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RESEARCH

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An improved target tracking scheme based on MC-MPMC method for mobile wireless sensor networks

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Abstract

Target tracking is crucial to many applications in wireless sensor networks (WSNs). Existing tracking schemes used in WSNs can basically be classified two categories, clustering and predicting. Considering network clustering consumes much energy for limited-energy WSNs, a predicting target tracking scheme is proposed called MC-MPMC (measurement compensation-based mixture population Monte Carlo) which tracks the target based on predicted locations in this work. Adaptive mixture PMC model for generating proposals varying from each iteration is proposed to guarantee sampling diversity. And also, extra measurements or observations generating method is introduced to compensate missed prediction locations or false estimations, avoiding tracking behavior degradation. Firstly, samples drawn from the proposals of next iteration can be generated by a mixture method to avoid sample degeneracy. Secondly, sample weights are jointly computed based on adaptive fusion of compensation measurement and true measurements. Thirdly, HTC method is combined to MC-MPMC scheme to decrease energy consumption in WSNs. Then, the proposed method is verified through comprehensive experiments about tracking error, delay and consumption predictions. Moreover, performance comparisons of MC-MPMC with other tracking schemes are also proposed.

Keywords: Target tracking, WSNs, MC-MPMC scheme, HTC scheme, Tracking delay

1 Introduction

WSNs have been applied to many domains, such as environmental and habitat monitoring, precision agriculture, animal tracking, disaster rescue, military surveillance, the Internet of things, aging healthcare application and almost touch upon all aspects of our life [1–3]. Moving target tracking is a representative application of WSNs. Localization and tracking of moving target need to be supported by energy efficiency tracking technology. Although many advantages presented by WSNs, such as cheap, non-infrastructure, large-scale, and long-term work, bring new perspective for tracking applications, the intrinsic characteristics of sensor nodes with limited energy, limited computation capacity, limited data process capacity [4], poor reliability, large scale, random distribution, and short communication distance also present great challenges to target tracking in WSNs.

Tracking could be defined as a process in which target states indicated the target position, movement and other kinematic behaviors are estimated through measurements available from various sensors or through establishing coherent relations of targets between successive events. Target tracking for unmanned systems in terrestrial, aerial or underwater environment, such as unmanned aerial vehicle (UAV), unattended air system (UAS) and autonomous underwater vehicle (AUV), mostly utilizes artificial intelligence, positional information collection and environmental understanding [5–7], considering 2D or 3D kinematic information [8, 9].

Classical tracking algorithms exist in most applications, such as Bayesian algorithm [10–13], Kalman filter [14, 15] and CLS algorithm [16]. Most of target tracking used in WSNs can basically be classified into two categories: clustering and predicting [17, 18]. In clustering method, cluster member nodes detect the target and send the data to cluster head node, and then the proximate location or behavior can be fused by cluster head to track the moving targets [19–24]. The most prominent characteristic of clustering method is that the network needs maintain coverage and network connectivity. Clustering, routing and connecting usually need to establish a plenty of communication between nodes, which can consume much energy [25]. In predicting method, the states indicated target position, movement and other kinematic behaviors are predicted based on the measurements available from various sensors. Less energy is consumed for predicting method for less communication need to be established between nodes.

There are also some other tracking methods, such as energy-based auto regressive neural network [26, 27], deep learning method [28] and genetic algorithm [29]. Considering network clustering consumes much energy for limited-energy WSNs, a predicting target tracking scheme is proposed in this work, called MC-MPMC which tracks the target based on predicted locations. To guarantee the sample diversity, adaptive mixture PMC model for generating proposals varying from each iteration is presented. Supernumerary measurements generating method is introduced to compensate missing predicted locations or false estimations, avoiding tracking behavior degradation. And also, HTC scheme is performed at the beginning of each iteration to obtain the specific 1-hop and 2-hop neighbors of target or sensor nodes (including normal nodes and anchors), which can dramatically reduce energy consumption and time delay.

The rest of this paper is structured as follows. Section 2 gives a summary of related works and analysis premise of our model. A novel MC-MPMC scheme is proposed in Sect. 3, after presenting the original PMC algorithm. Performance analysis models of MC-MPMC accompanying with HTC scheme are also presented in Sect. 3. In Sect. 4, accurate analyses and validations of localization error, delay and consumption are presented, and performance comparisons of MC-MPMC scheme with other tracking schemes are also proposed. Finally, results and discussion are presented in Sect. 5.

2 Related works

State and period are estimated based on the Bayesian tracking scheme after determining the sequence of Markovian states maximizing the probability given the measurements and the semi-hidden Markov model (SHMM) parameters in [11]. A multi-target

Bayes filter with the target detection is developed in [12] by applying a method for target detection based on the rule-based track initiation technique, to enhance the capability of the marginal distribution Bayes (MDB) filter and the probability hypothesis density (PHD) filter on target detection.

