mathrm{norm}(p_k^{\mathrm{agent\_UWB}} - p_{l_i}^{\mathrm{agent\_UWB}})$ is the relative reaching via UWB, and the navigation platform provides high-precision positioning via UWB, which can be obtained through position compensation through INS solution or GPS / INS combined navigation solution according to

$$\begin{aligned} &\mathrm{norm}(p_k^{\mathrm{agent\_UWB}} - p_{l_i}^{\mathrm{agent\_UWB}}) \\ &\quad = \sqrt{\sum_{j=E,N,U} ((p_{k,j}^{\mathrm{UAV}} + \delta p_{k,j}) - (p_{l_i,j}^{\mathrm{UAV}} + \delta p_{l_i,j}))^2} \end{aligned} \tag{4}$$

B. PROBLEM STATEMENT

The swarm UAVs navigation schedule is given in Figure 1, which is illustrated as a general message schedule for collaborating navigation and location in GPS/INS/UWB heterogeneously. Figure 1 introduces a message schedule that

UAV node self-locates thanks to GPS/INS in absolute parallel navigation, and multiple navigation agents compute for relative location in collaboration. Both intra-user GPS/INS measures and inter-user UWB/INS measures constraint of the spatial and temporal message transfer. When intra-user measures or inter-user measures suffer from intermittent jammer, GPS/INS individual infers to intermittent measurement update in parallel, and all UWB/INS conclude to intermittent measurement update in collaborative. Our previous paper has proposed the Gaussian filter for an individual platform with intermittent measurement based on the Bayes framework. We develop a Bayesian scheme for spatiotemporal collaborative navigation (the corresponding red estimator, defined as SPBP-RPL) due to heterogeneous measurement intermittent jammers.

Some fundamental assumptions have illustrated as follows, which are rational in this context.

a) The agents' state is independent priority and movement in the way of the memoryless random walk.

$$p\left(\mathrm{x}^{(0)}\right)=\prod\nolimits_{i=1}^{N}p(\mathrm{x}_i^{(0)});$$
$$p\left(\mathrm{x}^{(0:T)}\right)=p\left(\mathrm{x}^{(0)}\right)\prod_{t=1}^{T}p(\mathrm{x}^{(n)}|\mathrm{x}^{(n-1)});$$
$$p(\mathrm{x}^{(n)}|\mathrm{x}^{(n-1)})=\prod_{i=1}^{N}p(\mathrm{x}_i^{(n)}|\mathrm{x}_i^{(n-1)}) \tag{5}$$

b) Cooperative localization consists of absolute internal navigation and relative location, independent, considering the states.

$$p\left(\mathrm{z}_{\mathrm{rel}}^{(1:T)}|\mathrm{z}_{\mathrm{rel}}^{(0:T)},\mathrm{x}^{(0:T)},\mathrm{z}_{\mathrm{self}}^{(1:T)}\right)=p\left(\mathrm{z}_{\mathrm{rel}}^{(1:T)}|\mathrm{z}_{\mathrm{rel}}^{(0:T)},\mathrm{x}^{(0:T)}\right) \tag{6}$$

The state vector of a collaborative platform of kth goal agent and the neighbors on the communication link is $\overline{\mathrm{x}}_k^n=\{x_k^{\mathrm{T}}x_{l_1}^{\mathrm{T}}x_{l_2}^{\mathrm{T}}\cdots x_{l_{|N_k|}}^{\mathrm{T}}\}$ where $\{k,l_i\}\in\varepsilon k\in\{1,2,\ldots,K\}l_i\in\{1,2,\ldots,K\}\backslash\{k\}$.

The posterior probability of Bayesian estimation is established for a collaborative navigation filter [11].

$p\left(\mathrm{x}^{(0:T)}|\mathrm{z}^{(1:T)}\right)\propto p\left(\mathrm{x}^{(0:T)},\mathrm{z}_{\mathrm{self}}^{(1:T)}\right)p\left(\mathrm{z}_{\mathrm{rel}}^{(1:T)}|\mathrm{x}^{(0:T)}\right)$ is factorized as:

$$\begin{aligned}
&p\left(\mathrm{x}^{(0:T)}|\mathrm{z}^{(1:T)}\right)\\
&\propto p(\mathrm{x}^{(0)})\prod_{t=1}^{T}\{p\left(\mathrm{x}^{(t)}|\mathrm{x}^{(t-1)}\right)\\
&\quad\times p\left(\mathrm{z}_{\mathrm{self}}^{(t)}|\mathrm{x}^{(t)},\mathrm{x}^{(t-1)},\mathrm{z}_{\mathrm{self}}^{(t-1)}\right)\times p\left(\mathrm{z}_{\mathrm{rel}}^{(t)}|\mathrm{x}^{(t)},\mathrm{z}_{\mathrm{rel}}^{(t-1)}\right)\}
\end{aligned} \tag{7}$$

$p(\mathrm{x}^{(t)}|\mathrm{x}^{(t-1)})$ is independent movement from $p(\mathrm{z}_{\mathrm{self}}^{(t)}|\mathrm{x}^{(t)},\mathrm{x}^{(t-1)},\mathrm{z}_{\mathrm{self}}^{(t-1)})$ and $p(\mathrm{z}_{\mathrm{self}}^{(t)}|\mathrm{x}^{(t)},\mathrm{z}_{\mathrm{self}}^{(t-1)})$, hence partial expression in (7) can be factorized as.

$$\begin{aligned}
p\left(\mathrm{z}_{\mathrm{self}}^{(t)}|\mathrm{x}^{(t)},\mathrm{x}^{(t-1)},\mathrm{z}_{\mathrm{self}}^{(t-1)}\right)=&\prod_{n=1}^{T}p\left(\mathrm{x}^{(t)}|\mathrm{x}^{(t-1)}\right)\\
&\times p\left(\mathrm{z}_{\mathrm{self}}^{(t)}|\mathrm{x}^{(t)},\mathrm{z}_{\mathrm{self}}^{(t-1)}\right)
\end{aligned} \tag{8}$$

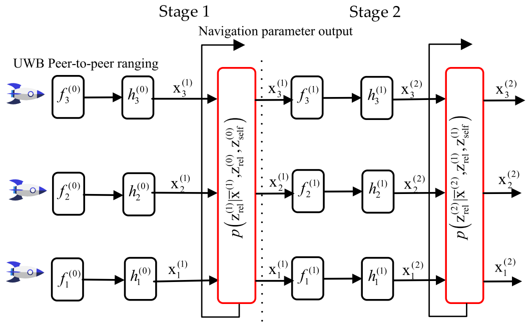

FIGURE 2. **The factor graph of** $p\left(\overline{\mathrm{x}}^{(0:2)}|\mathrm{z}_{\mathrm{rel}}^{(1:2)},\mathrm{z}_{\mathrm{self}}^{(1:2)}\right)$.

$$p\left(\mathrm{z}_{\mathrm{rel}}^{(t)}|\mathrm{x}^{(t)},\mathrm{z}_{\mathrm{rel}}^{(t-1)}\right)=\prod_{n=1}^{T}p\left(\mathrm{z}_{\mathrm{rel},k}^{(t)}|\mathrm{x}^{(t)},\mathrm{z}_{\mathrm{rel},k}^{(t-1)}\right) \tag{9}$$

The factor graph $p\left(\mathrm{x}^{(0:2)}|\mathrm{z}^{(1:2)}\right)$ in collaboration navigation filter is structured as Figure 2.

Some simplified form in $f(\mathrm{x}^{(0)})=p(\mathrm{x}^{(0)})$ and $h_k^{(t-1)}=p\left(\mathrm{x}_k^{(t)}|\mathrm{x}_k^{(t-1)}\right)p\left(\mathrm{z}_{\mathrm{self},k}^{(t)}|\mathrm{x}^{(t)},\mathrm{x}_k^{(t-1)}\mathrm{z}_{\mathrm{rel}}^{(t-1)},\mathrm{z}_{\mathrm{self},k}^{(t-1)}\right)$. The vertices in the corresponding red factor in Figure 2, $t=1,2$. $p\left(\mathrm{z}_{\mathrm{rel}}^{(t)}|\overline{\mathrm{x}}^{(t)},\mathrm{z}_{\mathrm{rel}}^{(t-1)},\mathrm{z}_{\mathrm{self}}^{(t-1)}\right)=p\left(\mathrm{z}_{\mathrm{rel},k}^{(t)}|\overline{\mathrm{x}}^{(t)},\mathrm{z}_{\mathrm{rel},k}^{(t-1)}\right)=\prod_{l}g(\mathrm{z}_{k,l}|\mathrm{x}_k,\mathrm{x}_l)$

The Co-navigation filter in the red box is to establish the posterior probability of Bayesian estimation

$$f(\mathrm{x}|\mathrm{z})\propto\prod_{k=1}^{K}f(\mathrm{x}_k)\prod_{\substack{k',l\in\varepsilon\\k'>l}}^{K}g(\mathrm{z}_{k',l}|\mathrm{x}_{k'},\mathrm{x}_l) \tag{10}$$

c) The measurement z (Here $\mathrm{z}_{\mathrm{rel},k}^{(t)}$ is the relative measurement using UWB and is abbreviated as z) transmitting to the filter may suffer multi-step packet dropout or delay [8][9][24]. Considering the process of fundamental principles and derivation simplification, we adopted a 1-step delay model as follows.

$$\mathrm{y}^{(n)}=(1-r^{(n)})\mathrm{z}^{(n)}+r^{(n)}\mathrm{z}^{(n-1)}\quad n=0:T,\ \mathrm{y}^{(1)}=\mathrm{z}^{(1)} \tag{11}$$

$\mathrm{z}^{(n)}\in\mathrm{R}^m$ is ideal measurement output; $\mathrm{y}^{(n)}\in\mathrm{R}^m$ is a measured value in reality;$r^{(n)}$ is assumed to be a sequence of Bernoulli distribution, and its values are 0 and 1, and Prob$\{r^{(n)}\}$is associated with $p^{(n)}$. When $r^{(n)}=0$, the system has obtained the actual observation measurement, and the observation noise is a presupposed value; when $r^{(n)}=1$, the system has not received the physical observation measurement, and the system uses the measurement value of the previous moment instead. It is necessary to estimate the UAVs state at the current moment and associated observation noise. SPBP message passing scheme should be modified due to transmission delays, multiple packet dropouts, and correlated noises.

