# Channel-Aware Tracking in Multi-Hop Wireless Sensor Networks with Quantized Measurements

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**A channel-aware target tracking approach is proposed for multi-hop sensor networks based on $M$-bit quantized measurements. For two cases where the fusion center has the knowledge of the instantaneous fading channel gains and where only the knowledge of fading channel statistics is available, particle filtering (PF)-based channel-aware tracking algorithms are developed. Furthermore, the posterior Cramér-Rao lower bounds (PCRLBs) for the tracking filters are derived. The improved tracking accuracy and robustness of the proposed approach are demonstrated through simulations.**

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## I. INTRODUCTION

Recent advances in micro-electromechanical systems, wireless communication technologies, and digital electronics are responsible for the emergence of wireless sensor networks (WSNs) that deploy a large number of low-cost sensor nodes integrating sensing, processing, and communication capabilities. Sensor networks have been employed in a wide variety of applications, ranging from military surveillance to civilian and environmental monitoring [1]. A fundamental problem addressed by these applications is target tracking in the field of interest. The sensors sense and measure signals that provide information about the events of interest and send them to the fusion center through wireless channels. The fusion center combines the received information to estimate the target state. However, the WSNs employ low-cost densely deployed sensors that have very limited resources, such as energy and communication bandwidth. They also have limited sensing and communication ranges. The wireless communication channels between sensors and the fusion center are not ideal in that the transmitted information has to endure both channel fading and noise impairments. Therefore, issues that are related to these limitations and specific to the application have to be resolved.

Recently, some new issues related to tracking in WSNs have been studied, such as structure of networks, routing and clustering protocols, and collaborative signal processing [2, 3]. For estimation in WSNs the conventional way is to consider communication and estimation as two separate parts. In [4]–[7] the original analog measurements of sensors were used by the fusion center to localize or track the target. However, this scheme is not practical for many WSNs since communication within the network has to be kept limited to conserve available resources, such as energy and bandwidth. Actually, two viewpoints exist in the literature on this subject. One approach is to reduce the number of messages within the network. Censoring-based distributed detection [36], distributed estimation [44], and distributed tracking [45] schemes have been proposed where the sensors are assumed to censor their observations so that each sensor sends only informative observations to the fusion center and leaves those deemed uninformative untransmitted. Another approach is to reduce the number of delivered bits [37–41]. In order to limit the number of bits for communication within the WSNs, data from local sensors are quantized before being delivered to the fusion center.

In this paper we follow the second approach where target tracking is based on quantized measurements. In [37] the communication approach is taken to one extreme by employing just one single delivered bit. In [38]–[41] a binary proximity sensor model where each sensor's value is converted to 1 bit of information was presented and tracking methods employing such binary sensors were developed. Based on quantized data particle filtering (PF) algorithms have been proposed to track the target in [8]–[10]. In [11], [12] target localization methods based on quantized sensor data were developed. However, perfect communication channels between sensors and the fusion center were assumed in these methods which did not consider wireless channel imperfections. For nonideal communication channels the issues of communication constraints in the context of channel-aware distributed detection have been investigated in [13]–[18]. In [19], [20] the channel-aware approaches for localization and tracking were introduced, respectively, which consider the imperfect nature of the wireless communication channels along with some physical layer design parameters. The channel-aware approach with one-hop communication between the sensors and the fusion center, while theoretically important and analytically tractable, may not reflect the way a real WSN operates. In most WSN applications resource constraints, especially the energy constraint in applications involving in-situ unattended sensors operating on irreplaceable power supplies, often limit the transmission range for each sensor node. This is because the required transmission energy is proportional to the distance between the transmitter and the receiver raised to a certain power. Hence, in order to reach the fusion center, the measurement at a local sensing node may need to go through multiple hops for minimal energy consumption.

In [17], [18] channel-aware decision fusion rules in multi-hop WSNs were presented for binary decisions transmitted over multi-hop wireless channels undergoing channel fading and noise in the context of target detection. In [21] a distributed Kalman filter for target tracking via networked sensors with communication delays was presented where the sensors communicate with each other by means of a multi-hop protocol. Note that the channel-aware multi-hop tracking framework proposed in our paper is different from the multi-hop protocols presented in [21]. First, in [21] the nonideal channel was represented by delays and packet losses, while in our work, the fading and noisy channels are considered and addressed explicitly. Second, in our proposed framework, quantized data transmission is assumed, in contrast to the analog data communication assumed in [21]. Third, the Kalman filter or extended Kalman filter has been used in [21], while our proposed algorithm is based on the particle filter, which can deal with any nonlinearities in measurements and in target dynamics. It is well known that the distributed tracking schemes have some advantages, such as scalability and robustness [21, 42, 43]. However, distributed implementation in [21], which is based on gossip and in-network processing, requires substantial computational power, memory, and communication overhead for each sensor. Moreover, it often needs a very long time for all the sensors to achieve consensus. On the other hand, in a resource-constrained sensor network, by efficient sensor selection and management, optimal tracking accuracies and minimal total power consumption can be achieved for fusion center-based architecture [30–33]. Therefore, a centralized sensor network structure has been adopted in this paper.

The objective of this work is to extend channel-aware target tracking to more realistic WSN models that involve multi-hop transmissions. We also generalize the approach to consider multi-bit quantization data. The sensors process their raw observations and quantize them to get $M$-bit data which are then transmitted to the fusion center through noisy and fading wireless channels. We show that the proposed algorithms can significantly mitigate the degradation in the tracking performance resulting from the fading wireless channels, meanwhile they are energy and bandwidth efficient due to the use of multi-hop communication and quantization schemes.

With the recent advances in computation power, application of Monte Carlo based statistical signal processing, i.e., PF, for sequential estimation of unknown states of a nonlinear dynamical system has become quite popular and practical. One of the advantages of PF is that it enables us to incorporate any statistical information we have about the specific system. In our previous work [22] we proposed an efficient tracking algorithm based on PF for multi-hop target tracking in WSNs, incorporating the imperfect nature of communication channels. Based on the methods developed in [22], in this paper, we derive the posterior Cramér-Rao lower bound (PCRLB) of the state estimates and an efficient computation procedure by Monte Carlo approximation. Further, the proposed PCRLB is used as a criterion for sensor selection for target tracking in WSNs in order to meet the physical constraints, such as energy and communication bandwidth.

The organization of this paper is as follows. In the next section we formulate the problem of target tracking using quantized data in a WSN. In Section III we provide the model for the multi-hop wireless transmission channel and the computation of the observation likelihood for a multi-hop WSN in two cases. In the first case we assume that the fusion center has knowledge of the instantaneous fading channel gains, followed by the case where only the fading channel statistics are known. We introduce our channel-aware approach and derive two different channel-aware multi-hop PF algorithms in Section IV. In Section V we derive the PCRLB and present the Monte Carlo based methodology to calculate the PCRLB. In Section VI simulation results are presented to assess the performance of our developed PF algorithms. Finally, concluding remarks are presented in Section VII.

## II. PROBLEM FORMULATION

We consider a WSN that consists of $N$ sensors deployed randomly. We assume that the fusion center knows the locations of all the sensors. The deployed sensors measure a signal of interest and quantize it to $M$-bits. The quantized data at local sensors are transmitted to the fusion center through nonideal multi-hop wireless communication channels where they are fused to estimate the target state. Each relay node tries to retrieve the quantized data sent from the last relay node from fading and noise impaired observations and relays them to the next node until they reach the fusion center.

We consider a single target moving in the surveillance area of WSN. The target movement is assumed to evolve according to

$$\bar{\mathbf{x}}_k = f(\bar{\mathbf{x}}_{k-1}, \mathbf{u}_{k-1}) \tag{1}$$

where $\bar{\mathbf{x}}_k = [x_{1k}, x_{2k}, \dot{x}_{1k}, \dot{x}_{2k}]^T$ is the state vector, which indicates the position and the velocity of the target in a two-dimensional Cartesian coordinate system. A discretized continuous-time white noise acceleration model [23] for target movement is described by the linear equation

$$\bar{\mathbf{x}}_k = \Phi\bar{\mathbf{x}}_{k-1} + \mathbf{u}_{k-1} \tag{2}$$

where

$$\Phi = \begin{bmatrix} 1 & 0 & T & 0 \\ 0 & 1 & 0 & T \\ 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 1 \end{bmatrix} \tag{3}$$

and process noise $\mathbf{u}_{k-1}$ is a white, zero-mean and Gaussian random process with the following covariance matrix

$$Q = q \begin{bmatrix} \frac{T^3}{3} & 0 & \frac{T^2}{2} & 0 \\ 0 & \frac{T^3}{3} & 0 & \frac{T^2}{2} \\ \frac{T^2}{2} & 0 & T & 0 \\ 0 & \frac{T^2}{2} & 0 & T \end{bmatrix} \tag{4}$$

where $T$ denotes the sampling period and $q$ is the power spectral density of the process noise before discretization [23], which has a unit of $\mathrm{m}^2/\mathrm{s}^3$. We assume that the initial state $\bar{\mathbf{x}}_0$ follows a known prior distribution, i.e., $\bar{\mathbf{x}}_0 \sim p(\bar{\mathbf{x}}_0)$. Note that the proposed approach for target tracking in multi-hop WSNs is very general and can be applied to nonlinear dynamic systems (see [22], where a nonlinear nearly constant turn (CT) model has been used for the target dynamic model). The linear dynamic model is used here for simplicity and to illustrate the effectiveness of the proposed channel-aware tracking approach. Further, it is assumed that the fusion center has perfect information about the target state-space model.

The target is assumed to be any source that follows an isotropic power attenuation model. At any given time step $k$, the received signal strength (RSS) at the $n$th sensor is the following

$$a_{n,k} = \sqrt{\varphi_k \left(\frac{d_0}{d_{n,k}}\right)^{\alpha}} \tag{5}$$

where $\varphi_k$ is the emitted signal power of the target measured at a reference distance $d_0$ and $d_{n,k}$ is the Euclidean distance between the target and the $n$th sensor $d_{n,k} = \sqrt{(\xi_{1,n} - x_{1,k})^2 + (\xi_{2,n} - x_{2,k})^2}$, in which $(\xi_{1,n}, \xi_{2,n})$ and $(x_{1,k}, x_{2,k})$ are the locations of the $n$th sensor and the location of the target at time $k$, respectively, and $\alpha$ is an attenuation parameter that depends on the transmission medium which is considered to be known. At each sensor the RSS measurement $a_{n,k}$ is corrupted by an additive Gaussian noise

$$y_{n,k} = a_{n,k} + \varpi_{n,k} \tag{6}$$

where $y_{n,k}$ is the noisy RSS measurement at the $n$th sensor at time $k$. Here, we assume that the noise $\varpi_{n,k}$ is independent and identically distributed (IID) across sensors with zero-mean Gaussian distribution, i.e., $\varpi_{n,k} \sim N(0, \sigma_{\varpi}^2)$, which represents the cumulative effects of sensor background noise and the modeling error of the RSS. When the emitted signal power $\varphi_k$ is unknown and varies with time randomly, we can model $\varphi_k$ as a dynamic process

$$\varphi_k = \varphi_{k-1} + \beta_k \tag{7}$$

where $\beta_k \sim N(0, \sigma_\beta^2)$. Then, we can augment the original state vector $\bar{\mathbf{x}}_k$ in (1) with $\varphi_k$ to form an augmented state vector $\mathbf{x}_k = [\bar{\mathbf{x}}_k, \varphi_k]^T$, and the corresponding augmented state-space model equation can be easily obtained. For the linear model (2), the augmented state-space equation is still linear.