A new pseudolinear Kalman filter (PLKF) for target tracking in 2D-plane is presented in [14], using AOA (angle-of-arrival), TDOA (time difference of arrival) and FDOA (frequency difference of arrival) measurements sensed by stationary sensors. A closed-form PLKF is developed by rearranging measurement equations to compensate for the nonzero mean of the noise vector. A bias compensation PLKF (BCPLKF) estimator is presented to tackle the bias issue of PLKF, and an instrumental variable-based Kalman filter (IVKF) is presented to alleviate the bias by utilizing BCPLKF estimates instead of noisy measurements to compute the measurement matrix, in which the posterior Cramér–Rao lower bound (PCRLB) is derived for the nonlinear filtering problem. An improved strong tracking Kalman filter algorithm for tracking analysis is proposed in [15], in which a location is identified with the GPS and basic GSM with message setting. This KF-based scheme is outstanding for its real-time behavior.

An enhanced least-square algorithm (CLS) based on improved Bayesian scheme BELS is developed in [16] for moving target localization and tracking in WSNs, in which an improved Bayesian algorithm obtains a set of sub-range probability based on target predictive locations, and forming a range joint probability matrix. The weight of every measurement is calculated and normalized based on the range probability matrix, and the correction value of the target prediction position is calculated according to the weighted least-square algorithm.

A distributed energy optimization method for target tracking is carried out using particle swarm optimization in [30]. This P-EETT work is comprised of the estimation phase and prediction phase, in which clustering is performed using the maximum entropy method. And, grid exclusion is used for the coverage of nodes in the network. An IMM-based target tracking in WSN ITTWSN is proposed in [31], which adopts multiple models (velocity and acceleration) to handle both maneuvering and non-maneuvering targets and multiple sensors to detect and identify the targets. This method can overcome some problems of the KF scheme, such as non-availability of target data at regular intervals, missing of packets and identifying the target rather than just detecting the target. Energy-efficient management approach of target tracking for WSNs is proposed in [32]. After comprehensive analyses of the structure of WSNs and energy consumption sources, two indicators, including target detection probability and tracking accuracy, are combined to be regarded as the constraints of the energy conserving objective function.

An innovative target tracking algorithm that combines learning regression tree approach and filtering methods using the RSSI metric is developed in [33] for the availability and low cost of RSSI.T-S fuzzy model identification method based on physical membership function is proposed for maneuvering target tracking [34], separating inputs–outputs system spaces. A physical membership function with interpretability and physical meanings is proposed, and a hyper-planed FSC algorithm is utilized. Then, UKF is used to identify parameters and the physical membership function is used to fuse local models and estimate final states. After simplifying the existing approximate likelihood function where the distribution of the scaling factor is approximated by Gaussian one, a feasible weighting scheme is obtained and a novel particle filtering algorithm (NPFA) is proposed in [35]. A maneuvering target tracking scheme under measurement origin uncertainties is derived based on the approximation and propagation of the target state posterior distribution by combining Bayesian decision theory and suitable hypothesis merging procedures in [36], in which very low levels of track loss rate are obtained even for scenarios with high false alarm probability and trajectories with a high degree of maneuverability.

According to the complexity and uncertainty of the detection environment, a novel MC-SMC-PHD scheme is proposed in [37], which develops a compensatory measurement generating mechanism and presents a novel measurement compensation-based SMC-PHD filter to avoid unreliable clustering. Similar missed detection and corrected strategy for target tracking is involved in [38], in which beta distribution is employed to describe unknown detection probability. And, beta gamma Gaussian inverse Wishart (BGGIW) mixture form accompanying with Poisson multi-Bernoulli mixture (PMBM) filter (BGGIW-PMBM) is developed to enhance tracking behaviors. And also, missed detection problem for target tracking is also concerned in [39], besides the coalescence problem. A novel fusion framework for the Poisson multi-Bernoulli (PMB) filter based on the arithmetic average (AA) fusion is proposed, in which integrates both the advantages of the TOMB/P filter in dealing with missed detection and the advantages of the MOMB/P filter in dealing with coalescence. Bernoulli components in different multi-Bernoulli (MB) distributions are associated with each other by Kullback–Leibler divergence (KLD) minimization to fuse the different PMB distributions. The semantic probability hypothesis density (SPHD) filter is introduced in [40] to simultaneously track multiple classes of targets despite measurement uncertainty, including false positive detections, false negative detections, measurement noise and target misclassification.