III. SPBP-RPL MESSAGE PASSING SCHEME

Firstly, we elaborate on the SPBP-RPL algorithm that integrates message-passing based on the Bayesian framework, a sigma point belief propagation of random packet loss to exploit spatiotemporal cooperation and measurement knowledge. Secondly, we present the algorithm on the base of the SPBP-RPL message-passing scheme. Both problem formulation and assumptions [10] about the Bayesian cooperative will be considered. For the sake of the illustration, we address the graphical model of measurement jammers. We then deduce the collaborative relative navigation algorithm with GPS/INS/UWB jammers using belief propagation algorithm. The steps of SPBP-RPL correction operation are detailed following.

A. THE SPBP-RPL MESSAGE PASSING SCHEME

A marginal approximation is established by using the factor graph of BP message passing [11][12], and the belief of variable agent kth $b^{(p)}(\overline{\mathrm{x}}_k^n)$ is approximate by a posterior distribution $f(\overline{\mathrm{x}}_k^n \left|\overline{\mathrm{z}}_k^n\right.)$, which is suitable for timely measurement, and p is the number of message iterations.

$$b^{(p)}(\overline{\mathrm{x}}_k^n) \approx f(\overline{\mathrm{x}}_k^n \left|\overline{\mathrm{z}}_k^n\right.) \tag{12}$$

The measured value of cooperative relative navigation filters $\mathrm{z}_{\mathrm{rel},k}^{(t)}$ is abbreviated as $\overline{\mathrm{z}}_k^{(t)} = [\mathrm{z}_k^{(t)}\mathrm{z}_{l_1}^{(t)}\mathrm{z}_{l_2}^{(t)}\cdots\mathrm{z}_{l_{|N_k|}}^{(t)}]^{\mathrm{T}}$, which represents the observational measurement with the navigation platform kth; the measurement value is composed of the pairwise measure of the corresponding platform lth associated with the navigation platform kth:

$$\mathrm{z}_{\mathrm{rel},k,l}^{(t)} = g(\mathrm{x}_k, \mathrm{x}_l) + \mathrm{v}_{\mathrm{rel},k,l}^{(t)} \quad \{k, l_i\} \in \varepsilon \tag{13}$$

$\mathrm{z}_{\mathrm{rel},k,l}^{(t)}$ abbreviated as $\mathrm{z}_{k,l}^{(t)}$ and discretized $\mathrm{z}_{k,l}^{(n)}$, and fulfilled $g(\mathrm{x}_k, \mathrm{x}_l) = g(\mathrm{x}_l, \mathrm{x}_k)$.

Relative measurements are depending on the adjacent time slot based on the states of all agents.

$$p\left(\mathrm{z}_{\mathrm{rel}}^{(1:T)}|\mathrm{x}^{(1:T)}\right) = \prod_{n=1}^{T} p(\mathrm{z}_{\mathrm{rel}}^{(n)}|\mathrm{z}_{\mathrm{rel}}^{(n-1)}, \mathrm{x}_k^{(n)}) \tag{14}$$

Since the BP message passing in (14) is the physical observation measurement form. It is difficult to use this method directly due to the intermittent with unknown measurement jammers. It is necessary to gather intermittent measurement information and estimate UAVs state at the current moment, associated observation noise. (14) is rearranged as

$$\begin{aligned} &p\left(\mathrm{z}_{\mathrm{rel}}^{(n)}|\mathrm{z}_{\mathrm{rel}}^{(n-1)}, \mathrm{x}^{(n)}\right) \\ &\quad = \prod_{i=1}^{N} \prod_{j\in\Theta_{\to i}^{(n)}} p\left(\mathrm{z}_{j\to i}^{(n)}|\mathrm{z}_{j\to i}^{(n-1)}, \mathrm{r}_{j\to i}^{(n-1)}, \mathrm{x}_k^{(n)}, \mathrm{x}_j^{(n)}\right) \end{aligned} \tag{15}$$

$\Theta_{\to i}^{(n)}$ is the set of agent nodes. Node i may receive a message from which during time slot n. $\mathrm{z}_{j\to i}^{(n)}$ presents that platform i receives relative ranging observations from platform j.

A posteriori distribution can be described as

$$\begin{aligned} p\left(\mathrm{x}^{(0:T)}, \mathrm{v}^{(0:T)}|\mathrm{z}_{\mathrm{rel}}^{(1:T)}\right) &= \prod_{n=1}^{T} p\left(\mathrm{x}^{(n)}, \mathrm{v}^{(n)}|\mathrm{z}_{\mathrm{rel}}^{(n)}\right) \\ &= \prod_{n=1}^{T} p\left(\mathrm{x}^{(n)}, \mathrm{v}^{(n)}|\mathrm{z}_{\mathrm{rel}}^{(n)}, \mathrm{z}_{\mathrm{rel}}^{(n-1)}\right) \end{aligned} \tag{16}$$

The direct posterior PDF $p\left(\mathrm{x}^{(n)}, \mathrm{v}^{(n)}|\mathrm{z}_{\mathrm{rel}}^{(n)}, \mathrm{z}_{\mathrm{rel}}^{(n-1)}\right)$ is infeasibly obtained the state of the mean vector and covariance matrix. In such a situation, one turn to BP message passing $b_{\overline{\mathrm{x}}}(\cdot)$.

$$\begin{aligned} &p\left(\mathrm{z}_{\mathrm{rel}}^{(n)}, \mathrm{z}_{\mathrm{rel}}^{(n-1)}|\mathrm{x}^{(n)}, \mathrm{v}^{(n)}\right) \\ &\quad = \prod_{k=1}^{N} \prod_{j\in\Theta_{\to k}^{(n)}} p\left(\mathrm{z}_{j\to k}^{(n)}|\mathrm{z}_{j\to k}^{(n-1)}, \mathrm{x}_k^{(n)}, \mathrm{v}_k^{(n)}, \mathrm{x}_j^{(n)}, \mathrm{v}_j^{(n)}\right) \end{aligned} \tag{17}$$

We define $\mathrm{x}_a^{(n)} = [\mathrm{x}_k^{(n)}\mathrm{v}_k^{(n)}]^T$ (17) is rearranged as

$$p\left(\mathrm{z}_{\mathrm{rel}}^{(n)}, \mathrm{z}_{\mathrm{rel}}^{(n-1)}|\mathrm{x}_a^{(n)}\right) = \prod_{k=1}^{N} \prod_{j\in\Theta_{\to k}^{(n)}} p\left(\mathrm{z}_{j\to k}^{(n)}|\mathrm{z}_{j\to k}^{(n-1)}, \mathrm{x}_{a,k}^{(n)}, \mathrm{x}_{a,j}^{(n)}\right) \tag{18}$$

The joint PDF can obtain BP message passing

$$\begin{aligned} b^{(p)}(\mathrm{x}_{a,k}^{(n)}) &\propto f(\mathrm{x}_{a,k}^{(n)}|\mathrm{z}_{a,k}^{(n)}) \\ &= \int b^{(p)}(\overline{\mathrm{x}}_{a,k}^{(n)}) d\overline{\mathrm{x}}_{a,k}^{\sim k} \\ &= \int g(\overline{\mathrm{z}}_{a,k}^{(n)} \left|\overline{\mathrm{x}}_{a,k}^{(n)}\right., \overline{\mathrm{z}}_{a,k}^{(n-1)}) f^{(p-1)}(\overline{\mathrm{x}}_{a,k}^{(n)}) d\overline{\mathrm{x}}_{a,k}^{\sim k} \end{aligned} \tag{19}$$

where $\overline{\mathrm{x}}_{a,k}^{(n)} = \left[[\mathrm{x}_{a,k}^{(n)}]^T[\mathrm{x}_{a,N_{k1}}^{(n)}]^T\,[\mathrm{x}_{a,N_{k2}}^{(n)}]^T \cdots [\mathrm{x}_{aN_k}^{(n)}]^T\right]^T$ $\mathrm{x}_{a,N_{k1}}^{(n)}$ is the first collaborative platform adjacent to the goal platform k. $\overline{\mathrm{x}}_{a,k}^{\sim k}$ is express $\overline{\mathrm{x}}_{a,k}^{(n)}$ after removing $[\mathrm{x}_k^{(n)}\mathrm{v}_k^{(n)}]^T$. Define its neighbor set as $N_{\mathrm{k}} = \{l_1, l_2, \ldots l_{|N_k|}\}$ of node $k \in \{1, 2, \cdots K\}$ include all $l \in \{1, 2, \cdots K\}\backslash\{k\}$. $f^{(p-1)}(\overline{\mathrm{x}}_{a,k}^{(n)})$ and $g(\overline{\mathrm{z}}_{a,k}^{(n)} \left|\overline{\mathrm{x}}_{a,k}^{(n)}\right., \overline{\mathrm{z}}_{a,k}^{(n-1)})$ in (19) can be approximate as the following.