In order to reduce the amount of communication so that the energy consumption is decreased, each sensor obtains the RSS measurement $y_{n,k}$ and quantizes it locally before sending it to the fusion center. The quantized observation model is given by

$$D_{n,k} = \begin{cases} 0 & \eta_{n,0} < y_{n,k} < \eta_{n,1} \\ 1 & \eta_{n,1} < y_{n,k} < \eta_{n,2} \\ \vdots & \\ L-1 & \eta_{n,L-1} < y_{n,k} < \eta_{n,L} \end{cases} \tag{8}$$

where $D_{n,k}$ is the quantized measurement of the $n$th sensor at time $k$, and $\eta_{n,0}, \eta_{n,1}, \ldots, \eta_{n,L}$ are the predetermined thresholds for an $M = \log_2^L$ bit

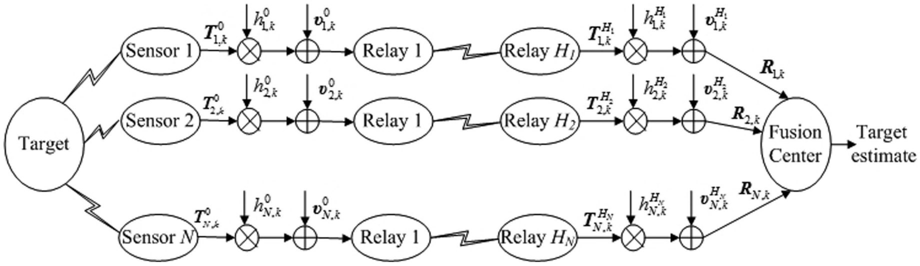


Fig. 1. Multi-hop wireless transmission model in a WSN.

quantizer, where $\eta_{n,0} = -\infty, \eta_{n,L} = \infty$. Each quantized observation $D_{n,k}$ is encoded to produce $M$-bit data as

$$\mathbf{B}_{n,k} = [b_{n,1}, b_{n,2}, \ldots, b_{n,M}]^T, \qquad b_{n,j} \in \{0,1\}. \quad (9)$$

The $M$-bit data are transmitted using binary digital modulation. Basically, any binary digital modulation system can be used. For simplicity we use binary phase shift keying (BPSK) modulation as follows

$$\mathbf{T}_{n,k}^0 = [t_{n,1}^0, t_{n,2}^0, \ldots, t_{n,M}^0]^T \quad (10)$$

where $t_{n,j}^0 = 2b_{n,j} - 1$, $t_{n,j}^0 \in \{-1,1\}$. Here, symbols $\{0,1\}$ are mapped to $\{-1,1\}$ so that the effect of the fading channel reduces to a real scalar multiplication for phase coherence reception [15].

If one neglects the effects of unreliable wireless channels between sensors and the fusion center, then the fusion center could be assumed to receive an exact replica of $\mathbf{T}_{n,k}^0$. However, this assumption is not always valid for a WSN due to the noise and fading.

## III. MULTI-HOP WIRELESS TRANSMISSION CHANNEL STATISTICS

In most WSN applications the communications between sensors and the fusion center are multi-hop transmissions in order to minimize energy consumption. Consider a WSN channel model with multi-hop transmission as illustrated in Fig. 1. At a given time step $k$, the original measurement $y_{n,k}$ of the $n$th sensor is quantized to $D_{n,k}$, encoded to $M$-bit data $[b_{n,1}, b_{n,2}, \ldots, b_{n,M}]^T$, and then transmitted to the fusion center through several relay nodes. Decode-and-forward is used at each relay node to transmit the data in a multi-hop network. Each relay node tries to retrieve the $M$-bit data sent by its source node from its faded and noise impaired observation and relay it to the next node until it reaches the fusion center.

Suppose there are $H_n$ relay nodes between the $n$th local sensor and the fusion center, then the number of hops from the $n$th local sensor to the fusion center is $H_n + 1$. Let $\mathbf{T}_{n,k}^i = [t_{n,1}^i, t_{n,2}^i, \ldots, t_{n,M}^i]^T$ denote the retrieved $M$-bit data from the $n$th local sensor corresponding to the $i$th relay node, where $i = 1, 2, \ldots, H_n$ is the hop index and $\mathbf{T}_{n,k}^0 = [t_{n,1}^0, t_{n,2}^0, \ldots, t_{n,M}^0]^T$ is the original $M$-bit data. The following assumptions are used in the subsequent analysis.

1) All the channels are independent of each other, and each of them can be modeled as a discrete-time flat fading channel with a phase coherent reception; hence, the effect of a fading channel is simplified as a real scalar multiplication.

2) We assume block-fading where the channel conditions do not change during the transmission of the $M$-bit data $\mathbf{T}_{n,k}^i$.

3) Additive noise on all the channels is IID and follows a Gaussian distribution with zero mean and variance $\sigma_n^2$.

Similar to [17] each relay node employs a binary relay scheme whereby the relay output is inferred from the channel impaired observation received from its source node. Given that the noises in all the channels follow independent Gaussian distributions, we have the decode-and-forward relayed $M$-bit data expressed as

$$\mathbf{T}_{n,k}^i = \mathrm{sign}(h_{n,k}^{i-1}\mathbf{T}_{n,k}^{i-1} + \boldsymbol{\upsilon}_{n,k}^{i-1}), \qquad i = 1, \ldots, H_n \quad (11)$$

where $h_{n,k}^{i-1}$ is the corresponding channel gain, $\boldsymbol{\upsilon}_{n,k}^{i-1} = [\upsilon_{n,1}^{i-1}, \upsilon_{n,2}^{i-1}, \ldots, \upsilon_{n,M}^{i-1}]^T$ is an $M$-dimensional vector whose components are IID relay channel noises with zero mean and variance $\sigma_n^2$.

Let $\mathbf{R}_{n,k} = [r_{n,1}, r_{n,2}, \ldots, r_{n,M}]^T$ denote the input to the fusion center corresponding to the $n$th local sensor at time step $k$. Thus,

$$\mathbf{R}_{n,k} = h_{n,k}^{H_n}\mathbf{T}_{n,k}^{H_n} + \boldsymbol{\upsilon}_{n,k}^{H_n}. \quad (12)$$

Let $\mathbf{x}_k = [x_{1k}, x_{2k}, \dot{x}_{1k}, \dot{x}_{2k}, \varphi_k]^T$ denote the target state vector at a given time step $k$. The fusion center sequentially estimates the target state when the observation set $\bar{\mathbf{R}}_k = [\mathbf{R}_{1,k}^T, \ldots, \mathbf{R}_{n,k}^T, \ldots, \mathbf{R}_{N,k}^T]^T$ arrives. Since sensor noises and wireless links are assumed to be independent, the likelihood function at the fusion center can be written as

$$p(\bar{\mathbf{R}}_k \mid \mathbf{x}_k) = \prod_{n=1}^{N} p(\mathbf{R}_{n,k} \mid \mathbf{x}_k) \quad (13)$$

where

$$p(\mathbf{R}_{n,k} \mid \mathbf{x}_k) = \sum_{D_{n,k}=0}^{L-1} p(\mathbf{R}_{n,k} \mid D_{n,k}) p(D_{n,k} \mid \mathbf{x}_k) \quad (14)$$

and

$$p(\mathbf{R}_{n,k} \mid D_{n,k}) = p(\mathbf{R}_{n,k} \mid \mathbf{T}^0_{n,k}). \tag{15}$$

Due to the Gaussian noise assumption, the probability of a quantized sensor measurement taking a specific value conditioned on the target state is

$$p(D_{n,k} = l \mid \mathbf{x}_k) = Q\left(\frac{\eta_{n,l} - a_{n,k}}{\sigma_\varpi}\right) - Q\left(\frac{\eta_{n,l+1} - a_{n,k}}{\sigma_\varpi}\right) \tag{16}$$

where $Q(.)$ denotes the complementary cumulative distribution function of the standard Gaussian distribution, which is defined as

$$Q(x) = \int_x^\infty \frac{1}{\sqrt{2\pi}} e^{-t^2/2} dt. \tag{17}$$

Note that (14) uses the fact that $\mathbf{x}_k$, $D_{n,k}$, and $\mathbf{R}_{n,k}$ form a Markov chain, i.e., $p(\mathbf{R}_{n,k} \mid D_{n,k}, \mathbf{x}_k) = p(\mathbf{R}_{n,k} \mid D_{n,k})$. The conditional probability density function (pdf) $p(\mathbf{R}_{n,k} \mid D_{n,k}) = p(\mathbf{R}_{n,k} \mid \mathbf{T}^0_{n,k})$ characterizes the channel transmission statistics and $p(D_{n,k} \mid \mathbf{x}_k)$ denotes the quantized observation likelihood for sensor node $k$.

For a WSN one has the flexibility to design the communication link layer. The functions of the link layer that need to be designed include modulation schemes, data encryption techniques, transceiver architectures, and decoding schemes. In this paper we consider a soft-decoding link layer where the received measurements at the fusion center are used directly to track the target and Rayleigh flat fading channels are assumed for soft-decoding links. Note that for a soft-decoding link, the knowledge of the channel needs to be incorporated in the tracking algorithm. In this paper we investigate two different kinds of channel knowledge. In the first case we assume complete channel knowledge, i.e., instantaneous channel gains are available at the fusion center. In the second case we assume that only channel fading statistics are known.

## A. The Likelihood Function with Known Channel Gains

We start with the derivation of the observation likelihood assuming known channel gain. We assume that the fusion center knows all the instantaneous channel gains $h^i_{n,k}$ for $n = 1,\ldots,N$ and $i = 0,1,\ldots,H_n$.