An improved cardinalized probability hypothesis density (CPHD) filter is developed in [41], to estimate the time-varying target birth cardinality distribution (i.e., probability distribution on number of newborn targets appearing during one sampling time) at each processing step adopting a discrete kernel estimator in conjunction with the exponential weighted moving average scheme. Target birth intensity is updated according to the resulting estimated birth cardinality distribution, and estimated birth intensity and cardinality distribution can be employed by a tracker based on Gaussian mixture CPHD (GMCPHD) to modulate its filtering strength for target tracking.

Inspired by the missed detection and corrected strategy in [38] or compensation strategy [37], an improved MPLC filter accompanied by a measurement compensation scheme is proposed in this work. Original PMC algorithm [42, 43] is presented briefly, with its degradation performance because of its sample generating uncertainty and proposal generating uncertainty. And an adaptive mixture PMC model for generating proposals varying from each iteration is proposed to guarantee the sample diversity. Then, measurement compensation method is introduced to resolve the missed detection. For energy-constrained target tracking in WSNs, either clustering or lots of communication can consume much energy, which is not suitable for WSNs. So, information exchange with small packets exists only at the beginning of each iteration adopting the HTC scheme [44], accompanied by less consecutive communications between nodes or targets. And then, tracking performance, such as tracking error, delay and consumption, especially delay, is presented comprehensively taking parameters such as anchor rate γ, node density λ_0, proposal generating Poisson distribution parameter λ_k and location detection probability p_D into account. Moreover, performance comparisons between MC-MPMC algorithm and other tracking schemes based on the system parameters, such as BELS [16], P-EETT [30], ITTWSN [31] and MC-SMC-PHD [37]. These comparisons demonstrate that delay of MC-MPMC scheme is superior to other predict-based tracking schemes, and the performance of tracking error and consumption also presents the superiority over other schemes when the numbers of mobile nodes and iterations are increased.

The main contributions of this paper are threefold. Firstly, the adaptive mixture PMC model (MPMC), generating proposals according to Poisson process varied from each iteration, is presented to guarantee the sample diversity. Secondly, the supernumerary measurements generating method is introduced to compensate for missing predicted locations or false estimations, avoiding tracking behavior degradation. Finally, the HTC scheme is performed at the beginning of each iteration to obtain the relative locations from specific 1-hop and 2-hop neighbors of target considered as the target states, which can dramatically reduce energy consumption and time delay.

3 Proposed tracking method

For limited-energy WSNs, less computational cost and less complexity method for target tracking is anticipated. And then, communications between nodes or target can consume a lot of energy. So, MPMC scheme accompanying with no clustering and less communication is proposed.

3.1 Problem statement

Figure 1 shows target tracking overview in our WSN. Sensors (including normal sensors denoted as S, and anchor sensors denoted as A) are randomly located $20\,\mathrm{m} \times 20\,\mathrm{m}$ indoor area, according to a two-dimensional Poisson distribution with a density of λ_0, in which the ratio of anchors is γ. A target, whose path is presented as a solid thick line, moves along with its maneuvering trajectory in WSN deployment area and is detected by sensor nodes (normal sensors or anchors), adopting an acceptable tracking strategy. The target, equipped a recognizable sensor, can also communicate with other sensors in this WSN. Because the clustering algorithm can consume much energy for WSN, the proposed method tracks the target without clustering but through establishing the 1-hop and 2-hop neighbor lists by HTC scheme [44]. In each sampling interval, nodes including the target can execute HTC algorithm to obtain its 1-hop and 2-hop neighbors. Each HTC request packet contains node ID, location and current moment. Receiving this request packet, nodes (including the target) can obtain distance information of their 1-hop and 2-hop neighbors. Consecutive position information obtained from request packet of the specific target is used to obtain the target's velocity. Location and velocity information can be used for iterative MPMC filter to obtain target tracking. For example, target can obtain its 1-hop and 2-hop neighbors through performing HTC scheme in iteration k. And then it can