$$f^{(p-1)}(\overline{\mathrm{x}}_{a,k}^{(n)}) \propto f(\mathrm{x}_{a,k}) \prod_{l\in N_k} n_{l\to k}^{(p-1)}(\mathrm{x}_{a,k}) \tag{20}$$

$$g(\overline{\mathrm{z}}_{a,k}^{(n)}|\overline{\mathrm{x}}_{a,k}^{(n)}, \overline{\mathrm{z}}_{a,k}^{(n-1)}) = \prod_{l\in N_k\backslash\{k\}} g(\overline{\mathrm{z}}_{k,l}^{(n)} \left|\overline{\mathrm{z}}_{k,l}^{(n-1)}\right., \overline{\mathrm{x}}_{a,k}^{(n)}, \overline{\mathrm{x}}_{a,l}^{(n)}) \tag{21}$$

B. THE GRAPHICAL MODEL OF MEASUREMENT JAMMERS

Bayesian estimation of the belief of node k at iteration p is deduced in [[24]] for the sake of SPBP

$$b_{\mathrm{x}_k^{(n)}}^{(p)} \propto f(\mathrm{x}_k^{(n)}) \prod_{i\in N_k^{(n)}} m_{n_{i\to k}^{(n)}\to \mathrm{x}_k^{(n)}}^{(p)}(\mathrm{x}_k^{(n)})$$

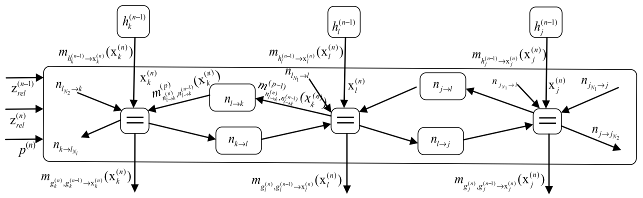

FIGURE 3. SPBP-RPL using information interaction factor diagram due to jammers measured.

where $m^{(p)}_{n^{(n)}_{i\to k}\to x^{(n)}_k}(x^{(n)}_k) = \int g(z^{(t)}_{l\to k}|\overline{x}^{(t)}_l, \overline{x}^{(t)}_k) n^{(p-1)}_{l\to k}(x^{(t)}_l) dx_l$ $l \in N_k$ with

$$n^{(p-1)}_{l\to k}(x^{(t)}_l) = f(x_l) \prod_{i\in N^{(t)}_k \setminus \{k\}} m^{(p-1)}_{n^{(t)}_{i\to k}\to x^{(t)}_k}(x^{(t)}_k) \quad (i,k) \in \varepsilon$$

It is initialized the recursion by setting $n^{(0)}_{l\to k}(x^{(t)}_l)$ as the prior of $x^{(0)}_l$. When measurement jammers occur during information interaction with relative navigation, the proposed SPBP-RPL message passing differs from the standard SPBP. The interaction factor diagram of SPBP-RPL message passing is shown in Figure 3. The arrow represents the direction of information transfer. The schedule includes the prediction operation and correct operation. Considering the jammers in the case that the measurements are missed or randomly delayed by a sampling period, this algorithm extends the state of the mean state vector and the measurement noise vector. We substitute $x^{(n)}_{a,k}$ for $x^{(n)}_k$, gather intermittent information about the relationship of two adjacent measurement periods and elaborate the logic of technical research.

The message $m_{h^{(n-1)}_k \to x^{(n)}_k}(\cdot)$ is computed on the state model $p(x^{(n)}_k|x^{(n-1)}_k)$, the message $m_{g^{(n-2)}_k, g^{(n-1)}_k \to x^{(n-1)}_k}(\cdot)$, and the absolute measurement likelihood function $p(z^{(n)}_{\text{self},k}| x^{(n-1)}, \overline{z}^{(n)}_k)$ for the formal prediction operation. For the latter correction operation, the message $m_{g^{(n-1)}_k, g^{(n)}_k \to x^{(n)}_k}(\cdot)$ is computed on the appointed node kth relative measurements $g(z^{(n)}_{l\to k} \left| z^{(n-1)}_{l\to k}, \overline{x}^{(n)}_{a,l}, \overline{x}^{(n)}_{a,k} \right.)$ between all other nodes and all the messages $n^{(p)}_{l\to k}(x^{(n)}_{a,l})$. The message $n^{(p)}_{l\to k}(x^{(n)}_{a,l})$ is computed on $p(x^{(n)}_k|x^{(n-1)}_k)$ and the message $m_{n^{(n)}_{i\to k}, n^{(n-1)}_{i\to k} \to x^{(n)}_k}(\cdot)$. The message $m^{(p)}_{n^{(n)}_{l-k}, n^{(n-1)}_{l\to k}}(\cdot)$ is required to deliver information in all nodes, not only the moment but also the last moment.

$$m^{(p)}_{n^{(n)}_{l\to k}, n^{(n-1)}_{l\to k}}(x^{(n)}_k) = \int g(z^{(t)}_{l\to k}|z^{(t-1)}_{l\to k}, \overline{x}^{(t)}_{a,l}, \overline{x}^{(t)}_{a,k}) n^{(p-1)}_{l\to k}(x^{(t)}_{a,l}) dx_{a,l} \quad (22)$$

$$n^{(p-1)}_{l\to k}(x^{(t)}_{a,l}) = f(x_{a,l}) \prod_{i\in N^{(t)}_k \setminus \{k\}} m^{(p-1)}_{n^{(t)}_{i\to k}, n^{(t-1)}_{i\to k} \to x^{(t)}_k}(x^{(t)}_{a,k}) \quad (i,k) \in \varepsilon \quad (23)$$

The initial $n^{(0)}_{l\to k}(x^{(t)}_{a,l}) = f(x^{(0)}_{a,l})$

$$b^{(p)}_{x^{(n)}_{a,k}} = f(x^{(n)}_{a,k}) \prod_{i\in N^{(n)}_k} m^{(p)}_{n^{(n)}_{i\to k}, n^{(n-1)}_{i\to k} \to x^{(n)}_{a,k}}(x^{(n)}_{a,k}) \quad (24)$$

When $\overline{z}^k_{\text{rel},l\to k} = \overline{z}^k_{\text{rel},k\to l}$ it concludes that $n^{(p)}_{i\to k}(x^{(n)}_{a,l}) = b^{(p)}(x^{(n)}_{a,k})$, and (22) can be formulated as

$$m^{(p)}_{n^{(n)}_{i\to k}, n^{(n-1)}_{i\to k} \to x^{(n)}_k}(x^{(n)}_{a,k}) = b(x^{(n)}_{a,k}) \quad (25)$$

Since (22) denotes the $m^{(p)}_{n^{(n)}_{i\to k}, n^{(n-1)}_{i\to k} \to x^{(n)}_k}(x^{(n)}_{a,k})$ at iteration p, we need to calculate (23)

$$n^{(p-1)}_{l\to k}(x^{(t)}_{a,l}) = \int g(\overline{z}^{\sim k,(t)}_{\text{rel},l\to k} \left| \overline{x}^{\sim k,(t)}_{a,l}, \overline{z}^{\sim k,(t-1)}_{\text{rel},l\to k} \right.) f^{(p-1)}(\overline{x}^{\sim k}_{a,k}) d\overline{x}^{\sim k}_{a,k} \quad (26)$$

According to(22), (24) can be formulated as

$$b^{(p)}_{x^{(n)}_{a,k}} = \int g(\overline{z}^{(t)}_{\text{rel},k}|\overline{x}^{(t)}_{a,k}, \overline{z}^{(t-1)}_{\text{rel},k}) f^{(p-1)}(\overline{x}^{(t)}_{a,k}) d\overline{x}^{\sim k}_{a,k} \quad (27)$$

and $g(\overline{z}^{\sim k,(t)}_{\text{rel},l\to k} \left| \overline{x}^{\sim k,(t)}_{a,l}, \overline{z}^{\sim k,(t-1)}_{\text{rel},l\to k} \right.)$ can be driven by

$$g(\overline{z}^{\sim k,(t)}_{\text{rel},l\to k} \left| \overline{x}^{\sim k,(t)}_{a,l}, \overline{z}^{\sim k,(t-1)}_{\text{rel},l\to k} \right.) = \prod_{k'\in N_l \setminus \{k\}} g(\overline{z}^{(n)}_{k',l} \left| \overline{z}^{(n-1)}_{k',l}, \overline{x}^{(n)}_{a,k'}, \overline{x}^{(n)}_{a,l} \right.) \quad (28)$$

$g(\overline{z}^{(t)}_{\text{rel},k}|\overline{x}^{(t)}_{a,k}, \overline{z}^{(t-1)}_{\text{rel},k})$ in (27) is formulated accordingly (21). Employing (20)-(28), $b^{(p)}_{x^{(n)}_{a,k}}$ can be calculated recursively and $x^{(n)}_{a,k}$ intercepted $x^{(n)}_k$ to update the navigation platform information.

C. COLLABORATIVE RELATIVE NAVIGATION WITH GPS/INS/UWB JAMMERS USING BELIEF PROPAGATION ALGORITHM

In our case, there are two classes of measurement:

a). The intra-user messages of INS and GPS, $h(z^t_{k,\text{self}}|z^{t-1}_{k,\text{self}}, x^t_k)$, including INS measurements obtained from acceleration and angular velocity to perform strap-down calculations and GPS associated with the position and velocity measurements.

b). The inter-user messages $m_{n^{(n)}_{i\to k}, n^{(n)}_{i\to k}}(x^{(n)}_k)$, associated measurements of the relative navigation of swarm UAVs using UWB.