Under the independent channel noise assumption, each component in the data transmitted from the $n$th sensor is also independent. Conditioned on all relay channel gains $\mathbf{h}^{0:H_n}_{n,k} = [h^0_{n.k}, h^1_{n,k}, \ldots, h^{H_n}_{n,k}]$, we have

$$p(\mathbf{R}_{n,k} \mid D_{n,k}) = p(\mathbf{R}_{n,k} \mid \mathbf{T}^0_{n,k}) = \prod_{j=1}^{M} p(r_{n,j} \mid t^0_{n,j}, \mathbf{h}^{0:H_n}_{n,k}). \tag{18}$$

Using the multi-hop transmission model described in Fig. 1, we now derive the observation likelihood at the fusion center. First we introduce the notion of binary transmission conditional probability

$$p_{H_n}(t) = p(t^{H_n}_n = 1 \mid t^0_n = t), \qquad t \in \{1, -1\} \tag{19}$$

where $t^{H_n}_n$ is the retrieved symbol of the original symbol $t^0_n$ after $H_n$ relays. They are the probabilities of the output signal being equal to 1 at the last relay node while the original transmitted symbol at $n$th sensor is 1 or $-1$. The conditional pdf representing the channel transmission statistics can be described as follows

$$\begin{aligned} p(r_{n,j} \mid t^0_{n,j}, \mathbf{h}^{0:H_n}_{n,k}) &= p(t^{H_n}_{n,j} = 1 \mid t^0_{n,j}) p(r_{n,j} \mid t^{H_n}_{n,j} = 1) \\ &\quad + p(t^{H_n}_{n,j} = -1 \mid t^0_{n,j}) p(r_{n,j} \mid t^{H_n}_{n,j} = -1) \\ &= p_{H_n}(t^0_{n,j}) \frac{1}{\sqrt{2\pi}\sigma_n} \exp[(-(r_{n,j} - h^{H_n}_{n,k}))^2 / 2\sigma^2] \\ &\quad + (1 - p_{H_n}(t^0_{n,j})) \frac{1}{\sqrt{2\pi}\sigma_n} \exp[(-(r_{n,j} + h^{H_n}_{n,k}))^2 / 2\sigma^2]. \end{aligned} \tag{20}$$

We define binary transmission probabilities

$$p^n_{i-1,i} = p(t^i_n = 1 \mid t^{i-1}_n = 1) \tag{21}$$

and

$$p^n_{0,i} = p(t^i_n = 1 \mid t^0_n = 1). \tag{22}$$

Given the assumption of known channel gains, we have the following recursion according to [17].

$$\begin{aligned} p^n_{0,1} &= p(h^0_{n,k} + \upsilon^0_{n,k} > 0) = 1 - Q\left(\frac{h^0_{n,k}}{\sigma_n}\right) \\ p^n_{i-1,i} &= p(h^{i-1}_{n,k} + \upsilon^{i-1}_{n,k} > 0) = 1 - Q\left(\frac{h^{i-1}_{n,k}}{\sigma_n}\right) \end{aligned} \tag{23}$$

$$p^n_{0,m+1} = p^n_{m,m+1} p^n_{0,m} + (1 - p^n_{m,m+1})(1 - p^n_{0,m}). \tag{24}$$

Therefore, $p_{H_n}(1) = p(t^{H_n}_n = 1 \mid t^0_n = 1) = p^n_{0,H_n}$, which can be recursively calculated using (23)–(24).

$p_{H_n}(-1)$ can be similarly recursively determined. In fact, because each hop can be viewed as a binary symmetric channel (BSC), we can show that

$$p_{H_n}(-1) = p(t^{H_n}_n = 1 \mid t^0_n = -1) = 1 - p_{H_n}(1). \tag{25}$$

Once $p_{H_n}(1)$ and $p_{H_n}(-1)$ are available, we can substitute (20) in (18) and get the conditional pdf $p(\mathbf{R}_{n,k} \mid D_{n,k})$. Then, from (13) the observation likelihood function at the fusion center can be calculated.

To calculate the conditional probabilities in (20)–(24), which represent the observation likelihood, the fusion center needs to know the multi-hop routing structure and all the channel knowledge on each link along the routes. The assumption of knowing all the routes and associated channel knowledge is quite demanding in practice. For a WSN with very limited energy and bandwidth, it is prohibitive to spend resources on estimating the channel every time a local sensor sends its observation to the fusion center. Thus, it is imperative to avoid channel estimation and conserve resources at the possible cost of relatively small performance degradation. In many WSN scenarios the statistics of the fading channel and the additive Gaussian noise can be estimated in advance and used as prior information. In the next Subsection, assuming that only channel fading statistics are available, we derive the observation likelihood.

### B. Likelihood Function with Known Channel Fading Statistics

Let us consider Rayleigh and block-fading channels. For simplicity assume that all the links have identical fading statistics. With the mean squared value of the fading channel gain denoted as $2\sigma_c^2$, for $n = 1,\ldots,N$ and $i = 0,1,\ldots,H_n$, the pdf of channel gain $h_{n,k}^i$ is given by

$$p(h_{n,k}^i) = \frac{h_{n,k}^i}{\sigma_c^2}\exp\left(-\frac{(h_{n,k}^i)^2}{2\sigma_c^2}\right), \qquad h_{n,k}^i \geq 0. \quad (26)$$

THEOREM 1 *Under the Rayleigh fading channel assumption, the conditional pdf of received signal* $\mathbf{R}_{n,k}$ *given local quantized observation* $D_{n,k}$ *of sensor n is given by*

$$p(\mathbf{R}_{n,k} \mid D_{n,k}) = \sum_{\mathbf{T}_{n,k}^{H_n}} p(\mathbf{R}_{n,k} \mid \mathbf{T}_{n,k}^{H_n})p(\mathbf{T}_{n,k}^{H_n} \mid \mathbf{T}_{n,k}^0) \quad (27)$$

*where the first term in the product above is given by*

$$\begin{aligned} p(\mathbf{R}_{n,k} \mid \mathbf{T}_{n,k}^{H_n}) &= p([r_{n,1},\ldots,r_{n,M}]^T \mid [t_{n,1}^{H_n},\ldots,t_{n,M}^{H_n}]^T) \\ &= \frac{\beta^2}{(2\pi)^{M/2}\sigma_c^2\sigma_n^{M-4}}\exp\left[-\frac{\sum_{j=1}^M r_{n,j}^2}{2\sigma_n^2}\right] \\ &\times\left\{1+\sqrt{2\pi}\beta\left(\sum_{j=1}^M r_{n,j}t_{n,j}^{H_n}\right)\exp\left(\frac{\beta^2\left(\sum_{j=1}^M r_{n,j}t_{n,j}^{H_n}\right)^2}{2}\right)Q\left(-\beta\left(\sum_{j=1}^M r_{n,j}t_{n,j}^{H_n}\right)\right)\right\} \end{aligned} \quad (28)$$

*with parameter*

$$\beta = \frac{1}{\sigma_n\sqrt{\left(\frac{\sigma_n}{\sigma_c}\right)^2 + M}}.$$

*The second term* $p(\mathbf{T}_{n,k}^{H_n} \mid \mathbf{T}_{n,k}^0) = \prod_{j=1}^M p(t_{n,j}^{H_n} \mid t_{n,j}^0)$ *denotes channel transmission statistics to be given in the proof.*

PROOF Under the assumptions of Rayleigh fading channels and IID channel noises, the channel transmission statistics, i.e., the conditional pdf, can be written as

$$\begin{aligned} p(\mathbf{R}_{n,k} \mid D_{n,k}) &= p(\mathbf{R}_{n,k} \mid \mathbf{T}_{n,k}^0) \\ &= \sum_{\mathbf{T}_n^{H_n}} p(\mathbf{R}_{n,k} \mid \mathbf{T}_{n,k}^{H_n})p(\mathbf{T}_{n,k}^{H_n} \mid \mathbf{T}_{n,k}^0) \\ &= \sum_{t_{n,1}^{H_n},\ldots,t_{n,M}^{H_n}\in\{1,-1\}} p([r_{n,1},\ldots,r_{n,M}]^T \mid [t_{n,1}^{H_n},\ldots,t_{n,M}^{H_n}]^T) \\ &\quad \times p([t_{n,1}^{H_n},\ldots,t_{n,M}^{H_n}]^T \mid \mathbf{T}_{n,k}^0) \end{aligned} \quad (29)$$

where the summation is over the enumeration of all the different binary sequences $\mathbf{T}_{n,k}^{H_n}$ of length $M$.

Due to slow fading for the transmission of $M$-bit data, the entire set of symbols transmitted from the relay sensor experiences the same channel fading. Conditioning on the last relay output $\mathbf{T}_{n,k}^{H_n}$, the likelihood function of the received data has the form

$$\begin{aligned} p(\mathbf{R}_{n,k} \mid \mathbf{T}_{n,k}^{H_n}) &= p([r_{n,1},\ldots,r_{n,M}]^T \mid [t_{n,1}^{H_n},\ldots,t_{n,M}^{H_n}]^T) \\ &= \int_{h_{n,k}^{H_n}}\left(\prod_{j=1}^M p(r_{n,j} \mid t_{n,j}^{H_n}, h_{n,k}^{H_n})\right)p(h_{n,k}^{H_n})dh_{n,k}^{H_n}. \end{aligned} \quad (30)$$

The result of the integration described above is given by (28) (the detailed proof of (28) is omitted, and a similar proof can be found in [24]).

Under the assumption of IID channel noises, the binary sequence transmission probability from $\mathbf{T}_{n,k}^0$ to $\mathbf{T}_{n,k}^{H_n}$, i.e., $p([t_{n,1}^{H_n},\ldots,t_{n,M}^{H_n}]^T \mid [t_{n,1}^0,\ldots,t_{n,M}^0]^T)$, can be expressed as follows

$$\begin{aligned} p(\mathbf{T}_{n,k}^{H_n} \mid \mathbf{T}_{n,k}^0) &= p([t_{n,1}^{H_n},\ldots,t_{n,M}^{H_n}]^T \mid [t_{n,1}^0,\ldots,t_{n,M}^0]^T) \\ &= \prod_{j=1}^M p(t_{n,j}^{H_n} \mid t_{n,j}^0) \end{aligned} \quad (31)$$

where $t_{n,j}^{H_n}, t_{n,j}^0 \in \{1,-1\}$.