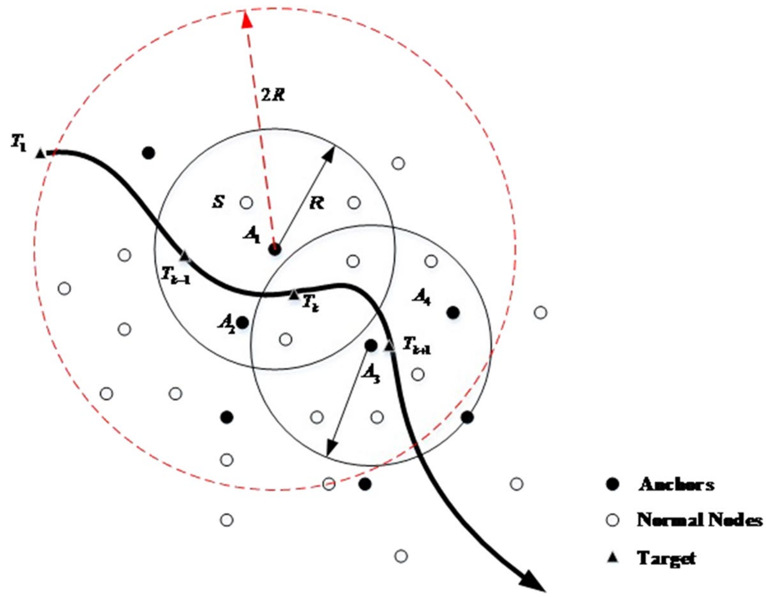

Fig. 1 Target tracking overview in WSN. Target can move with maneuvering trajectories

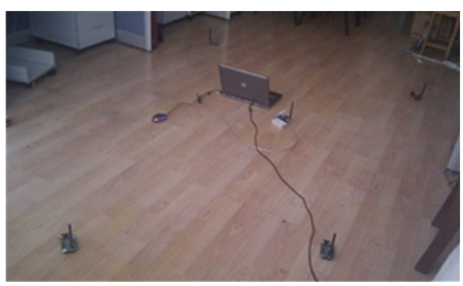

Fig. 2 Tracking environment for our indoor sensor networks

derive its relative locations to its neighbors [45]. MPMC filter can derive target tracking adopting N_k proposals within these locations, accompanied by measurements or observations detected by the target in this iteration k.

The tracking environment for our indoor sensor networks is illustrated in Fig. 2. A wireless sensor is made of a transceiver, data processing center, data storage module and battery, in addition to a sensing unit, such as a PIR sensor (to detect the information of a target, equipped in normal sensors and anchors), a Global Positioning System (GPS) receiver (to identify the location of the sensor node equipped in anchor nodes). A target, a tracked object, equips a PIR sensor moving as a normal sensing node. All nodes can move randomly in our test room. Sensor nodes (including normal nodes and anchors) collect the object tracking information and transmit this information to anchor nodes. Simultaneously, location and tracking of the target can also be obtained from the information of its 1-hop and 2-hop neighbors through executing MC-MPMC scheme. In the realistic target tracking scenario, the target is tracked and undergoes occasional maneuvers. That is, target may move with a linear trajectory (straight line or local straight line) and with a maneuver mode (random trajectory) at any time interval.

3.2 Maneuvering model

The target state is supposed to x_k at the time k in the state space X, and the measurement or observation model is supposed to m_k in the measurement or observation space M under random finite set (RFS) models [37]. Then target state and measurement set can be represented by $X_k \in F(X)$ and $M_k \in F(M)$, respectively. System model and measurement model can be generally described as follows [25, 31]:

$$x_k = F_k x_{k-1} + G_k q_{k-1} \tag{1}$$

$$m_k = H_k x_k + v_k \tag{2}$$

where x_k is the state vector at time k denoted as $x_k = (x_k\ \dot{x}_k\ y_k\ \dot{y}_k\ \omega_k)^T$, F_k is target transition matrix, G_k is control input matrix, and q_k is process noise which follows a Gaussian distribution with zero mean and covariance Q_k defined as $E[q_k q_k^T]$. In the state vector representation, x_k and y_k are the states of target position, $\dot{x}_k$ and $\dot{y}_k$ are the states of target velocity, ω_k is the turn rate. And m_k is the measurement at time k denoted as $m_k = (x_k\ y_k\ \omega_k)^T$, which presents the measurement of position and turn angle of the target, H_k is measurement matrix, and v_k is measurement noise which also follows a Gaussian distribution with zero mean and covariance V_k defined as $E[v_k v_k^T]$. The process noise and measurement noise are mutually uncorrelated to each other.

$$F_k = \begin{bmatrix} 1 & \frac{\sin(\omega_{k-1}T)}{\omega_{k-1}} & 0 & \frac{\cos(\omega_{k-1}T)-1}{\omega_{k-1}} & 0 \\ 0 & \cos(\omega_{k-1}T) & 0 & -\sin(\omega_{k-1}T) & 0 \\ 0 & \frac{1-\cos(\omega_{k-1}T)}{\omega_{k-1}} & 1 & \frac{\sin(\omega_{k-1}T)}{\omega_{k-1}} & 0 \\ 0 & \sin(\omega_{k-1}T) & 0 & \cos(\omega_{k-1}T) & 0 \\ 0 & 0 & 0 & 0 & 1 \end{bmatrix}$$

$$G_k = \begin{bmatrix} \frac{T^2}{2} & 0 & 0 \\ T & 0 & 0 \\ 0 & \frac{T^2}{2} & 0 \\ 0 & T & 0 \\ 0 & 0 & T \end{bmatrix}$$