The proposed belief propagation concludes the sum of sum-product messages and the SPBP-RPL correction operation. The steps of belief propagation are developed below.

---

step 1: **for** $n = 1$ to T do: (where T is Total time)
step 2: Initialize $x^{(0)}_i$, $\forall i, p^{(0)}$, $i \in N_k$ (where N_k is the Total number of mobile navigation platform)
Absolute navigation platforms

step 3: for node $k=1$ to N_k **in parallel**

$$n_{h_k^{n-1}\to x_k^n}(x_k^n) \propto \int f(x_k^t|x_k^{t-1}) n_{x_k^{t-1}\to h_k^{t-1}}(x_k^t) h(z_{k,\text{self}}^t|z_{k,\text{self}}^{t-1}, x_k^t) d\overline{x}_l^{\sim l}\; l \in N_k$$

step 4: **end parallel**
Cooperative Navigation Platforms
step 5: Initialize $b_{x_{a,k}^{(n)}}^{(p=0)} = n_{h_{a,k}^{(n-1)}\to x_{a,k}^{(n)}}(x_{a,k}^{(n)})$
step 6: for $p=1$: N_{iter} **in iteration**do: (where N_{iter} is the Total iteration)
step 7: for node $k=1$ to N_k **in parallel**
step 8: broadcast $b_{x_{a,k}^{(n)}}^{(p-1)}(x_{a,k}^{(n)})$ to its neighbors l. $\{k,l\} \in \varepsilon, l \in N_{k\to}$
step 9: receive $b_{x_{a,l}^{(n)}}^{(p-1)}(x_{a,l}^{(n)})$, from its neighbors l. $\{k,l\} \in \varepsilon, l \in N_{\to k}$
step 10: (22) is utilized to interact with the information between adjacent navigation platforms and $m_{n_{i\to k}^{(n)}, n_{i\to k}^{(n-1)}}^{(p-1)}(x_{a,k}^{(n)})$ is derived.
Step 11: (27) is utilized to renovate $b_{x_{a,k}^{(n)}}^{(p)}$ and $x_k^{(n)}$ is intercepted form $x_{a,k}^{(n)}$.
step 12: **end parallel**
step 13: **end iteration**
step 14: **nodes** $i=1$ to N, $x_i^{(0)}$, $\forall i$ **in parallel**
step 15: cooperative navigation message update $n_{x_k^{(n)}\to h_k^{(n)}}^{(n)}(x_k^{(n)}) = b_{x_k^{(n)}}^{(N_{iter})}(x_k^{(n)})$
step 16: **end parallel**
step 17: **end for**

The algorithm in step 5- step 16 is detailed in the following SPBP-RPL correction operation.

D. SPBP-RPL CORRECTION OPERATION

Since the measurements are jammed, it needs to estimate the posterior PDFs of the state from $p(x^n|z^n)$, as well as the posterior PDFs $p(v^n|z^n)$. The expanded state is $x_a^{(n)} = [x_k^{(n)} v_k^{(n)}]^T$, that is, the state vector of a collaborative platform of goal agent k and the neighbors on the communication link is $\overline{x}_{a,k}^{(n)} = [x_{a,k}^{(n)},\ x_{a,l_1}^{(n)},\ x_{a,l_2}^{(n)}, \cdots,\ x_{a,l_{|N_k|}}^{(n)}]^T$.

(20) is approximated as follows.

$$f^{(p-1)}(\overline{x}_{a,k}^{(n)}) \;\propto\; f(x_{a,k}) \prod_{l\in N_k}^{n_{l\to k}^{(p-1)}(x_{a,k})} \sim \boldsymbol{N}(\boldsymbol{\mu}_{\overline{x}_{a,k}}^{(p-1)}, \boldsymbol{C}_{\overline{x}_{a,k}}^{(p-1)}),$$

and the means and covariances in $f^{(p-1)}(\overline{x}_{a,k}^{(n)})$ are $\boldsymbol{\mu}_{\overline{x}_{a,k}}^{(p-1)}$ and $\boldsymbol{C}_{\overline{x}_{a,k}}^{(p-1)}$, specified as

$$\boldsymbol{\mu}_{\overline{x}_{a,k}}^{(p-1)} = (\boldsymbol{\mu}_{x_{a,k}^{(n|n)}}^{(p-1)^T}\ \boldsymbol{\mu}_{x_{a,l_1\to k}^{(n|n)}}^{(p-1)^T}\ \boldsymbol{\mu}_{x_{a,l_2\to k}^{(n|n)}}^{(p-1)^T} \cdots \boldsymbol{\mu}_{x_{a,l_{|N_k|}\to k}^{(n|n)}}^{(p-1)^T})^T \tag{29}$$

$$\boldsymbol{C}_{\overline{x}_{a,k}}^{(p-1)} = diag(\boldsymbol{C}_{x_{a,k}^{(n|n)}}^{(p-1)}\ \boldsymbol{C}_{x_{a,l_1\to k}^{(n|n)}}^{(p-1)}\ \boldsymbol{C}_{x_{a,l_2\to k}^{(n|n)}}^{(p-1)} \cdots \boldsymbol{C}_{x_{a,l_{|N_k|}\to k}^{(n|n)}}^{(p-1)})^T \tag{30}$$

The first element in (29) and (30) are the prior PDF $f(x_a^{(p-1)})$. The following components received messages from the neighbors on the communication link. $b_{x_{a,k}^{(n)}}^{(p)}$ in (27), it is calculated accordingly $b_{x_k^{(n)}}^{(p)} \sim \boldsymbol{N}(\boldsymbol{\mu}_{x_k^{(n|n)}}^{(p)}, \boldsymbol{C}_{x_k^{(n|n)}}^{(p)})$.

Expansion observed noise sequences as state variables $x_{a,k}^{(t)} = [x_k^{(t)} v_k^{(t)}]^T$ and discretization $x_{a,k}^{(n)} = [x_k^{(n)} v_k^{(n)}]^T$, and we obtain an approximate SPBP-RPL of $p(x_{a,k}^{(n)} \big| y_k^{(n)})$.

$$y^{(n)} = (1-r^{(n)})z^{(n)} + r^{(n)}z^{(n-1)} \quad n = 0:N,\ y^{(1)} = z^{(1)} \tag{31}$$

SPBP-RPL describes multiple measurement jammers using randomly delayed by one step, which is extended to randomly delayed by two steps. Initialization agent expanded state,

$$\hat{\overline{x}}_{a,k}^{(n)} = \begin{bmatrix} \boldsymbol{\mu}_{\hat{\overline{x}}_k^{(n|n)}}^{(p)} \\ \boldsymbol{\mu}_{\hat{v}_k^{(n|n)}}^{(p)} \end{bmatrix}, \quad \boldsymbol{C}_{\hat{\overline{x}}_{a,k}^{(n|n)}}^{(p)} = \begin{bmatrix} \boldsymbol{C}_{x\tilde{\overline{x}}_k^{(n|n)}}^{(p)} & \boldsymbol{C}_{\overline{x}\overline{v}_k^{(n|n)}}^{(p)} \\ (\boldsymbol{C}_{\overline{x}\overline{v}_k^{(n|n)}}^{(p)})^T & \boldsymbol{C}_{\overline{v}\overline{v}_k^{(n|n)}}^{(p)} \end{bmatrix} \tag{32}$$

Initialization swarm UAVs expended states, (33) and (34), as shown at the bottom of the next page, And $\boldsymbol{\mu}_{\hat{\overline{x}}_k^{(n|n)}}^{(p-1)} = E[\hat{\overline{x}}_k^{(n|n)}|y_k^{(n)}]$ and $\boldsymbol{\mu}_{\hat{\overline{v}}_k^{(n|n)}}^{(p-1)} = E[\hat{\overline{x}}_k^{(n|n)}|y_k^{(n)}]$, $\boldsymbol{C}_{\overline{x}\overline{v}_k^{(n|n)}}^{(p-1)} = E[\tilde{\overline{x}}_k^{(n|n)}\tilde{\overline{v}}_k^{(n|n)}|y_k^{(n)}]$, $\boldsymbol{C}_{x\tilde{\overline{x}}_k^{(n|n)}}^{(p-1)} = E[\tilde{\overline{x}}_k^{(n|n)}(\tilde{\overline{x}}_k^{(n|n)})^T|y_k^{(n)}]$ where we define $\tilde{\overline{x}}_k^{(n|n)} = \overline{x}_k^{(n|n)} - \hat{\overline{x}}_k^{(n|n)}$ and $\tilde{\overline{v}}_k^{(n|n)} = \overline{v}_k^{(n|n)} - \hat{\overline{v}}_k^{(n|n)}$.

Generally, the derivation of the SPBP-RPL includes the estimates of state and the measurement noise, which is updated in each iteration p. We can derivate the functions following the Bayesian framework of the Gaussian Filter [22], [25].