Given the assumption of known channel fading statistics, similar to the result in Section III-A, we have

$$p(t_{n,j}^{H_n} = 1 \mid t_{n,j}^0 = 1) = p_{0,H_n}^n$$
$$p(t_{n,j}^{H_n} = -1 \mid t_{n,j}^0 = 1) = 1 - p_{0,H_n}^n \tag{32}$$

$$p(t_{n,j}^{H_n} = 1 \mid t_{n,j}^0 = -1) = 1 - p_{0,H_n}^n$$
$$p(t_{n,j}^{H_n} = -1 \mid t_{n,j}^0 = -1) = p_{0,H_n}^n. \tag{33}$$

The term $p_{0,H_n}^n$ can be recursively determined as in (24) with the difference that for known channel statistics, we have

$$P_{0,1}^n = \int_0^\infty p(h_{n,k}^0 + \upsilon_{n,k}^0 > 0) p(h_{n,k}^0) dh_{n,k}^0$$
$$= \frac{1}{2} + \frac{\sigma_c}{2\sqrt{\sigma_c^2 + \sigma_n^2}} \tag{34}$$

$$P_{i-1,i}^n = \int_0^\infty p(h_{n,k}^{i-1} + \upsilon_{n,k}^{i-1} > 0) p(h_{n,k}^{i-1}) dh_{n,k}^{i-1}$$
$$= \frac{1}{2} + \frac{\sigma_c}{2\sqrt{\sigma_c^2 + \sigma_n^2}}. \tag{35}$$

Substituting (28) and (31) into (27), we get the conditional pdf of the received signal $\mathbf{R}_{n,k}$ at the fusion center.

$$p(\mathbf{R}_{n,k} \mid D_{n,k}) = \sum_{\mathbf{T}_{n,k}^{H_n}} p(\mathbf{R}_{n,k} \mid \mathbf{T}_{n,k}^{H_n}) p(\mathbf{T}_{n,k}^{H_n} \mid \mathbf{T}_{n,k}^0).$$

To compute the likelihood in (30)–(35), under the assumption that all the links have identical fading statistics and all the channel noises are IID, the fusion center does not need to know the exact route of the data or the instantaneous channel knowledge on each link along the routes. But the fusion center still needs to know the source of the data and the number of hops during data transmission. The statistics of the fading channel and the noise can be stored at the fusion center as prior information in advance. Moreover, as shown in the simulation, the particle filter with channel gain information does not offer dramatic performance advantage over that with only the knowledge of channel fading statistics. So, target tracking with only channel fading statistics will be less demanding for prior information and more practical for real scenarios.

## IV. CHANNEL-AWARE AUXILIARY PARTICLE FILTERING

PF [25] is an effective algorithm for nonlinear non-Gaussian target tracking by approximating the posterior distribution $p(\mathbf{x}_k \mid \bar{\mathbf{R}}_{1:k})$ using a set of weighted particles $\{\mathbf{x}_k^{(j)}, w_k^{(j)}\}_{j=1}^{N_p}$, where $w_k^{(j)}$ denotes the weight of the $j$th particle at time $k$, $N_p$ denotes the total number of particles, and $\bar{\mathbf{R}}_{1:k} = (\bar{\mathbf{R}}_1, \ldots, \bar{\mathbf{R}}_k)$ denotes the observations from all the sensors up to time instant $k$.

At each iteration sequential importance resampling (SIR) PF samples from the prior density of the target state and the importance weight becomes proportional to the observation likelihood. Although SIR PF is easy to implement, it becomes inefficient when the prior distribution is relatively diffused or the likelihood is extremely informative. The auxiliary particle filter (APF) was introduced by Pitt and Shephard [26] as a variant of the PF. The APF attempts to draw from an importance function which is as close as possible to the optimal one. The APF reduces the computational burden and is generally more efficient than the SIR method by giving extra importance to particles with larger predictive values.

At the beginning the initial set of particles $\mathbf{x}_0^{(j)}$, $j = 1, 2, \ldots, N_p$, are drawn from the prior distribution, and the initial weights of the particles are evenly set as $w_0^{(j)} = 1/N_p$. Suppose now that at time step $k-1$, we have the weighted particles $\{\mathbf{x}_{k-1}^{(j)}, w_{k-1}^{(j)}\}_{j=1}^{N_p}$. Then the steps of APF recursion can be implemented as follows.

ALGORITHM 1 Channel-Aware Auxiliary Particle Filtering

*Step 1: Auxiliary Variable Resampling Step*
*For $j = 1, \ldots, N_p$ compute the conditional mean of $\mathbf{x}_k$ given $\mathbf{x}_{k-1}^{(j)}$ using target state transition function* (1)*, and $\boldsymbol{\mu}_k^{(j)} = E(\mathbf{x}_k \mid \mathbf{x}_{k-1}^{(j)})$.*
*Sample auxiliary integer variable $i^j$ from the set $\{1, \ldots, N_p\}$ with the probability $p(i^j = i) \propto p(\bar{\mathbf{R}}_k \mid \boldsymbol{\mu}_k^{(i)}) w_{k-1}^{(i)}$. The conditional pdf $p(\bar{\mathbf{R}}_k \mid \boldsymbol{\mu}_k^{(i)})$ denotes the likelihood at the fusion center given by (13)–(15), where the term $p(\mathbf{R}_{n,k} \mid D_{n,k})$ is given by (18) if the channel gains are known or by (27) if only channel fading statistics are available, and $p(D_{n,k} \mid \boldsymbol{\mu}_k^{(i)})$ is calculated by* (16).

*Step 2: Importance Sampling Step*
*For $j = 1, \ldots, N_p$ propagate the current state particles one step ahead by sampling $\mathbf{x}_k^{(j)} \sim p(\mathbf{x}_k \mid \mathbf{x}_{k-1}^{(i^j)})$ from target state transition function* (1).

*Step 3: Weight Computation*
*Evaluate the corresponding importance weight and normalize $w_k^{(j)} \propto p(\bar{\mathbf{R}}_k \mid \mathbf{x}_k^{(j)}) / p(\bar{\mathbf{R}}_k \mid \mathbf{x}_k^{(i^j)})$, where the likelihood in the numerator and denominator can be calculated using* (13).

*Step 4: State Estimation*
*Once the weights are normalized, the pdf of the target state $p(\mathbf{x}_k \mid \bar{\mathbf{R}}_{1:k})$ can be approximated by the particles $\{\mathbf{x}_k^{(j)}, w_k^{(j)}\}_{j=1}^{N_p}$, from which one can compute the estimates of the unknown states, such as the minimum mean square error (MMSE) estimate*

$$\hat{\mathbf{x}}_k = \sum_{j=1}^{N_p} w_k^{(j)} \mathbf{x}_k^{(j)}. \tag{36}$$

## V. POSTERIOR CRAMÉR-RAO LOWER BOUND ANALYSIS

The PCRLB provides in general the lower bound for mean square error (MSE) of any estimator of random vector. In this section we derive the tracking performance bounds for our multi-hop target tracking problem. At time step $k$ let $\hat{\mathbf{x}}_k$ be an estimate of the state vector $\mathbf{x}_k$; given all the available measurements $\bar{\mathbf{R}}_{1:k}$ up to time $k$, we have the lower bound for the MSE matrix of the estimation error given by

$$C_k \stackrel{\Delta}{=} E\{(\hat{\mathbf{x}}_k - \mathbf{x}_k)(\hat{\mathbf{x}}_k - \mathbf{x}_k)^T\} \geq J_k^{-1} \tag{37}$$

where $J_k$ is the Fisher information matrix (FIM), whose inverse is the PCRLB matrix of $\mathbf{x}_k$. In [27] Tichavsky, et al. provided a recursive approach to calculate FIM $J_k$ without manipulating large matrices at each time $k$

$$J_{k+1} = D_k^{22} - D_k^{21}(J_k + D_k^{11})^{-1}D_k^{12} \tag{38}$$

$$D_k^{11} = E\{-\Delta_{\mathbf{x}_k}^{\mathbf{x}_k} \log p(\mathbf{x}_{k+1} \mid \mathbf{x}_k)\} \tag{39}$$

$$D_k^{12} = E\{-\Delta_{\mathbf{x}_k}^{\mathbf{x}_{k+1}} \log p(\mathbf{x}_{k+1} \mid \mathbf{x}_k)\} \tag{40}$$

$$D_k^{21} = E\{-\Delta_{\mathbf{x}_{k+1}}^{\mathbf{x}_k} \log p(\mathbf{x}_{k+1} \mid \mathbf{x}_k)\} = (D_k^{12})^T \tag{41}$$

$$\begin{aligned} D_k^{22} &= E\{-\Delta_{\mathbf{x}_{k+1}}^{\mathbf{x}_{k+1}} \log p(\mathbf{x}_{k+1} \mid \mathbf{x}_k)\} \\ &\quad + E\{-\Delta_{\mathbf{x}_{k+1}}^{\mathbf{x}_{k+1}} \log p(\bar{\mathbf{R}}_{k+1} \mid \mathbf{x}_{k+1})\} \\ &= D_k^{22,a} + D_k^{22,b} \end{aligned} \tag{42}$$

where $\Delta_{\mathbf{y}}^{\mathbf{x}} \stackrel{\Delta}{=} \nabla_{\mathbf{y}} \nabla_{\mathbf{x}}^T$ is the second derivative operator and $\nabla_{\mathbf{x}} = [\partial/\partial x_1, \ldots, \partial/\partial x_{n_x}]^T$ denotes the gradient operator with $n_x$ representing the dimension of $\mathbf{x}$. It is important to note that the expectations above (38)–(42) are taken with respect to the joint pdf $p(\mathbf{x}_{0:k+1}, \bar{\mathbf{R}}_{1:k+1})$. The recursion in (38) begins with

$$J_0 = E\{-\Delta_{\mathbf{x}_0}^{\mathbf{x}_0} \log p(\mathbf{x}_0)\}. \tag{43}$$

However, in most cases, direct computation of $D_k^{11}$, $D_k^{12}$, $D_k^{22}$ involves high-dimensional integration, and in general analytical solutions do not exist except for some special models, such as linear systems with additive Gaussian noise. Here, similar to the idea behind PF, Monte Carlo techniques are proposed to evaluate these terms.

Under the assumptions that the target states evolve according to a first-order Markov process and that the observations are conditionally independent given the state, the joint pdf used for the expectations in (39)–(42) can be factorized as

$$p(\mathbf{x}_{0:k+1}, \bar{\mathbf{R}}_{1:k+1}) = p(\mathbf{x}_{k+1} \mid \mathbf{x}_k) p(\bar{\mathbf{R}}_{k+1} \mid \mathbf{x}_{k+1}) p(\mathbf{x}_{0:k}, \bar{\mathbf{R}}_{1:k}) \tag{44}$$

For any nonlinear non-Gaussian system, we assume that the derivatives and expectations exist and the integration and derivatives are exchangeable. The term $D_k^{11}$ can be rewritten as

$$\begin{aligned} D_k^{11} &= E\{-\Delta_{\mathbf{x}_k}^{\mathbf{x}_k} \log p(\mathbf{x}_{k+1} \mid \mathbf{x}_k)\} \\ &= E\left\{ \frac{\nabla_{\mathbf{x}_k} p(\mathbf{x}_{k+1} \mid \mathbf{x}_k) \nabla_{x_k}^T p(\mathbf{x}_{k+1} \mid \mathbf{x}_k)}{p^2(\mathbf{x}_{k+1} \mid \mathbf{x}_k)} - \frac{\Delta_{\mathbf{x}_k}^{\mathbf{x}_k} p(\mathbf{x}_{k+1} \mid \mathbf{x}_k)}{p(\mathbf{x}_{k+1} \mid \mathbf{x}_k)} \right\}. \end{aligned} \tag{45}$$

Using decomposition (44) some variables in (45) can be integrated out and we have

$$\begin{aligned} &E\left\{ \frac{\Delta_{\mathbf{x}_k}^{\mathbf{x}_k} p(\mathbf{x}_{k+1} \mid \mathbf{x}_k)}{p(\mathbf{x}_{k+1} \mid \mathbf{x}_k)} \right\} \\ &= \int\int \Delta_{\mathbf{x}_k}^{\mathbf{x}_k} p(\mathbf{x}_{k+1} \mid \mathbf{x}_k) p(\mathbf{x}_k) d\mathbf{x}_k d\mathbf{x}_{k+1} \\ &= \int \left[ \int \Delta_{\mathbf{x}_k}^{\mathbf{x}_k} p(\mathbf{x}_{k+1} \mid \mathbf{x}_k) d\mathbf{x}_{k+1} \right] p(\mathbf{x}_k) d\mathbf{x}_k \\ &= \int \left[ \Delta_{\mathbf{x}_k}^{\mathbf{x}_k} \int p(\mathbf{x}_{k+1} \mid \mathbf{x}_k) d\mathbf{x}_{k+1} \right] p(\mathbf{x}_k) d\mathbf{x}_k \\ &= 0 \end{aligned} \tag{46}$$

since $\int p(\mathbf{x}_{k+1} \mid \mathbf{x}_k) d\mathbf{x}_{k+1} = 1$.