$$Q_k = \mathrm{cov}(G_k q_{k-1}) = \begin{bmatrix} \frac{1}{4}T^4\sigma_{x,k-1}^2 & \frac{1}{2}T^2\sigma_{x,k-1}^2 & 0 & 0 & 0 \\ \frac{1}{2}T^2\sigma_{x,k-1}^2 & T^2\sigma_{x,k-1}^2 & 0 & 0 & 0 \\ 0 & 0 & \frac{1}{4}T^4\sigma_{y,k-1}^2 & \frac{1}{2}T^2\sigma_{y,k-1}^2 & 0 \\ 0 & 0 & \frac{1}{2}T^2\sigma_{y,k-1}^2 & T^2\sigma_{y,k-1}^2 & 0 \\ 0 & 0 & 0 & 0 & T^2\sigma_{\omega,k-1}^2 \end{bmatrix}$$

Measurement matrix H_k can be demonstrate the position information of the target in x and y directions, which can be presented as,

$$H_k = \begin{bmatrix} 1 & 0 & 0 & 0 & 0 \\ 0 & 0 & 1 & 0 & 0 \\ 0 & 0 & 0 & 0 & 1 \end{bmatrix}$$

3.3 MC-MPMC-based tracking method

And now, an improved predicting method for target tracking-based MC-MPMC method is proposed. In generally, both measurements and states of the target are inherent uncertain. According to Bayesian estimation theory, target state posterior probability density $\pi_{k|k}(X_k|M_{1:k})$ can be obtained by Bayes recursion as [43]

$$\pi_{k|k-1}(X_k|M_{1:k-1}) = \int f_{k|k-1}(X_k|X_{k-1}, M_{1:k-1})\pi_{k-1|k-1}(X_{k-1}|M_{1:k-1})\mathrm{d}X_{k-1} \tag{3}$$

$$\pi_{kk}(X_k|M_{1:k}) = \frac{\ell_k(M_k|X_k)\pi_{kk-1}(X_k|M_{1:k-1})}{\int \ell_k(M_k|X_k)p_{kk-1}(X_k|M_{1:k-1})\mathrm{d}X_k} \tag{4}$$

in which $f_{k|k-1}(X_k|M_{1:k})$ is the state transition density function based on current observations or measurements, $\pi_{kk-1}(X_k|M_{1:k})$ denotes the target probability density and $\ell_k(M_k|X_k)$ denotes the target likelihood function, respectively. In many practical applications, the integrals in Bayes recursion of Eqs. 3 and 4 cannot be obtained in closed form or the computational complexity of the integrals grows sharply with samples increasing. So, the approximations should be proposed adopting importance sampling methods.

$$\pi_{kk-1}(\mathbf{x}) = g_k(\mathbf{x}) + \int f_{kk-1}(x|y)\pi_{k-1}(y)\mathrm{d}y + \int \beta_{kk-1}(x|y)\pi_{k-1}(y)\mathrm{d}y \tag{5}$$

$$\pi_k(\mathbf{x}) = [1 - p_{\mathrm{D},k}(\mathbf{x})]\pi_{kk-1}(\mathbf{x}) + \sum \frac{p_{\mathrm{D},k}(\mathbf{x})\ell_k(m|x)\pi_{kk-1}(\mathbf{x})}{\kappa_k(m) + \int p_{\mathrm{D},k}(y)\ell(m|y)\pi_{kk-1}(y)\mathrm{d}y} \tag{6}$$

in which $p_{\mathrm{D},k}(\mathbf{x})$ is the target detection probability, $\kappa_k(m)$ is the process clutter, $g_k(\mathbf{x})$ is the new generating distribution of state samples from the proposals and $\beta_{kk-1}(x|y)$ is the spawning distribution of state samples based on measurements.

In this work, an improved target tracking method based on MC-MPMC scheme accompanied by HTC algorithm is presented elaborately to approximate or estimate the distribution of target states. PMC filter [43] is a well-known iterative adaptive importance sampling technique, which is briefly described as follows.