Remark 1: Given $\overline{x}_k^{a_{\overline{x}},n+1|n}$ and $P_k^{a_{\overline{x}},n+1|n}$ of the mobile nodes $\boldsymbol{k}$ in each iteration,

$$\begin{aligned}
\hat{\overline{z}}_k^{a_{\overline{x}},n+1|n} &= \int h(\overline{x}_k^{a_{\overline{x}},n+1|n}) \\
&\quad \times N(\overline{x}_k^{a_{\overline{x}},n+1|n}; \hat{\overline{x}}_k^{a_{\overline{x}},n+1|n}, P_k^{a_{\overline{x}},n+1|n}) d\overline{x}_k^{a_{\overline{x}},n+1|n} \\
\hat{P}_{zz,m}^{n+1|n} &= \int (h(\overline{x}_k^{a_{\overline{x}},n+1|n}))(\cdot)^T \\
&\quad \times N(\overline{x}_k^{a_{\overline{x}},n+1|n}; \hat{\overline{x}}_k^{a_{\overline{x}},n+1|n}, P_k^{a_{\overline{x}},n+1|n}) d\overline{x}_k^{a_{\overline{x}},n+1|n} \\
&\quad - (E[z_{k+1}|y_k])(\cdot)^T \\
\hat{\overline{z}}_m^{a_{\overline{x}},n|n} &= E[z_k|y_k] \\
&= \int (h(\overline{x}_k^{a_{\overline{x}},n+1|n}) + v_k) \\
&\quad \times N(\overline{x}_k^{a_{\overline{x}},n+1|n}; \hat{\overline{x}}_k^{a_{\overline{x}},n+1|n}, P_k^{a_{\overline{x}},n+1|n}) d\overline{x}_k^{a_{\overline{x}},n+1|n} \\
\hat{P}_{\overline{zz},m}^{n+1|n} &= \int (h(\overline{x}_k^{a_{\overline{x}},n+1|n}) + v_k)(\cdot)^T \\
&\quad \times N(\overline{x}_k^{a_{\overline{x}},n+1|n}; \hat{\overline{x}}_k^{a_{\overline{x}},n+1|n}, P_k^{a_{\overline{x}},n+1|n}) d\overline{x}_k^{a_{\overline{x}},n+1|n} \\
&\quad - (\hat{\overline{z}}_m^{a_{\overline{x}},n|n})(\cdot)^T
\end{aligned}$$

It can update the measurement noise associated parameters, $\hat{\overline{v}}_m^{n+1}$, $\hat{P}_{\overline{vv},m}^{n+1|n+1}$, $K_{\overline{v},m}^{n+1|n}$, $\hat{\overline{y}}_m^{n+1|n}$, and $\hat{P}_{\overline{y}\overline{y},m}^{n+1|n}$.

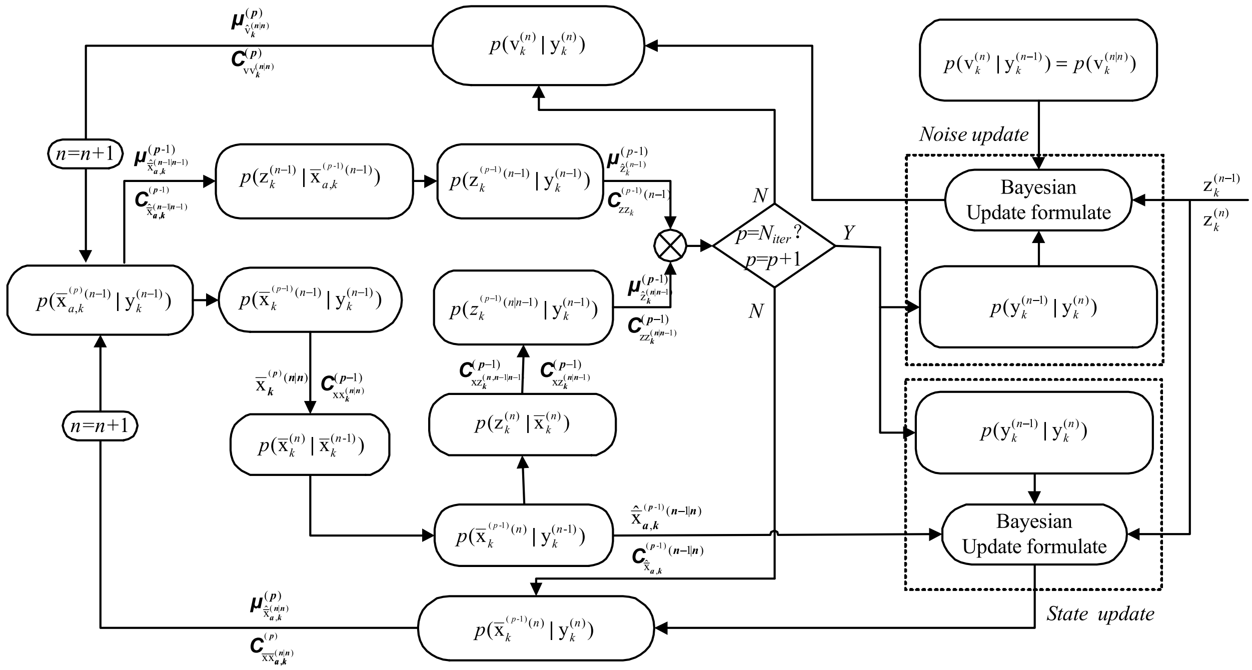

FIGURE 4. SPBP-RPL algorithm diagram due to jammers measure.

Remark 2: Given $\bar{x}_k^{a_{\bar{x}},n|n}$ and $P_k^{a_{\bar{x}},n|n}$ of the mobile nodes $\boldsymbol{k}$ in each iteration,

$$\begin{aligned}
\hat{x}_k^{a_{\bar{x}},n+1|n} &= \int f(\bar{x}_k^{a_{\bar{x}},n|n}) N(\bar{x}_k^{a_{\bar{x}},n|n}; \hat{x}_k^{a_{\bar{x}},n|n}, P_k^{a_{\bar{x}},n|n}) d\bar{x}_k^{a_{\bar{x}},n|n} \\
\hat{P}_k^{a_{\bar{x}},n|n} &= \int (f(\bar{x}_k^{a_{\bar{x}},n|n}))(\cdot)^T \\
&\quad \times N(\bar{x}_k^{a_{\bar{x}},n|n}; \hat{x}_k^{a_{\bar{x}},n|n}, P_k^{a_{\bar{x}},n|n}) d\bar{x}_k^{a_{\bar{x}},n|n} \\
&\quad - (\hat{x}_k^{a_{\bar{x}},n+1|n})(\cdot)^T \\
\hat{P}_{xz,k}^{n+1,n|n} &= \int (f(\bar{x}_k^{a_{\bar{x}},n|n}))(h(\bar{x}_k^{a_{\bar{x}},n+1|n}) + v_k)^T \\
&\quad \times N(\bar{x}_k^{a_{\bar{x}},n|n}; \hat{x}_k^{a_{\bar{x}},n|n}, P_k^{a_{\bar{x}},n|n}) d\bar{x}_k^{a_{\bar{x}},n|n} \\
&\quad - (\hat{x}_k^{a_{\bar{x}},n+1|n})(\hat{z}_k^{a_{\bar{x}},n|n})^T \\
\hat{P}_{xz,k}^{n+1|n} &= \int (\bar{x}_k^{a_{\bar{x}},n|n})(h(\bar{x}_k^{a_{\bar{x}},n+1|n}))^T \\
&\quad \times N(\bar{x}_k^{a_{\bar{x}},n|n}; \hat{x}_k^{a_{\bar{x}},n|n}, P_k^{a_{\bar{x}},n|n}) d\bar{x}_k^{a_{\bar{x}},n|n} \\
&\quad - (\hat{x}_k^{a_{\bar{x}},n+1|n})(\hat{z}_k^{a_{\bar{x}},n+1|n})^T
\end{aligned}$$

It can update the associated state parameters, $\hat{x}_k^{a_{\bar{x}},n+1|n+1}$, $\hat{P}_{x\bar{x},k}^{n+1|n+1}$, $K_{\bar{x},k}^{n+1|n}$, $\hat{P}_{x\bar{y},k}^{n+1|n}$, and $\hat{P}_{x\bar{v},k}^{n+1|n+1}$.

Remark 3: The expended state at pth iteration $\hat{x}_{a,k}^{(n)} = [\boldsymbol{\mu}^{(p)}_{\hat{x}_k^{(n|n)}}, \boldsymbol{\mu}^{(p)}_{\hat{v}_k^{(n|n)}}]^T$, including noise, is rearranged as the following equations,

$$\begin{aligned}
&E[h(\bar{x}_k^{a_{\bar{x}},n|n}) v_k^{(n|n)} | y_k] \\
&= \int (h(\bar{x}_k^{a_{\bar{x}},n|n}))(v_k^{(n|n)})^T N(\bar{x}_k^{a_{\bar{x}},n|n}; \hat{x}_k^{a_{\bar{x}},n|n}, P_k^{a_{\bar{x}},n|n}) d\bar{x}_k^{a_{\bar{x}},n|n} \\
&E[f(\bar{x}_k^{a_{\bar{x}},n|n}) v_k^{(n|n)} | y_k] \\
&= \int (f(\bar{x}_k^{a_{\bar{x}},n|n}))(v_k^{(n|n)})^T N(\bar{x}_k^{a_{\bar{x}},n|n}; \hat{x}_k^{a_{\bar{x}},n|n}, P_k^{a_{\bar{x}},n|n}) d\bar{x}_k^{a_{\bar{x}},n|n}
\end{aligned}$$

The right side of these equations is needed $\bar{x}_k^{a_{\bar{x}},n|n}$, which can be calculated recursively. The recursive algorithm diagram of SPBP-RPL due to jammers' measure is illustrated in Figure 4, and the algorithm is detailed as follows.