So, we have

$$\begin{aligned} D_k^{11} &= E\left\{ \frac{\nabla_{\mathbf{x}_k} p(\mathbf{x}_{k+1} \mid \mathbf{x}_k) \nabla_{\mathbf{x}_k}^T p(\mathbf{x}_{k+1} \mid \mathbf{x}_k)}{p^2(\mathbf{x}_{k+1} \mid \mathbf{x}_k)} \right\} \\ &= E_{p(\mathbf{x}_k)}\left\{ E_{p(\mathbf{x}_{k+1} \mid \mathbf{x}_k)}\left[ \frac{\nabla_{\mathbf{x}_k} p(\mathbf{x}_{k+1} \mid \mathbf{x}_k) \nabla_{\mathbf{x}_k}^T p(\mathbf{x}_{k+1} \mid \mathbf{x}_k)}{p^2(\mathbf{x}_{k+1} \mid \mathbf{x}_k)} \right] \right\} \\ &= E_{p(\mathbf{x}_k)}\{g_1(\mathbf{x}_k, \mathbf{x}_{k+1})\}. \end{aligned} \tag{47}$$

Following a similar procedure we have

$$D_k^{12} = E\{-\Delta_{\mathbf{x}_k}^{\mathbf{x}_{k+1}} \log p(\mathbf{x}_{k+1} \mid \mathbf{x}_k)\} = E_{p(\mathbf{x}_k)}\{g_2(\mathbf{x}_k)\} \tag{48}$$

$$D_k^{22,a} = E_{p(\mathbf{x}_k)}\{g_3(\mathbf{x}_k)\} \tag{49}$$

$$D_k^{22,b} = E\{-\Delta_{\mathbf{x}_{k+1}}^{\mathbf{x}_{k+1}} \log p(\bar{\mathbf{R}}_{k+1} \mid \mathbf{x}_{k+1})\} = E_{p(\mathbf{x}_k)}\{g_4(\mathbf{x}_k)\} \tag{50}$$

where

$$g_1(\mathbf{x}_k) = E_{p(\mathbf{x}_{k+1} \mid \mathbf{x}_k)}\left[ \frac{\nabla_{\mathbf{x}_k} p(\mathbf{x}_{k+1} \mid \mathbf{x}_k) \nabla_{\mathbf{x}_k}^T p(\mathbf{x}_{k+1} \mid \mathbf{x}_k)}{p^2(\mathbf{x}_{k+1} \mid \mathbf{x}_k)} \right] \tag{51}$$

$$g_2(\mathbf{x}_k) = E_{p(\mathbf{x}_{k+1} \mid \mathbf{x}_k)}\left[ \frac{\nabla_{\mathbf{x}_k} p(\mathbf{x}_{k+1} \mid \mathbf{x}_k) \nabla_{\mathbf{x}_{k+1}}^T p(\mathbf{x}_{k+1} \mid \mathbf{x}_k)}{p^2(\mathbf{x}_{k+1} \mid \mathbf{x}_k)} \right] \tag{52}$$

$$g_3(\mathbf{x}_k) = E_{p(\mathbf{x}_{k+1} \mid \mathbf{x}_k)}\left[ \frac{\nabla_{\mathbf{x}_{k+1}} p(\mathbf{x}_{k+1} \mid \mathbf{x}_k) \nabla_{\mathbf{x}_{k+1}}^T p(\mathbf{x}_{k+1} \mid \mathbf{x}_k)}{p^2(\mathbf{x}_{k+1} \mid \mathbf{x}_k)} \right] \tag{53}$$

$$\begin{aligned} g_4(\mathbf{x}_k) &= E_{p(\mathbf{x}_{k+1} \mid \mathbf{x}_k) p(\bar{\mathbf{R}}_{k+1} \mid \mathbf{x}_{k+1})} \\ &\quad \times \left[ \frac{\nabla_{\mathbf{x}_{k+1}} p(\bar{\mathbf{R}}_{k+1} \mid \mathbf{x}_{k+1}) \nabla_{\mathbf{x}_{k+1}}^T p(\bar{\mathbf{R}}_{k+1} \mid \mathbf{x}_{k+1})}{p^2(\bar{\mathbf{R}}_{k+1} \mid \mathbf{x}_{k+1})} \right]. \end{aligned} \tag{54}$$

The expectations in (51)–(54) can be approximately evaluated by converting them into summations using the Monte Carlo integration methodology. To do so we first generate a set of IID samples $\mathbf{x}_{k+1}^{(j)} \sim p(\mathbf{x}_{k+1} \mid \mathbf{x}_{k,\text{sample}})$, $j = 1, \ldots, M_p$

with identical weights $w_{k+1}^{(j)} = 1/M_p$, where $\mathbf{x}_{k,\text{sample}}$ denotes the state value at time step $k$ on a sample track from the target motion model. Then, we have the Monte Carlo approximation $p(\mathbf{x}_{k+1} \mid \mathbf{x}_k) \approx \sum_{j=1}^{M_p} w_{k+1}^{(j)} \cdot \delta(\mathbf{x}_{k+1} - \mathbf{x}_{k+1}^{(j)})$. So, the above expectations can be approximated as follows

$$g_1(\mathbf{x}_k) \approx \sum_{j=1}^{M_p} w_{k+1}^{(j)} \frac{\nabla_{\mathbf{x}_k} p(\mathbf{x}_{k+1}^{(j)} \mid \mathbf{x}_k) \nabla_{\mathbf{x}_k}^T p(\mathbf{x}_{k+1}^{(j)} \mid \mathbf{x}_k)}{p^2(\mathbf{x}_{k+1}^{(j)} \mid \mathbf{x}_k)} \tag{55}$$

$$g_2(\mathbf{x}_k) \approx \sum_{j=1}^{M_p} w_{k+1}^{(j)} \frac{\nabla_{\mathbf{x}_k} p(\mathbf{x}_{k+1}^{(j)} \mid \mathbf{x}_k) \nabla_{\mathbf{x}_{k+1}}^T p(\mathbf{x}_{k+1}^{(j)} \mid \mathbf{x}_k)}{p^2(\mathbf{x}_{k+1}^{(j)} \mid \mathbf{x}_k)} \tag{56}$$

$$g_3(\mathbf{x}_k) \approx \sum_{j=1}^{M_p} w_{k+1}^{(j)} \frac{\nabla_{\mathbf{x}_{k+1}} p(\mathbf{x}_{k+1}^{(j)} \mid \mathbf{x}_k) \nabla_{\mathbf{x}_{k+1}}^T p(\mathbf{x}_{k+1}^{(j)} \mid \mathbf{x}_k)}{p^2(\mathbf{x}_{k+1}^{(j)} \mid \mathbf{x}_k)} \tag{57}$$

$$\begin{aligned} g_4(\mathbf{x}_k) &\approx \sum_{j=1}^{M_p} w_{k+1}^{(j)} \\ &\quad \times \int \frac{\nabla_{\mathbf{x}_{k+1}} p(\bar{\mathbf{R}}_{k+1} \mid \mathbf{x}_{k+1}^{(j)}) \nabla_{\mathbf{x}_{k+1}}^T p(\bar{\mathbf{R}}_{k+1} \mid \mathbf{x}_{k+1}^{(j)})}{p(\bar{\mathbf{R}}_{k+1} \mid \mathbf{x}_{k+1}^{(j)})} d\bar{\mathbf{R}}_{k+1}. \end{aligned} \tag{58}$$

The final expectation with respect to $p(\mathbf{x}_k)$ in (47)–(50) can be obtained by averaging the above approximations in (55)–(58) over a number of Monte Carlo trials, i.e., over a number of sample tracks from the target motion model. Typically, for an $M_c$-run Monte Carlo trial, we have

$$\begin{aligned} D_k^{11} &= \frac{1}{M_c} \sum_{l=1}^{M_c} g_1(\mathbf{x}_k^{(l)}) \\ D_k^{12} &= \frac{1}{M_c} \sum_{l=1}^{M_c} g_2(\mathbf{x}_k^{(l)}) \\ D_k^{22,a} &= \frac{1}{M_c} \sum_{l=1}^{M_c} g_3(\mathbf{x}_k^{(l)}) \\ D_k^{22,b} &= \frac{1}{M_c} \sum_{l=1}^{M_c} g_4(\mathbf{x}_k^{(l)}). \end{aligned} \tag{59}$$

As a special case, for the linear target dynamic model (2), the quantities above can be simplified as follows

$$D_k^{11} = \Phi^T Q^{-1} \Phi, \qquad D_k^{12} = -\Phi^T Q^{-1}, \qquad D_k^{22,a} = Q^{-1}. \tag{60}$$

The matrix $D_k^{22,b}$ denotes the contribution of the observation at time $k$ to the PCRLB. Based on (13), (58) can be further written as

$$g_4(\mathbf{x}_k) \approx \sum_{j=1}^{M_p} \sum_{n=1}^{N} w_{k+1}^{(j)} \int \frac{\nabla_{\mathbf{x}_{k+1}} p(\mathbf{R}_{n,k+1} \mid \mathbf{x}_{k+1}^{(j)}) \nabla_{\mathbf{x}_{k+1}}^T p(\mathbf{R}_{n,k+1} \mid \mathbf{x}_{k+1}^{(j)})}{p(\mathbf{R}_{n,k+1} \mid \mathbf{x}_{k+1}^{(j)})} d\mathbf{R}_{n,k+1} \tag{61}$$

where the term $p(\mathbf{R}_{n,k+1} \mid \mathbf{x}_{k+1})$ is given in (14) and the expressions for partial derivatives are as follows

$$\begin{aligned} &\nabla_{\mathbf{x}_{k+1}} p(\mathbf{R}_{n,k+1} \mid \mathbf{x}_{k+1}) \\ &\quad = \sum_{D_{n,k+1}=0}^{L-1} p(\mathbf{R}_{n,k+1} \mid D_{n,k+1}) \nabla_{\mathbf{x}_{k+1}} p(D_{n,k+1} \mid \mathbf{x}_{k+1}). \end{aligned} \tag{62}$$