At each iteration k, it generates a set of samples $\{\mathbf{x}_k^i\}_{i=1}^N$, where i denotes the sample index and $\mathbf{x}$ denotes the variable of interest which means the object state distribution in our tracking system. That is, sampling or resampling iterates once in each time interval. In order to obtain the samples, PMC algorithm makes use of a collection of proposal densities $\{q_k^i(\mathbf{x})\}_{i=1}^N$, with each sample being drawn from a different proposal, $\mathbf{x}_k^i \sim q_k^i(\mathbf{x})$.Then, these samples are assigned an importance weight, respectively, denoted as $w_k^i = \frac{\pi(\mathbf{x}_k^i)}{q_k^i(\mathbf{x}_k^i|\mu_k^i,\mathbf{C}_i)}$, in which $\pi(\mathbf{x}_k^i)$ is the target posterior density function, μ_k^i is the adaptive parameters of proposal densities in the sampling period k and $\mathbf{C}_i$ is the static parameters. After normalizing these importance weights, the unbiased convergent estimator can be obtained,

$$\overline{w}_k = \frac{1}{TN}\sum_{i=1}^{N}\sum_{k=1}^{T}\frac{\pi(x_k^i)}{q_k^i(x_k^i)} \tag{7}$$

in which the parameter N and T refer to the maximum sample number and the maximum sampling period, respectively. PMC method performs multinomial resampling process by drawing N independent samples from the discrete probability random measurements, which is denoted as

$$w_k^i = \frac{\pi(x_k^i)}{\overline{w}_{k-1}q_k^i(x_k^i)} \tag{8}$$

$$\hat{\pi}_i^N(\mathbf{x}) = \sum_{i=1}^{N}\overline{w}_k^i\delta(\mathbf{x}-\mathbf{x}_k^i) \tag{9}$$

in which $\delta(\cdot)$ is the Dirac delta function. This method proceeds iteratively, building a global importance sampling estimator using different proposals at every iteration. This can partially avoid the sample degeneracy phenomenon. That is, samples with negligible weights or relatively low weights can avoid to be removed directly.

The proposal in each iteration of k, $q_k^i(\mathbf{x})$, can be formed according to the behaviors of the previous $q_{k-1}^i(\mathbf{x})$, or depending on the previous samples $\mathbf{x}_{k-1}^1, ..., \mathbf{x}_{k-1}^N$, or the joint dependence on them. To be clear, the relative previous or current locations of the target from its 1-hop and 2-hop neighbors can be considered as the samples in this location-based tracking strategy [46]. There is a series of improved PMC-based resampling scheme to predict the variable distribution, such as DM-PMC, GR-PMC and LR-PMC [43]. To avoid the sample degeneracy, deterministic mixture weighting method DM-PMC is presented. GR-PMC draws multiple samples generated by a proposal or mix band, instead of only one as done in PMC. And LR-PMC performs the resampling independently for each proposal. These improved PMC schemes improve the diversity of the population for PMC.

Inspired by the time-varying target birth distribution in [41], an iteration-varying proposal generating scheme is proposed in this work. Moreover, measurement or observation remedy scheme is introduced to correct the missed detection issue. This improved MC-MPMC scheme estimates target states, which is presented elaborately as follows.

Step 1 Tracking initialization

In the initial period of $k = 1$, all nodes in the network, containing the target and sensing nodes (normal nodes and anchors), can establish their 1-hop and 2-hop neighbor lists (NL) and update these NLs every iteration stage adopting HTC scheme. Suppose that sample generation function of target state distribution can be complied with the Poisson distributions, that is, $x_1^i \sim P(\lambda_1)$. And then, select the initial parameters defining the N proposals,

The adaptive parameters $a_1 = \{\lambda_1^1, \lambda_1^2, ..., \lambda_1^N\}$.

The corresponding set of static parameters, $\{\mathbf{C}_i\}_{i=1}^N$.

The adaptive parameters in a_1 are the means of $E[\lambda_1^i]$, which is $\lambda_1^1, \lambda_1^2, ..., \lambda_1^N$. And the parameters $\{\mathbf{C}_i\}_{i=1}^N$ are the covariances of $cov[a_1^i]$, which is $\lambda_1, \lambda_1, ..., \lambda_1$.

Initial sample candidates generated by initial proposals can be denoted as $SL_{1\text{-hop}}$ and $SL_{2\text{-hop}}$, which refers to locations between target and its 1-hop possible neighbors and with 2-hop possible neighbors, respectively, which can be seen in [38]. That the target obtains location information used for tracking state establishment can be seen from [39] elaborately.

$$p(\mathbf{x}_1) = \frac{1}{SL_{1\text{-hop}} + SL_{2\text{-hop}}} \tag{10}$$

$$\pi(\mathbf{x}_1) = \ell(m_1|\mathbf{x}_1)p(\mathbf{x}_1) \tag{11}$$

Step 2 Mixture weighting and predicting

After initialization step, samples of target states $x_k^i(i = 1, 2, ..., N_k)$ are generated from the proposals $q_k^i(\mathbf{x})$ in iteration k according to the behaviors of the previous $q_{k-1}^i(\mathbf{x})$ and measurements m_k of locations at the period k. In PMC scheme, each sample is drawn from a different proposal. An improved DM-PMC is proposed in [37], which considers the average of weighted mixture of all proposals around kernel iteration point as the kernel density approximation of target pdf. This simple mixture can mitigate sample degeneracy to a certain extent. But DM-PMC brings weighted mixture only through obtaining the mean, without actually taking the sample diversity into account. And also, the minimum mean integrated square error (MISE) estimator is obtained based on the infinity of N (sample number) [37], while N is finite in our work.