The SPBP-RPL correction operation

Step 1: **for** $n = 1$ to T, do: (where T is the total time)
Step 2: for $\boldsymbol{p}$=1 to N_{iter} **in iteration** (N_{iter} is the total number of iterations)
idx $= -\text{mod}(N_{iter}, 2) + 2$;
idx1 $= \text{mod}(p, 2) + 1$;
idx2 $= -\text{mod}(p, 2) + 2$;

$$\boldsymbol{\mu}^{(p-1)}_{\hat{x}_{a,k}^{(n|n)}} = \begin{bmatrix} \boldsymbol{\mu}^{(p-1)^T}_{\hat{x}_k^{(n|n)}} & \boldsymbol{\mu}^{(p-1)^T}_{\hat{v}_k^{(n|n)}} & \boldsymbol{\mu}^{(p-1)^T}_{\hat{x}_{l_1\to k}^{(n|n)}} & \boldsymbol{\mu}^{(p-1)^T}_{\hat{v}_{l_1\to k}^{(n|n)}} & \cdots & \boldsymbol{\mu}^{(p-1)^T}_{\hat{x}_{l_{|N_k|}\to k}^{(n|n)}} & \boldsymbol{\mu}^{(p-1)^T}_{\hat{x}_{l_1\to k}^{(n|n)}} \end{bmatrix}^T \tag{33}$$

$$\boldsymbol{C}^{(p-1)}_{\hat{x}_{a,k}^{(n|n)}} = diag(\boldsymbol{C}^{(p-1)}_{\hat{x}_{a,k}^{(n|n)}} \boldsymbol{C}^{(p-1)}_{\hat{x}_{a,l_1\to k}^{(n|n)}} \boldsymbol{C}^{(p-1)}_{\hat{x}_{a,l_2\to k}^{(n|n)}} \cdots \boldsymbol{C}^{(p-1)}_{\hat{x}_{a,l_{|N_k|}\to k}^{(n|n)}}) \tag{34}$$

initial $C^{(p-1)}_{\bar{x}_{a,k}} = C^{(p-1)}_{\bar{x}_{a,k},\mathrm{idx1}} = C^{(p-1)}_{\bar{x}_{a,k},\mathrm{idx2}}$

Step 3: ① for $p = 1$ (**first iteration** index)
Broadcast and receive $b^{(p-1)}_{x^{(n)}_{a,k}}(x^{(n)}_{a,k})$ together with its neighbors $\{k, l\} \in \varepsilon$ in parallel, then Singular Value Decomposition is factorized as:

$$[\mathrm{U, S, V}] = \mathrm{svd} C^{(p-1)}_{\bar{x}_{a,k},\mathrm{idx1}}$$

Construct and propagate Sigma points:

$$\xi^{(p)n|n}_{a,k,i} = \begin{bmatrix} \xi^{\bar{x},n|n}_{i,k} \\ \xi^{\bar{v},n|n}_{i,k} \end{bmatrix} = \mathrm{U}\sqrt{\mathrm{S}}\xi_i + \hat{\bar{x}}^{(p)n|n}_{a,k,i} \quad i = 1 : N'_p \tag{35}$$

$$\chi^{\bar{x},n+1|n}_{i,k} = f_k(\xi^{\bar{x},n|n}_{i,k}),$$
$$\lambda^{\bar{x},n+1|n}_{i,k} = h_k(\xi^{\bar{x},n|n}_{i,k}), \quad i = 1 : N'_p \tag{36}$$

$$\hat{\bar{x}}^{a_{\bar{x}},n+1|n}_{k,\mathrm{idx}} = \sum_{i=1}^{N'_P} \omega_i \chi^{\bar{x},n+1|n}_{i,k} \tag{37}$$

$$\hat{P}^{a_{\bar{x}},n+1|n}_{k,\mathrm{idx1}} = \sum_{i=1}^{N_{p'}} \omega_i \chi^{\bar{x},n+1|n}_{i,k}(\cdot)^T - \hat{\bar{x}}^{a_{\bar{x}},n+1|n}_{k,\mathrm{idx1}}(\cdot)^T + \hat{Q}_v \tag{38}$$

end first iteration ň.

Step 4: Propagate sigma points and calculate $\hat{\bar{x}}^{a_{\bar{x}},n+1|n}_{k,\mathrm{idx}}$ and $\hat{P}^{a_{\bar{x}},n+1|n}_{k,\mathrm{idx1}}$
Do pth in parallel except for the first iteration (if p!=1 then do)

$$\hat{\bar{x}}^{a_{\bar{x}},n+1|n}_{k,\mathrm{idx1}} = \sum_{i=0}^{N'_P} \omega_i \chi^{a_{\bar{x}},n+1|n}_{i,k} i = 1 : N'_p \tag{39}$$

$$\hat{P}^{a_{\bar{x}},n+1|n}_{k,\mathrm{idx1}} = \sum_{i=1}^{N_{p'}} \omega_i \chi^{a_{\bar{x}},n+1|n}_{i,k}(\cdot)^T - \hat{\bar{x}}^{a_{\bar{x}},n+1|n}_{k,\mathrm{idx1}}(\cdot)^T + \hat{Q}_{\mathrm{k}} \tag{40}$$

End do p th in parallel
Do mobile nodes m=1: N_k **in iteration**
Considering the order of message passing and iteration schedules, rearrange the element off $\hat{\bar{x}}^{a_{\bar{x}},n+1|n}_{k,\mathrm{idx1}}$ and $\hat{P}^{a_{\bar{x}},n+1|n}_{k,\mathrm{idx1}}$ then reconstruct $\hat{\bar{x}}^{a_{\bar{x}},n+1|n}_{m,\mathrm{idx}}$ and $C^{(p-1)}_{\hat{\bar{x}}_{a,k,\mathrm{idx1}}}$. Decomposed [U, S, V] = svd$C^{(p-1)}_{\hat{\bar{x}}_{a,k},\mathrm{idx1}}$

$$\xi^{a_{\bar{x}},n+1|n}_{k,m} = \mathrm{U}\sqrt{\mathrm{S}}\xi_i + \hat{\bar{x}}^{a_{\bar{x}},n+1|n}_{m,\mathrm{idx1}} \quad i = 1 : N'_p \tag{41}$$
$$\Theta^{a_{\bar{x}},n+1|n}_{i,m} = h_k(\xi^{a_{\bar{x}},n+1|n}_{i,m}) \quad i = 1 : N'_p \tag{42}$$

State and measurement noise estimation update

$$\hat{\bar{z}}^{a_{\bar{x}},n+1|n}_m = \sum_{i=0}^{N_{p'}} \omega_i \Theta^{a_{\bar{x}},n+1|n}_{i,m} \tag{43}$$

$$\hat{P}^{n+1|n}_{\bar{z}\bar{z},m} = \sum_{i=1}^{N_{p'}} \omega_i \Theta^{\bar{x},n+1|n}_{i,m}(\cdot)^T - \hat{\bar{z}}^{a_{\bar{x}},n+1|n}_m(\cdot)^T + \hat{R}_{\mathrm{v}} \tag{44}$$

$$\hat{\bar{z}}^{a_{\bar{x}},n|n}_m = \sum_{i=1}^{N'_p} \omega_i(\chi^{\bar{x},n+1|n}_{i,k} + \xi^{\bar{v},n|n}_{i,k}) \tag{45}$$

$$\hat{P}^{n|n}_{\bar{z}\bar{z},m} = \sum_{i=1}^{N_p} \omega_i(\chi^{\bar{x},n+1|n}_{i,m} + \xi^{\bar{v},n|n}_{i,k})(\cdot)^T - \hat{\bar{z}}^{a_{\bar{x}},n+1|n}_m(\cdot)^T + \hat{R}_{\mathrm{v}} \tag{46}$$

$$\hat{P}^{n+1|n}_{\bar{x}\bar{z},m} = \sum_{i=1}^{N_p} \omega_i \xi^{a_{\bar{x}},n+1|n}_{k,m}(\Theta^{\bar{x},n+1|n}_{i,m})^T - \hat{\bar{x}}^{a_{\bar{x}},n+1|n}_{k,\mathrm{idx1}}(\hat{\bar{z}}^{a_{\bar{x}},n+1|n}_m)^T \tag{47}$$

$$\hat{P}^{n+1,n|n}_{\bar{x}\bar{z},m} = \sum_{i=1}^{N_p} \omega_i \chi^{\bar{x},n+1|n}_{i,m}(\chi^{\bar{x},n+1|n}_{i,m} + \xi^{\bar{v},n|n}_{i,k})^T - \hat{\bar{x}}^{a_{\bar{x}},n+1|n}_{k,\mathrm{idx1}}(\hat{\bar{z}}^{a_{\bar{x}},n|n}_m)^T \tag{48}$$