The elements of the gradient $\nabla_{\mathbf{x}_{k+1}} p(D_{n,k+1} \mid \mathbf{x}_{k+1})$ are as follows (for details see [11], [20])

$$\begin{aligned} &\frac{\partial p(D_{n,k+1} = l \mid \mathbf{x}_{k+1})}{\partial x_{1,k+1}} \\ &\quad = \frac{\alpha a_{n,k+1} d_{n,k+1}^{-2} (\xi_{1,n} - x_{1,k+1}) \lambda_{n,l} d_0^2}{2\sqrt{2\pi}\sigma_{\varpi}} \\ &\frac{\partial p(D_{n,k+1} = l \mid \mathbf{x}_{k+1})}{\partial x_{2,k+1}} \\ &\quad = \frac{\alpha a_{n,k+1} d_{n,k+1}^{-2} (\xi_{2,n} - x_{2,k+1}) \lambda_{n,l} d_0^2}{2\sqrt{2\pi}\sigma_{\varpi}} \\ &\frac{\partial p(D_{n,k+1} = l \mid \mathbf{x}_{k+1})}{\partial \dot{x}_{1,k+1}} \\ &\quad = \frac{\partial p(D_{n,k+1} = l \mid \mathbf{x}_{k+1})}{\partial \dot{x}_{2,k+1}} = 0 \\ &\frac{\partial p(D_{n,k+1} = l \mid \mathbf{x}_{k+1})}{\partial \varphi_{k+1}} \\ &\quad = \frac{d_{n,k+1}^{-\alpha/2} \lambda_{n,l} d_0^{\alpha/2}}{2\sqrt{2\pi}\sigma_{\varpi}\sqrt{\varphi_{k+1}}} \end{aligned} \tag{63}$$

where $\lambda_{n.l} = \exp[-(\eta_{n,l} - a_{n,k+1})/2\sigma_{\varpi}^2] - \exp[-(\eta_{n,(l+1)} - a_{n,k+1})/2\sigma_{\varpi}^2]$.

The conditional probability $p(\mathbf{R}_{n,k+1} \mid D_{n,k+1})$ is given by (18) if the channel gains are available or by (27) if only channel fading statistics are known.

Note that the integration with respect to $\mathbf{R}_{n,k+1}$ in (61) is an $M$-fold integration over the received symbols $\mathbf{R}_{n,k+1} = [r_{n,1}, r_{n,2}, \ldots, r_{n,M}]^T$, and each element can take any value in $(-\infty, \infty)$. For the case where the integration in (61) does not have a closed-form solution, it can be approximated by numerical integration approaches [46].

The PCRLB provides a bound on the optimal achievable accuracy of target state estimation. Closely related to PCRLB is the concept of conditional PCRLB [28, 29], which is the PCRLB on the MSE of the state estimate for the next time step, conditioned on the measurements up to the current time. The sensor management technique based on the conditional PCRLB has proved to be particularly effective in automating multi-sensor resource management [30–33]. The basis of the sensor management technique is to quantify and adaptively control the MSE of the target state estimation at the next time based on the information available up to the current time. In Section VI we adopt an approach based on one particular form of the conditional PCRLB to select a subset of sensors for conserving energy and communication bandwidth.

## VI. SIMULATION RESULTS

In this section we present results of some computer simulations that illustrate the performance of the proposed channel-aware target tracking algorithms where multi-bit quantized data of sensors are transmitted over multi-hop fading channels. We consider a scenario where the examined network consists of 100 sensors deployed randomly in a 300 m $\times$ 350 m field. The attenuation parameter is set to $\alpha = 2$ and the reference signal power to $\varphi = 200$ at $d_0 = 1$ m. We assume the measurement noise in (6) has identical variance $\sigma_{\varpi}^2 = 0.01$. The target motion process noise parameter is $q = 1$. The sampling interval is $T = 1$ s and observation length is 20 s. We assume that all the channels follow the Rayleigh fading model with unit mean square value, i.e., $2\sigma_c^2 = 1$. The channel coefficients $h_n^i$ for $n = 1,\ldots,N$ and $i = 0,1,\ldots,H_n$ are generated using the Rayleigh fading model. The channel noise variance $\sigma_n^2$ is chosen to yield an average channel signal-to-noise ratio (SNR) of 10 dB. In the implementation of the proposed algorithms, we use $N_p = 3000$ particles. We assume that the emitted signal power $\varphi_k$ is unknown and needs to be estimated. The prior for the augmented target's state is a Gaussian distribution with mean $\mathbf{x}_0 = [30,30,10,10,200]^T$ and covariance matrix diag$\{20,20,5,5,35\}$. The variance of the noise $\beta_k$ in the target signal power model as provided in (7) is $\sigma_\beta^2 = 1$. We use $M = 4$ to quantize analog measurements at the sensors. For simplicity we assume that all the sensors employ identical thresholds, and uniform quantization thresholds are used in the simulation.

For target tracking in WSNs, it is assumed that the fusion center receives data only from a certain maximum number of sensors due to the available communication bandwidth and other physical limitations. Thus, even though a large number of sensors are available, only a few sensors are used at a time. Here, we use a particular form of the conditional PCRLB as the criterion to select sensors in the WSN for target tracking.

For sensor selection, in order to use the information from the current measurement and provide a one-step predicted estimator performance limit for the upcoming time step $k + 1$, when the new measurement $z_k$ becomes available, the FIM $J_k$ is reinitialized using the target state estimation covariance $C_k$ which was calculated from the PF-based estimate of the posterior target state pdf. The FIM $J_{k+1}$ at time $k + 1$ is then calculated by one-step recursion using (38)–(42). Note that a bound obtained this way is one form of conditional PCRLB discussed in [29]. At every time step $k$, we choose the summation of the position bound along each axis as the cost function to select sensors for the next time step, i.e., $\mathbb{C}_{k+1} = J_{k+1}^{-1}(1,1) + J_{k+1}^{-1}(2,2)$, where $J_{k+1}^{-1}(1,1)$ and $J_{k+1}^{-1}(2,2)$ are the bounds on the MSE corresponding to position coordinates $x_{1,k+1}$ and $x_{2,k+1}$, respectively.

Typically in target tracking we are most interested in minimizing the target position estimation error, which is one way of maintaining the track of the target. An alternative cost function is the trace of the MSE matrix or the PCRLB matrix. However, the trace of the MSE (or PCRLB) matrix is the sum of the position and velocity MSEs, which does not have a clear physical meaning, since the MSE of position and the MSE of velocity have different units. For comparison purposes we rerun the simulation using the trace of the PCRLB matrix as the cost function. The simulation results are not distinguishable from those based on position MSEs only. Actually, in most of the simulation runs, the two methods select the same sensors. The simulation results corresponding to this comparison are not shown here due to limited space.

Note that an alternative sensor selection method is based on the nearest neighbor criterion, where the sensors nearest to the predicted position of the target are selected. In our previous work [7, 10, 12, 33] simulation results have shown that the PCRLB-based sensor selection outperformed the nearest neighbor sensor selection scheme significantly, and much more accurate tracking results were achieved by the PCRLB-based approach. Moreover, the derived PCRLB in this paper is a channel-aware PCRLB which considers the effect of an imperfect channel, while the nearest neighbor sensor selection does not take this into consideration.

Those sensors that collectively minimize the above cost function are activated at the next time $k + 1$. The optimal sensor subset $S^*(k + 1)$ is then given by

$$S^*(k+1) = \arg\min_{\{S(k+1)\}} \mathbb{C}_{k+1}(S(k+1)). \qquad (64)$$

In our simulation, out of 100 available sensors, only $N_s = 3$ sensors are selected using the optimal exhaustive search method to minimize the cost function at every time step $k$, which is the constraint for the optimization problem given in (64).

In the simulation scenario we do not consider communication delay and routing issues for simplicity. We assume there is one fixed fusion center. Due to

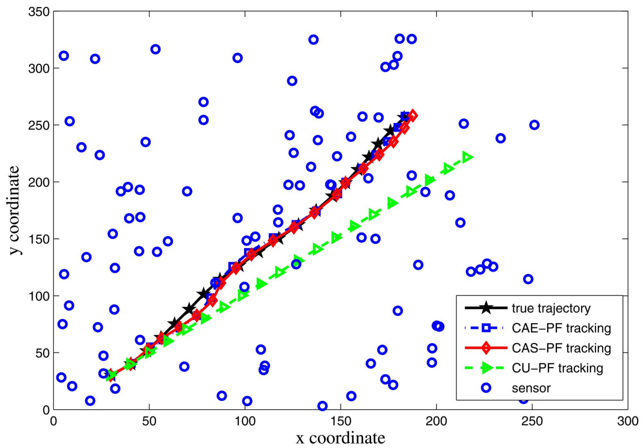

Fig. 2. Realization of target trajectory, its estimate, and randomly deployed WSN.

the sensor selection approach used here, observations from only 3 local sensors at every time step are transmitted to the fusion center, and other sensors only serve as relay nodes. We assume that all the selected sensors require the same number of hops to reach the fusion center, and the number of hops is 3 (or $H_n = 2$) without loss of generality.

For comparison we empirically define the channel-unaware particle filter (CU-PF) by ignoring relay channel fading, i.e., from the measurements $\mathbf{R}_{n,k}$ at the fusion center we simply reconstruct $\mathbf{T}^0_{n,k} = \mathrm{sign}(\mathbf{R}_{n,k})$ as the original $M$-bit quantized measurement of local sensor $n$ and calculate its likelihood function using (16). In Fig. 2 we give a realization obtained from one simulation run of the geometry of the randomly deployed WSN, the true target trajectory, and its estimates under imperfect channel conditions by channel-aware PF with channel gain knowledge (CAE-PF), channel-aware PF with channel fading statistics (CAS-PF), and its channel-unaware counterpart CU-PF, respectively. The experimental results clearly show that the two channel-aware PFs track the target closely, whereas the CU-PF loses track most of the time due to the fact that channel fading is ignored. The two channel-aware PFs show similar performances. Moreover, the CAE-PF outperforms the CAS-PF. Compared with CAE-PF there is small performance loss for CAS-PF.

Note that in a CU-PF, the communication channel is still nonideal. But the fusion center is unaware of the imperfect channel and still calculates the measurements' likelihood as if they were transmitted over perfect channels. As a result there is a mismatch between the actual measurements received at the fusion center and the likelihood calculated by the fusion center, which leads to the divergence of the PF. In contrast the channel-aware PFs take the channel imperfection into consideration and their estimation performance is improved.