A prominent feature of PMC method is that not only the number but also the distribution of the proposals in iteration k can be different from each other, without jeopardizing the validity [36]. Both the weights and component parameters of a mixture importance sampling density are jointly taken into account for M-PMC scheme to obtain the adaptive mixture PMC scheme in [47]. The adaption of importance sampling density can be presented as weights combined with component density parameters in M-PMC. Inspired from DM-PMC and M-PMC, a mixture weighting combined with sample generating process and measurement process is proposed in MC-MPMC scheme, that is, proposals at the period k are generated based on the previous samples at the period $(k-1)$ sensed by 1-hop and 2-hop neighbors of the target and the current measurements m_k. And then, the global current samples are generated from these proposals with a mixture weighting. In MC-MPMC scheme, samples in iteration k are drawn from proposals $q_k^i(\mathbf{x})$, which can be presented as

$$\mathbf{x}_k^j \sim \left\{P\left(\lambda_j^{k-1}, \mathbf{C}_j^{k-1}\right)\right\} \cup \left\{m_k^j(x)\right\} \quad j = 1, 2, ..., n_k \tag{12}$$

$$p(\mathbf{x}_k^j) = \sum_{j=1}^{n_k} p_j P\left(\lambda_j^k, \mathbf{C}_j^k\right) m_k^j(x) \tag{13}$$

The proposal can be presented with a distribution of a Poisson process with a parameter $\lambda_j(j = 1, 2, ..., n_k)$, with a probability of $p_1, p_2, ..., p_{n_k}$, respectively, in which the sum of p_j is 1, that is, $\sum_{j=1}^{n_k} p_j = 1$. That is, several samples are drawn from different proposals with a mixture pattern rather than each sample being drawn from a specific proposal as in PMC. The distribution and the number of the proposals vary from one iteration to another. And then, weights of the mixture PMC can be derived as

$$w_k^i(\mathbf{x}) = \frac{f(\mathbf{x}_k^i \Big| (P_j)_{j=1}^{n_k}, (\mathbf{C}_j)_{j=1}^{n_k})m_k^i(\mathbf{x})}{\prod_{j=1}^{n_k} \varphi((\mathbf{x}_k^i)^j \Big| (P_j)_{j=1}^{n_{k-1}}, (\mathbf{C}_j)_{j=1}^{n_{k-1}})m_k^i(\mathbf{x})} \tag{14}$$

in which $\varphi(q_k|\lambda_k, \mathbf{C}_k)$ is the density of Poisson distribution with mean value λ_k and covariance $\mathbf{C}_k$ at the condition of q_k for iteration k. And $\mathrm{f}(\mathbf{x}_k^i|\lambda_k, \mathbf{C}_k)$ is the density function of generating samples sensed by 1-hop and 2-hop neighbors of the target according to the proposals for iteration k. So, the probability distribution of target states can be derived based on the set of $\{\mathbf{x}_{k-1}^i, \mathrm{w}_{k-1}^i\}_{i=1}^{n_k}$, which is presented as

$$\pi_{k-1}(x) = \sum_{i=1}^{n_k} w_k^i(\mathbf{x})\delta(\mathbf{x} - \mathbf{x}_k^i) \tag{15}$$

And then, the probability distribution of target states can be predicted as

$$\pi_{kk-1}(\mathbf{x}) = \sum_{i=1}^{n_k} \tilde{w}_{k|k-1}^i(\mathbf{x})\delta(\mathbf{x} - \tilde{\mathbf{x}}_{k|k-1}^i) \tag{16}$$

in which $\tilde{\mathbf{x}}_{k|k-1}^i$ is obtained according to the proposal distributions $q_k^i(\mathbf{x})$ and measurements m_k of locations in the period k,

$$\tilde{x}_{k|k-1}^i = q(x_{k|k-1}^i \Big| x_{k-1}^i, m_k) \quad i = 1, 2, ..., n_k \tag{17}$$

$$\widetilde{w}_{k|k-1}^i(\mathbf{x}) = \frac{f_{k|k-1}(\tilde{\mathbf{x}}_{k|k-1}^i|\mathbf{x}_{k-1}^i)w_{k-1}^i}{q_k(\tilde{\mathbf{x}}_{k|k-1}^i|\mathbf{x}_{k-1}^i, m_k)} \tag{18}$$

Step 3 Update and resampling

According to updating strategy in Eq. 9 of PMC scheme, target state sample distributions can be updated based on Eq. 15 ~ 16.