According to an agent state vector and measurement vector, the first partition $\hat{P}^{n+1,n|n}_{\mathrm{xz},m}$ is stripped from $\hat{P}^{n+1,n|n}_{\bar{x}\bar{z},m}$, and that of $\hat{P}^{n+1|n}_{\mathrm{xz},m}$ is $\hat{P}^{n+1|n}_{\bar{x}\bar{z},m}$, respectively.
taking $\hat{P}^{n+1|n}_{\mathrm{v}\bar{y},m} = (1 - p_n)\hat{R}_{\mathrm{v}}$

$$\hat{P}^{n+1|n}_{\bar{y}\bar{y},m} = (1 - p_n)\hat{P}^{n+1|n}_{\bar{z}\bar{z},m} + p_n\hat{P}^{n|n}_{\bar{z}\bar{z},m} - (1 - p_n)p_n(\hat{\bar{z}}^{a_{\bar{x}},n+1|n}_m - \hat{\bar{z}}^{a_{\bar{x}},n|n}_m)(\cdot)^T \tag{49}$$

$$\hat{K}^{n+1|n}_{\bar{v},m} = \hat{P}^{n+1|n}_{\mathrm{v}\bar{y},m}(\hat{P}^{n+1|n}_{\bar{y}\bar{y},m})^{-1} \tag{50}$$
$$\hat{\bar{y}}^{n+1|n}_m = (1 - p_n)\hat{\bar{z}}^{a_{\bar{x}},n+1|n}_m + p_n\hat{\bar{z}}^{a_{\bar{x}},n|n}_m \tag{51}$$
$$\hat{P}^{n+1|n+1}_{\bar{v}\bar{v},\mathrm{idx2},m} = R_{\mathrm{v}} - \hat{K}^{n+1|n}_{\bar{v},m}\hat{P}^{n+1|n}_{\bar{y}\bar{y},m}(\hat{K}^{n+1|n}_{\bar{v},m})^T \tag{52}$$
$$\hat{\bar{v}}^{n+1}_{m,\mathrm{idx2}} = \hat{K}^{n+1|n}_{\bar{v},m}(\bar{y}^{n+1}_m - \hat{\bar{y}}^{n+1|n}_m) \tag{53}$$
$$\hat{P}^{n+1|n}_{\mathrm{xy},m} = (1 - p_n)\hat{P}^{n+1|n}_{\mathrm{xz},m} + p_n\hat{P}^{n+1,n|n}_{\mathrm{xz},m} \tag{54}$$
$$\hat{K}^{n+1|n}_{\mathrm{x},m} = \hat{P}^{n+1|n}_{\mathrm{xy},m}(\hat{P}^{n+1|n}_{\bar{y}\bar{y},m})^{-1} \tag{55}$$
$$\hat{\bar{x}}^{a_{\bar{x}},n+1|n}_{m,\mathrm{idx2}} = \hat{\bar{x}}^{a_{\bar{x}},n+1|n}_{m,\mathrm{idx1}} + \hat{K}^{n+1|n}_{\mathrm{x},m}(\mathrm{y}_{n+1} - \hat{\bar{y}}^{n+1|n}_m) \tag{56}$$

The m-th partition stripped from $\hat{P}^{a_{\bar{x}},n+1|n}_{k,\mathrm{idx1}}$ is $\hat{P}^{a_{\mathrm{x}},n+1|n}_{k,\mathrm{idx1}}$, which is fed as follows.

$$\hat{P}^{a_{\mathrm{x}},n+1|n}_{k,\mathrm{idx2}} = \hat{P}^{a_{\mathrm{x}},n+1|n}_{k,\mathrm{idx1}} - \hat{K}^{n+1|n}_{\mathrm{x},m}\hat{P}^{n+1|n}_{\bar{y}\bar{y},m}(\hat{K}^{n+1|n}_{\mathrm{x},m})^T \tag{57}$$

then $\hat{P}^{a_{\mathrm{x}},n+1|n}_{k,\mathrm{idx2}}$ is stuck into $C^{(p-1)}_{x\bar{x}_{a,k},\mathrm{idx2}}$ as the m-th partition, as well $\hat{P}^{a_{\mathrm{x}},n+1|n}_{k,\mathrm{idx1}} = \hat{P}^{a_{\mathrm{x}},n+1|n}_{k,\mathrm{idx}}$

$$\hat{P}^{n+1|n}_{\mathrm{xv},\mathrm{idx2},m} = -\hat{K}^{n+1|n}_{\bar{v},m}\hat{P}^{n+1|n}_{\bar{y}\bar{y},m}(\hat{K}^{n+1|n}_{\bar{v},m})^T \tag{58}$$

$\hat{x}^{a_{\mathrm{x}},n+1|n+1}_{m,\mathrm{idx}i}$ is stuck into $\hat{x}^{a_{\bar{x}},n+1|n+1}_{m,\mathrm{idx}i}$, and $\hat{P}^{n+1|n}_{\mathrm{xv},\mathrm{idx2},m}$ is trapped into $C^{(p-1)}_{\bar{x}\bar{v}_{a,k},\mathrm{idx2}}$ as the m-th partition, $\hat{P}^{n+1|n}_{\bar{v}\bar{v},\mathrm{idx2},m}$ is wedged into $C^{(p-1)}_{\bar{v}\bar{v}^{(n|n)}_k}$ as well, and then iteration ordinal number p is increased gradually. Board and receive messages $b^{(p)}_{\mathrm{x}^{(n)}_{a,k}}(\mathrm{x}^{(n)}_{a,k})$ among UAVs.

End Do m in iteration

End p in iteration

Step 5: if p ==Niter then do

$\hat{\mathrm{x}}^{a_{\bar{x}},n+1|n+1}_{m,\mathrm{idx}i}$ and $\hat{\mathrm{v}}^{a_{\bar{x}},n+1|n+1}_{m,\mathrm{idx}i}$ are fed to (33), formulated the mean of the extended state vector. $\boldsymbol{C}^{(p)}_{\bar{\mathrm{x}}_{a,k},\mathrm{idx}i}$ and $\boldsymbol{C}^{(p)}_{\bar{\mathrm{x}}\bar{\mathrm{v}}_{a,k},\mathrm{idx}i}$ have concluded, and then $\hat{\mathrm{x}}^{a_{\bar{x}},n+1|n+1}_{m,\mathrm{idx}i}$ and $\boldsymbol{C}^{(p)}_{\bar{\mathrm{x}}^{(n|n)}_{a,k}}$ can be recomputed in Eq. (32).

End for

Remark 4: This paper conducts the collaborative jammer problem in case the measurements are missed or randomly delayed by a sampling period, and the proposed algorithm integrates message passing based on the Bayesian framework of the Gaussian Filter, SPBP-RPL to exploit spatiotemporal cooperation and measurement knowledge.

IV. SIMULATIONS AND RESULTS

Our paper develops the proposed algorithm's performance requirements in two dynamic scenarios; furthermore, we investigate the quantifiability of the SPBP-RPL by comparing it with the SPBP [12] in network localization and swarm UAVs collaborative navigation, respectively. The proposed SPBP-RPL algorithm is compared with SPBP if the measurements are Bernoulli missed or randomly delayed. Bernoulli's measurement sequence is detailed in Figure 5, and the packet loss probability($r(n) = 1$) is up to 80%. When the agent has not received the physical observation, the agent may utilize the previous moment's measurement value instead. All two methods make use of the SPAWN message-passing schedule.

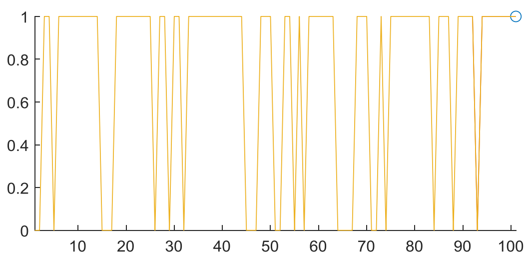

FIGURE 5. **The measurement sequence of Bernoulli distribution, its values 1 signify measurement jammer and vice versa.**

A. DYNAMIC SCENARIOS IN-NETWORK WITH UWB JAMMERS

The simulation is a simple model of cooperative location for verifying the correctness of the algorithm. The scenario [12] using two anchors and three agents are simulated. SPBP-Full is the method in [12] when measurement vectors arrive on time and orderly. SPBP is the general SBPP method suffering from measurement jammers in-network; in other words, when the system has not received the physical observation measurement, the system uses the measurement value of the previous moment instead. SPBP-RPL is the proposed method copping with measurement jammer, and SPBP-RPL-5 and SPBP-RPL-1 differentiate in the iteration number, respectively.

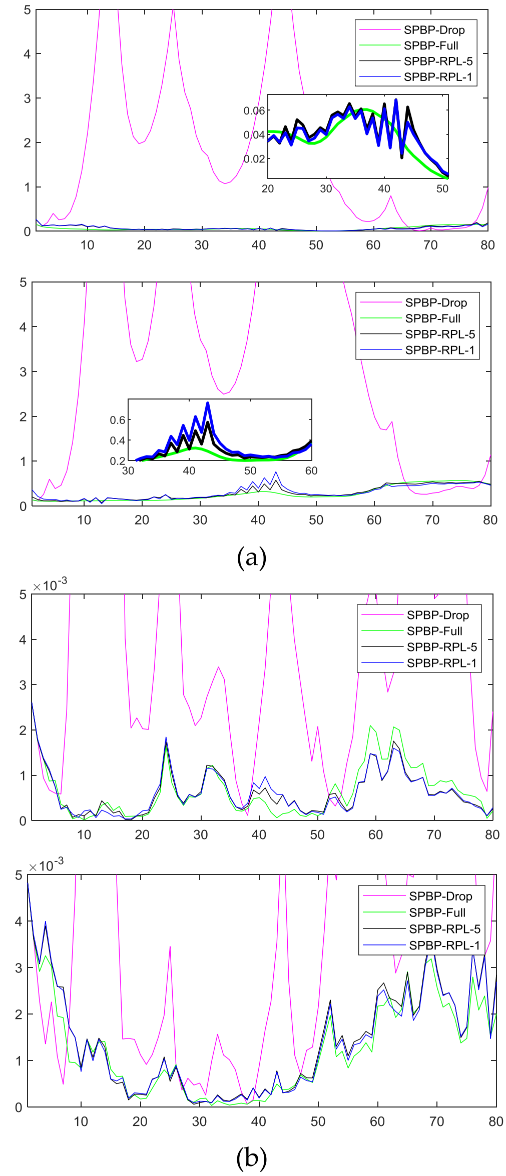

FIGURE 6. **The algorithms error of RMSE position and velocity in-network self-localization.**

(a) the position error of the x-axis and the y-axis; (b) the velocity error of the x-axis and the y-axis.