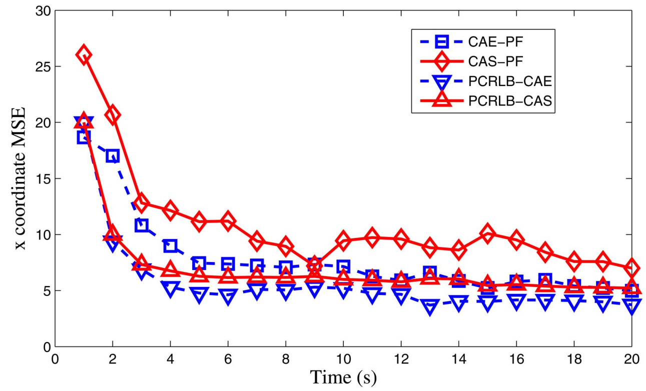

Fig. 3. MSEs and PCRLBs for coordinate $x$ of target.

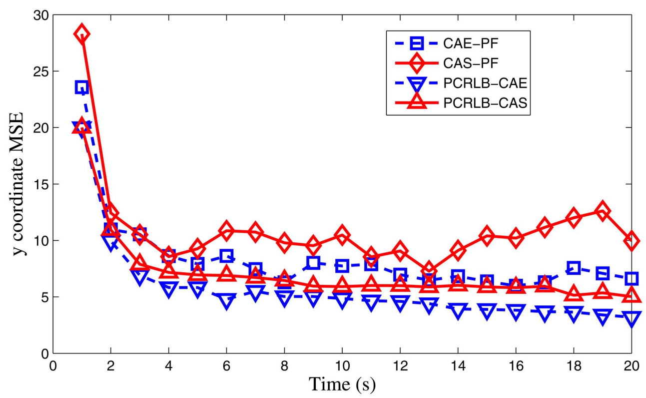

Fig. 4. MSEs and PCRLBs for coordinate $y$ of target.

In order to assess the performance improvement by employing two kinds of channel-aware PFs, we display the MSEs at each time step of estimates for location coordinates $x_{1,k}$ and $x_{2,k}$ in Figs. 3 and 4, respectively. The MSEs of the signal power estimate $\hat{\varphi}$ are shown in Fig. 5. The corresponding PCRLBs on the MSEs of coordinate and signal power estimates with known channel gains (PCRLB-CAE) and channel fading statistics (PCRLB-CAS) are also shown as performance bounds in the figures, respectively. The MSEs and PCRLBs are obtained by taking the average over 100 different Monte Carlo runs. In each run we randomly generate sensor locations in the region of interest, randomly generate a trajectory of target, then run the channel-aware PF and sensor selection scheme to obtain the square of the estimation error, and obtain the PCRLB based on the selected sensors and their locations. The figures show the MSEs of estimates and the average PCRLBs.

When a sensor selection scheme is adopted, the selected subsets of sensors vary over time and also vary in different Monte Carlo simulation runs. In general we have a different set of selected sensors in each Monte Carlo run at each particular time step. We also notice the jumpy behavior of the MSEs and PCRLBs. This is partially due to the geometry of the target and the varying subset of selected sensors. It can be observed from the figures that the MSEs

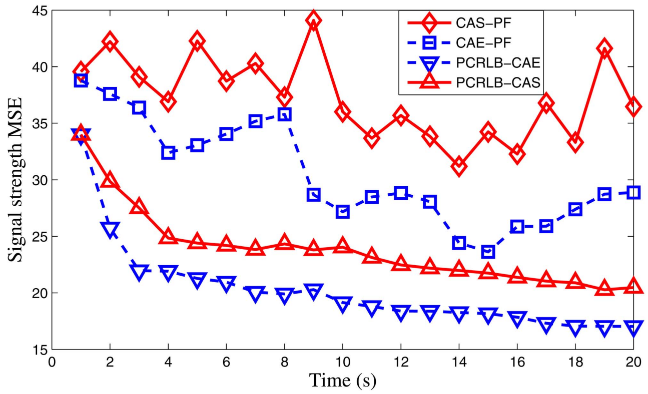


Fig. 5. MSEs and PCRLBs for target signal power.

TABLE I
Percentage of Lost Tracks versus Different Average Channel SNRs

| Algorithm | SNR = 10 dB | SNR = 5 dB | SNR = 0 dB |
|---|---|---|---|
| CAE-PF | 0 | 6 | 27 |
| CAS-PF | 0 | 11 | 33 |
| CU-PF | 54 | 98 | 100 |

nearly follow their PCRLBs and that there is a slight difference between the MSE and the corresponding PCRLB which could be due to the nonlinearity of the problem and suboptimality of the filter. There is certain performance degradation for the CAS-PF in comparison with the CAE-PF, but the former is less demanding in terms of prior information.

We define a lost track when the estimation error of the target position is greater than 50 m and is increasing over five consecutive time steps. Based on this definition Table I shows the number of lost tracks corresponding to channel-aware PFs and CU-PFs in 100 Monte Carlo trials for different average channel SNRs. It is clear from Table I that as the channel becomes noisier, all the filters result in more lost tracks. However, the two channel-aware PFs (CAE-PF and CAS-PF) are much more robust against channel noise and have much fewer lost tracks than the CU-PF.

In Fig. 6 the performances of channel-aware PFs, CAE-PF, and CAS-PF, are compared for different numbers of hops ($H_n + 1$) between the selected sensors and the fusion center. The performance criterion is the averaged MSE in position over all time steps computed as follows from the MMSE estimates with respect to the true simulated target states, i.e.,

$$\frac{1}{M_c K}\sum_{m=1}^{M_c}\sum_{k=1}^{K}(\hat{x}_{1,k}^m - x_{1,k}^m)^2 + (\hat{x}_{2,k}^m - x_{2,k}^m)^2 \qquad (65)$$

where $x_{1,k}^m$, $x_{2,k}^m$, $\hat{x}_{1,k}^m$, and $\hat{x}_{2,k}^m$ are the actual and estimated target coordinates at time k in the m$^{\text{th}}$ Monte Carlo trial, respectively, $M_c$ is the number of Monte Carlo trials, and $K$ is the predefined final time of the track. As can be seen in the figure, the

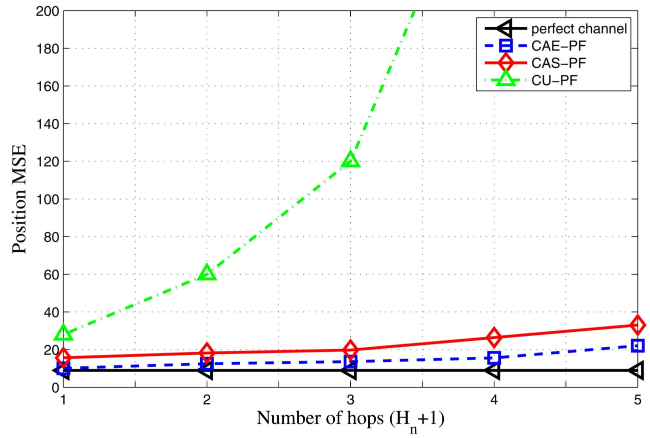


Fig. 6. Averaged MSE versus number of hops (4-bit quantization and 10 dB average channel SNR).

performances of all the PFs degrade with an increase in the number of hops. In contrast to CU-PF there is a very slow degradation for channel-aware PFs. It is shown that the performances of the CAE-PF and CAS-PF are quite robust to multiple hops and imperfections of the wireless channels since channel information has been included in the estimation process. The CU-PF has severe performance degradation and diverges even for a relatively small number of hops. Furthermore, the comparison with respect to the PF under the perfect channel conditions as a benchmark, where we assume that there is no channel fading or noise, shows that the channel-aware PFs can overcome the degradation due to multi-hop relay such that it is almost negligible for a small number of hops. Although the multi-hop relay affects the accuracy of target tracking, it leads to significant reduction in communication energy [21]. Therefore, there should be a tradeoff between tracking accuracy and the consumption of communication energy in the design of the tracking system. In [34], [35] the tradeoff between performance and network lifetime was investigated as optimization problems in a multi-hop sensor network.

Finally, the averaged MSE in position for CAS-PF is shown in Fig. 7 as a function of the number of activated sensors ($N_s$), which are selected by using the cost function defined in (64), and the number of bits $M$ per sensor varying from 1 to 6, respectively. As can be seen in the figure, the averaged MSE decreases and the performance improves with the increase of the number of bits and activated sensors. Moreover, for our simulation scenario, selecting more than 3 sensors and more than 4 bits offers little performance improvement. A similar trend can be found for CAE-PF which is omitted here.

## VII. CONCLUSION

In this paper we focused on a resource-constrained multi-hop WSN with nonideal channels. We proposed

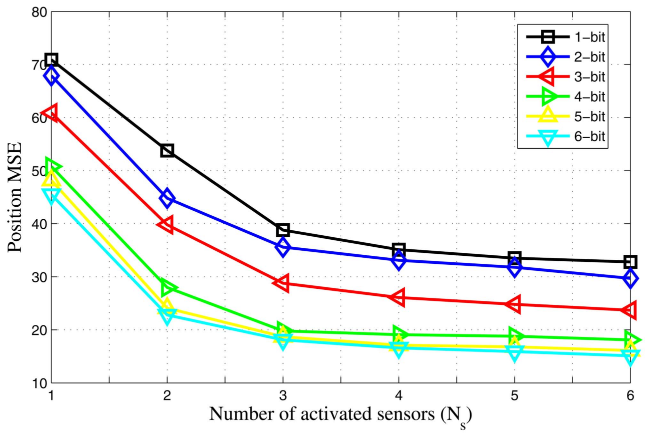


Fig. 7. Averaged MSE versus number of selected sensors and number of bits (10 dB average channel SNR).

a channel-aware target tracking approach based on APF. The measurements of sensors are quantized to $M$-bit data which are transmitted to the fusion center over multi-hop relay fading channels. Each relay node employs a binary decision decode-and-forward relay scheme. We derived the observation likelihood function at the fusion center which incorporates wireless channel transmission statistics and decoding scheme characteristics at the receiver. In addition we derived the PCRLB of the estimated unknowns and proposed a Monte Carlo solution to compute these terms recursively.

We have also shown that channel-aware PFs are more robust to low channel SNR and a large number of hops than the CU-PF. In addition we also showed that the channel-aware PF provides a performance that is very close to the case where complete channel information is available for a small number of hops. As channel SNR increases, the PF with only the knowledge of the channel fading statistics yields a similar estimation performance as that of the PF with the knowledge of the instantaneous channel gain. Although there is a small performance loss for CAS-PF compared with CAE-PF, the former is less demanding in terms of prior information and more practical than the latter. There are some open issues which are interesting topics that deserve further attention. Future research will focus on effective solutions to quantization, error control coding, routing, and data relay schemes.

REFERENCES


[1] Chong, Y. and Kumar, S. P.
Sensor networks: Evolution, opportunities and challenges. *Proceedings of the IEEE*, **91**, 8 (Aug. 2003), 1247–1256.

[2] Kumar, S., Zhao, F., and Sheperd, D. (Eds.)
*IEEE Signal Processing Magazine* (special issue on collaborative signal and information processing for microsensor networks), **19**, 2, Mar. 2002.

[3] Sayeed, A., et al. (Eds.)
*IEEE Journal of Selected Areas on Communication*, (special issue on self-organizing distributed collaborative sensor networks), **23**, 4 (Apr. 2005), 689–872.

[4] Guo, D. and Wang, X.
Dynamic sensor collaboration via sequential Monte Carlo. *IEEE Journal on Selected Areas in Communications*, **22**, 6 (Aug. 2004), 1037–1047.

[5] Sheng, X. and Hu, Y.
Maximum likelihood multiple-source localization using acoustic energy measurements with wireless sensor networks.
*IEEE Transactions on Signal Processing*, **53**, 1 (Jan. 2005), 44–53.

[6] Zuo, L., et al.
Bandwidth-efficient target tracking in distributed sensor networks using particle filters.
*Proceedings of the 2006 9th International Conference on Information Fusion*, Florence, Italy, July 2006, pp. 1–4.

[7] Zuo, L., Niu, R., and Varshney, P. K.
Posterior CRLB based sensor selection for target tracking in sensor networks.
*Proceedings of the IEEE International Conference on Acoustics, Speech and Signal Processing*, (ICASSP 2007), vol. 2, Honolulu, HI, pp. II-1041–II-1044.

[8] Djuric, P. M., Vemula, M., and Bugallo, M. F.
Target tracking by particle filtering in binary sensor networks.
*IEEE Transactions on Signal Processing*, **56**, 6 (June 2006), 2229–2238.

[9] Ruan, Y., et al.
Practical fusion of quantized measurements via particle filtering.
*IEEE Transactions on Aerospace and Electronic Systems*, **44**, 1 (Jan. 2008), 15–29.

[10] Zuo, L., Niu, R., and Varshney, P. K.
A sensor selection approach for target tracking in sensor networks with quantized measurements.
*Proceedings of the IEEE International Conference on Acoustics, Speech, and Signal Processing* (ICASSP 2008), Las Vegas, NV, Apr. 2008, pp. 2521–2524.

[11] Niu, R. and Varshney, P. K.
Target location estimation in sensor networks with quantized data.
*IEEE Transactions on Signal Processing*, **54**, 12 (Dec. 2006), 4519–4528.

[12] Masazade, E., Niu, R., and Varshney, P. K.
Energy aware iterative source localization for wireless sensor networks.
*IEEE Transactions on Signal Processing*, **58**, 9 (Dec. 2010), 4824–4835.

[13] Chen, B., et al.
Channel aware decision fusion in wireless sensor networks.
*IEEE Transactions on Signal Processing*, **52**, 12 (Dec. 2004), 3454–3458.

[14] Jiang, R. and Chen, B.
Fusion of censored decisions in wireless sensor networks. *IEEE Transactions on Wireless Communications*, **4**, 6 (Nov. 2005), 2668–2673.

[15] Niu, R., Chen, B., and Varshney, P. K.
Fusion of decisions transmitted over Rayleigh fading channels in wireless sensor networks.
*IEEE Transactions on Signal Processing*, **54**, 3 (Mar. 2006), 1018–1027.

[16] Chen, B., Tong, L., and Varshney, P. K.
Channel-aware distributed detection in wireless sensor networks.
*IEEE Signal Processing Magazine*, (special issue on distributed signal processing for sensor networks), **23**, 4 (July 2006), 16–26.

[17] Lin, Y., Chen, B., and Varshney, P. K.
Decision fusion rules in multi-hop wireless sensor networks.
*IEEE Transactions on Aerospace and Electronic Systems*, **41**, 2 (Apr. 2005), 475–488.

[18] Tian, Q. J. and Coyle, E. J.
Optimal distributed detection in clustered wireless sensor networks.
*IEEE Transactions on Signal Processing*, **55**, 7 (July 2007), 3892–3904.

[19] Ozdemir, O., Niu, R., and Varshney, P. K.
Channel aware target location with quantized data in wireless sensor networks.
*IEEE Transactions on Signal Processing*, **57**, 3 (Mar. 2009), 1190–1202.

[20] Ozdemir, O., Niu, R., and Varshney, P. K.
Tracking in wireless sensor networks using particle filtering: Physical layer considerations.
*IEEE Transactions on Signal Processing*, **57**, 5 (May 2009), 1987–1999.

[21] Rahman, R., Alanyali, M., and Saligrama, V.
Distributed tracking in multihop sensor networks with communication delays.
*IEEE Transactions on Signal Processing*, **55**, 9 (2007), 4656–4668.

[22] Yang, X., et al.
Channel aware target tracking in multi-hop wireless sensor networks.
*Proceedings of the 14th International Conference on Information Fusion*, Chicago, IL, July 2011, pp. 1–8.

[23] Bar-Shalom, Y., Li, X. R., and Kirubarajan, T.
*Estimation with Applications to Tracking and Navigation.*
Hoboken, NJ: Wiley, 2001.

[24] Masazade, E.
Resource aware distributed detection and estimation of random events in wireless sensor networks.
Doctoral dissertation, Sabanc University, Istanbul, Turkey, 2010.

[25] Arulampalam, M. S., et al.
A tutorial on particle filters for online nonlinear/non-Gaussian Bayesian tracking.
*IEEE Transactions on Signal Processing*, **50**, 2 (Feb. 2002), 174–188.

[26] Pitt, M. and Shephard, N.
Filtering via simulation: Auxiliary particle filters.
*Journal of the American Statistical Association*, **94**, 446 (June 1999), 590–599.

[27] Tichavsk, P., Muravchik, C. H., and Nehorai, A.
Posterior Cramér-Rao bounds for discrete-time nonlinear filtering.
*IEEE Transactions on Signal Processing*, **46**, 5 (May 1998), 1386–1395.

[28] Zuo, L., Niu, R., and Varshney, P. K.
Conditional posterior Cramer-Rao lower bounds for nonlinear sequential Bayesian estimation.
*IEEE Transactions on Signal Processing*, **59**, 1 (Jan. 2011), 1–14.

[29] Zheng, Y., et al.
New conditional Posterior Cramér-Rao lower bounds for nonlinear sequential Bayesian estimation.
*IEEE Transactions on Signal Processing*, **60**, 10 (Oct. 2012), 5549–5556.

[30] Hernandez, M. L., Kirubarajan, T., and Bar-Shalom, Y.
Multisensor resource deployment in the presence of clutter using Cramér-Rao lower bounds.
*IEEE Transactions on Aerospace and Electronic Systems*, **40**, 2 (Apr. 2004), 399–416.

[31] Tharmarasa, R., Kirubarajan, T., and Hernandez, M. L.
Large-scale optimal sensor array management for multitarget tracking.
*IEEE Transactions on Systems, Man and Cybernetics—Part C: Applications and Review*, **37**, 5 (Sept. 2007), 803–814.

[32] Zuo, L.
Conditional posterior Cramér-Rao lower bound and distributed target tracking in sensor networks.
Doctoral dissertation, Syracuse University, Syracuse, NY, Dec. 2010.

[33] Masazade, E., Niu, R., and Varshney, P. K.
Dynamic bit allocation for object tracking in wireless sensor networks.
*IEEE Transactions on Signal Processing*, **60**, 10 (Oct. 2012), 5048–5063.

[34] Chen, H., Feng, J., and Tse, C. K.
Performance-lifetime tradeoff for source extraction in multihop sensor networks.
*International Journal on Communication Systems*, **23** (2010), 1613–1631.

[35] Chen, H.
Performance-energy tradeoffs for decentralized estimation in a multihop sensor network.
*IEEE Sensors Journal*, **10**, 8 (Aug. 2010), 1304–1309.

[36] Rago, C., Willett, P., and Bar-Shalom, Y.
Censoring sensors: A low-communication-rate scheme for distributed detection.
*IEEE Transactions on Aerospace and Electronic Systems*, **32**, 2 (1996), 554–568.

[37] Braca, P., Marano, S., and Matta, V.
Single-transmission distributed detection via order statistics.
*IEEE Transactions on Signal Processing*, **60**, 4 (2012), 2042–2048.

[38] Aslam, J., et al.
Tracking a moving object with a binary sensor network.
*Proceedings of the 1st International Conference on Embedded Networked Sensor Systems* (SenSys'03), Los Angeles, CA, Nov. 5–7, 2003, pp. 150–161.

[39] Kim, W., et al.
On target tracking with binary proximity sensors.
*Proceedings of the 4th International Symposium on Information Processing in Sensor Networks* (IPSN'05), Los Angeles, CA, Apr. 2005, pp. 251–264.

[40] Shrivastava, N., et al.
Target tracking with binary proximity sensors.
*ACM Transactions on Sensor Networks*, **5**, 4 (2009), 1–33.

[41] Singh, J., et al.
Multiple-target tracking with binary proximity sensors.
*ACM Transactions on Sensor Networks*, **8**, 1 (2011), 1–26.

[42] Olfati-Saber, R.
Distributed Kalman filtering for sensor networks.
*Proceedings of the 46th IEEE Conference on Decision Control*, New Orleans, LA, Dec. 2007, pp. 5492–5498.

[43] Cattivelli, F. S. and Sayed, A. H.
Diffusion strategies for distributed Kalman filtering and smoothing.
*IEEE Transactions on Automatic Control*, **55**, 9 (Sept. 2010), 2069–2084.

[44] Msechu, E. J. and Giannakis, G. B.
Sensor-centric data reduction for estimation with WSNs via censoring and quantization.
*IEEE Transactions on Signal Processing*, **60**, 1 (Jan. 2012), 400–414.

[45] Zheng, Y., Niu, R., and Varshney, P. K.
Sequential Bayesian estimation with censored data.
*Proceedings of the 2012 IEEE Statistical Signal Processing Workshop* (SSP), Ann Arbor, MI, Aug. 2012, pp. 57–60.

[46] Atkinson, K. E.
*An Introduction to Numerical Analysis* (2nd ed.).
Hoboken, NJ: Wiley, 1989.

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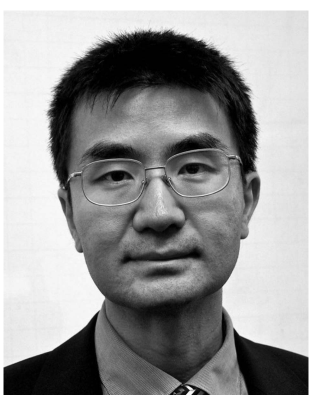

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