The average elapsed time of those four implementations on Intel(R) Core(TM)-i7-7Y75 CPU of Matlab + toolbox for 100 steps of one-run simulation is about 0.6530 s, 0.6370 s 2.7980 s, and 0.9581 s corresponding to SPBP-Drop, SPBP-Full, SPBP-RPL-5, and SPBP-RPL-1, respectively. The average RMSE position errors are 1.4850 m, 0.0835 m, 0.0915 m, and 0.0933 m. The first 80 seconds error curve is shown in Figure 6. Thus, the curve of SPBP-Drop is severely divergent, and accurate positioning cannot be com-

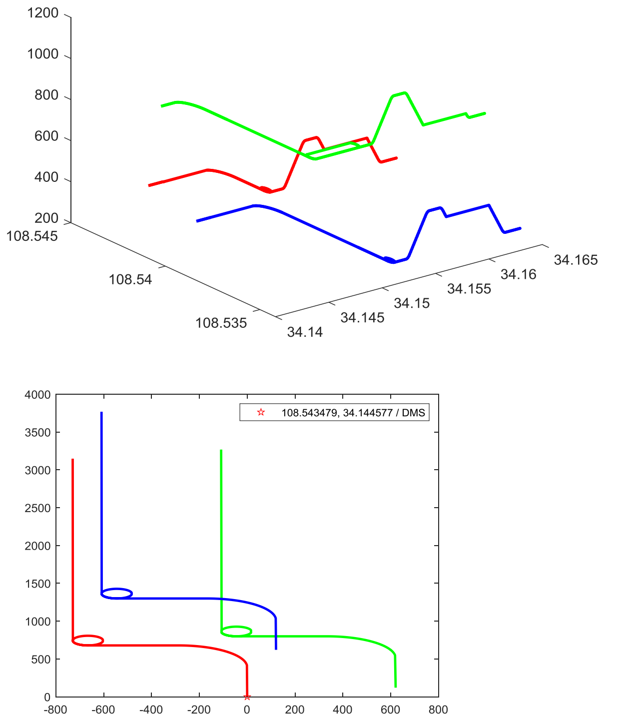

FIGURE 7. The trajectory of swarm UAVs.

pleted due to measurement jammers of UWB. SPBP-RPL is approximate to the self-localization precision of SPBP-Full, which is capable of handing measurement jammer problems. SPBP-RPL will build up precision by the number of iterations comparing SPBP-RPL-5 with SPBP-RPL-1. However, SPBP-RPL is more complicated than SPBP methods due to gather intermittent measurement information and estimate UAVs state at the current moment, associated with observation noise. Thus SPBP-RPL requires significantly more compute the speed of computer hardware than general SPBP.

B. DYNAMIC SCENARIOS IN COLLABORATIVE NAVIGATION OF SWARM UAVs WITH GPS/INS/UWB JAMMERS

We simulated a cooperative, decentralized, dynamic swarm UAVs with GPS/INS/UWB navigation using a network of $K = 6$, where there are three UAV agents and three anchors. The absolute navigation outputs of three UAVs swarming include the position and the velocity, and the altitude. The state of the system is $x_k = [\delta L\ \delta\lambda\delta H\ \delta Ve\ \delta Vn\ \delta Vu\ \varphi_e\varphi_n\varphi_u\ \varepsilon_x\varepsilon_y\varepsilon_z\nabla_x\nabla_y\nabla_z]^T$, corresponding to the errors of position, the velocity and the attitude angle, the constant gyro drift, the accelerator offset. The trajectory is shown in Figure 7. The initial position central of swarm UAVs is North latitude 34.25° and East longitude 108.91° and height 380 m. The swarm UAVs relative locations are {[0 0 0], [125 625 0], [625 125 0]}. The static UWB anchors are {[18 20 0], [20 57 0], [55 18 0]}. The parameters of the IMU sensors are $= 100$ ug, $w = N(0,(0.001\text{g})^2)$ and $\varepsilon = 0.3°/\text{h}$, $w\varepsilon = N(0,(0.1°/\text{h})^2)$.The GPS signal receiver accuracy is 5 / 5/ 30 m, which is fed to integrated navigation and matched the position errors with INS's intra-user measurements. The UWB measurement error is 0.1 m. The probability of measurement jammers is 80%.

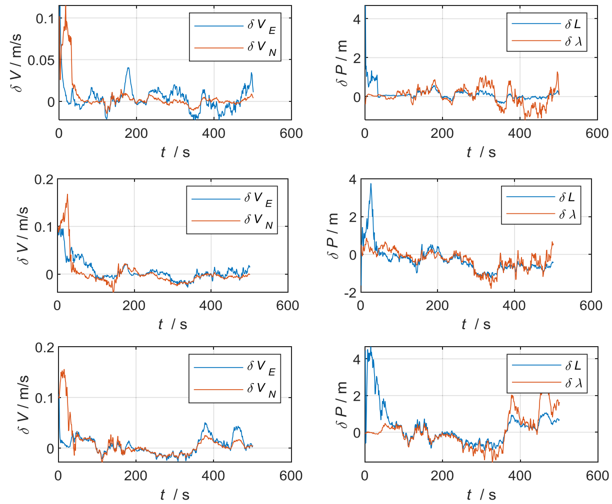

FIGURE 8. The SPBP-Full algorithm error sequence diagrams of position and velocity in swarm UAVs of three agents.

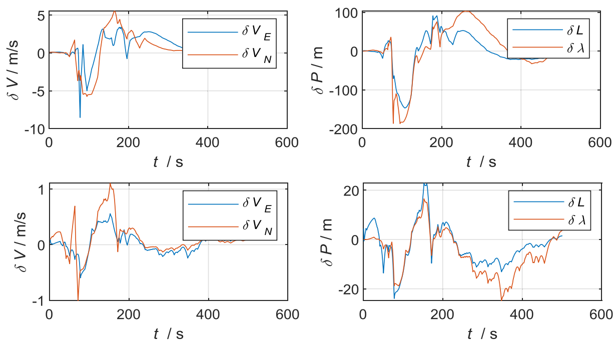

FIGURE 9. The SPBP- Drop algorithm error sequence diagrams of position and velocity in swarm UAVs due to measurement jammers.

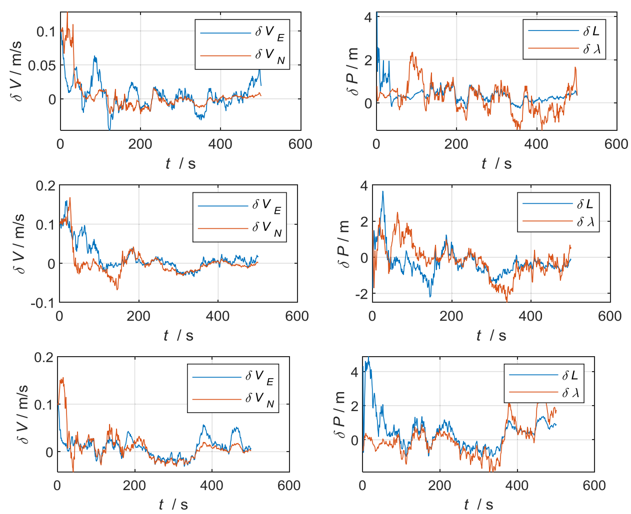

FIGURE 10. The SPBP-RPL algorithm error sequence diagrams of position and velocity in swarm UAVs due to measurement jammers.

We compare the proposed SPBP-RPL with SPBP-Full and SPBP-Drop. The position and velocity errors of the swarm UAVs versus time are shown in Figure 8-10. Three UAVs average RMSE position errors of SPBP-Full in Figure 8 are 0.12/0.50 m, 0.32/0.31 m, and 0.3/0.51 m, and the std errors of which are 0.32/0.52 m, 0.71/0.58 m, and 1.10/0.91 m when all measurements arrive timely. However, the average RMSE of SPBP-Drop 0.8/1.6 m, 4.0/3.0 m, and 2.5/5.5 m and the std errors of which are 3.4/8.0 m, 48/65 m and 8.0/8.6 m in Figure 9 severely divergently due to measurement jammers. In Figure 10, those of SPBP-RPL are 0.36/0.53 m, 0.35/0.37 m, 0,50/0.55 m, and 0.36/0.68 m, 0,75/0.90 m, 1.21/1.00 m, respectively when suffering the same scenario of measurement jammers. Thus SPBP-RPL can deal with measurement interference.

V. CONCLUSION

We proposed SPBP-RPL methodology for the case that the navigation in spatiotemporal cooperative agents suffering measurement jammer. SPBP-RPL is derived from a Bayesian framework and based on recurrent measurements and previous moment measurements. We develop a message passing of distributed belief propagation on sigma point-based, gathering intermittent measurement information, and estimating system state at the current moment and associated observation state. Our simulations validated that the algorithm can significantly improve collaborative agents' location precision in the case of network congestion of communication. The proposed methodology can be extended to a scalable swarm involving an unknown specific number of cooperative and noncooperative navigation agents. Our future work direction will focus on using an immune optimization algorithm for network collaboration in a particular range and reducing the computational burden of the system and extending its flexibility concerning the net swarm size. In future work, we will experimentally validate results.

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