$$\pi_k(\mathbf{x}) = \sum_{i=1}^{n_k} \tilde{w}_k^i(\mathbf{x})\delta(\mathbf{x} - \tilde{\mathbf{x}}_{k|k-1}^i) \tag{19}$$

in which weights are updated in Eq. 18. Two weight updating parts are contained in Eq. 18, whose first factor is the target weight of undetected probability which is denoted as $w_{k,c}^i$ and the second factor is that of detected probability which is denoted as $w_{\mathrm{k,t}}^{\mathrm{i}}$.

$$\tilde{w}_k^i(\mathbf{x}) = [1 - p_{\mathrm{D},k}(\tilde{\mathbf{x}}_{k|k-1}^i)]\tilde{w}_{k|k-1}^i(\mathbf{x}) + \frac{\sum p_{\mathrm{D},k}(\tilde{\mathbf{x}}_{k|k-1}^i)\ell_k(m\Big|\tilde{\mathbf{x}}_{k|k-1}^i)}{\kappa_k(m) + \pi_k(m)}\tilde{w}_{k|k-1}^i(\mathbf{x}) \tag{20}$$

$$\ell_k(m_k|\mathbf{x}_k) = \prod_{S_1 \in S_{1\text{-hop}}} p(S_1 \Big| x_k^i) \prod_{S_2 \in S_{2\text{-hop}}} p(S_2 \Big| x_k^i) \tag{21}$$

$$\pi_k(m) = \sum_{i=1}^{n_k} p_{D,k}(\widetilde{x}^i_{k|k-1})\ell(m_k\left|\tilde{x}^i_{k|k-1}\right.)\tilde{w}^i_{k|k-1} \tag{22}$$

When the value of $p_{\mathrm{D},k}(\mathbf{x})$, shown in Eq. 18, is not equal to 1, that is, the target may not be detected in iteration k with the probability of $(1-p_{\mathrm{D},k}(\mathbf{x}))$. $p(S_1\left|x^i_k\right.)$ and $p(S_2\left|x^i_k\right.)$ refers to the probability of state sample within in 1-hop and 2-hop area of target, respectively, which is used to obtain the target distribution. Target states may be falsely estimated under undetected occasions, especially for the smaller value of $p_{\mathrm{D},k}$. The undetected target can increase tracking time and tracking energy, and consequently result in poor tracking performance.

Comprehensive analyses for tracking performance degradation because of undetected target were proposed in [38], and the number of measurements is increased to resolve this undetected target problem as related, called as measurement compensatory MPMC (MC-MPMC) method.

The predicted state estimation of $\hat{X}_{k,p}$ and its measurement set $\hat{M}_{k-1,p}$ can be computed by Eqs. 23 and 24, based on $\hat{X}_{k-1,t}$ and process noise and measurement noise.

$$\hat{X}_{k,p} = F_{k-1}\hat{X}_{k,t} + G_k q_{k-1} \tag{23}$$

$$\hat{M}_{k,p} = H_{k-1}\hat{X}_{k,t} + v_k \tag{24}$$

Target is detected successfully meaning that one of predicted measurement $\hat{M}_{k,p}$ (footnote p denotes prediction) is very close to the true measurement $M_{k,t}$ (footnote t denotes true), which is detected by anchors or normal sensors for the location or state information.

$$\widehat{M}_{k,p} = \left\{M^i_{k,p}\left|(M^j_{k,t} - \hat{M}^i_{k,p})^T P_k^{-1}(M^j_{k,t} - \hat{M}^i_{k,p}) < \gamma_{th}\right.\right\} \quad j = 1, 2, ..., n_t \tag{25}$$

in which N_t is the number of true measurements $M_{k,t}$, γ_{th} is a threshold and P_k is called as Prediction covariance.

$$\widehat{M}_{k,c} = \hat{M}_{k,p} - \widehat{M}_{k,p} \tag{26}$$

Compensatory measurement set can be computed according to Eqs. 23–26.

The missing detection weight of $w^i_{k,c}$ in Eq. 20 can be rewritten as Eq. 27, which is the compensatory weight of $\tilde{x}^i_{k,c}$.

$$\tilde{w}^{\mathrm{i}}_{\mathrm{k,c}} = \sum_{j=1}^{n_c}[1 - p_{\mathrm{D},k}(\tilde{\mathbf{x}}^i_{k|k-1})]\tilde{w}^{i,j}_{k|k-1}(\mathbf{x}) \tag{27}$$

$$\tilde{w}^i_{k,t} = \frac{\sum p_{\mathrm{D},k}(\tilde{\mathbf{x}}^i_k)\ell_k(m_{j,t}\left|\tilde{\mathbf{x}}^i_k\right.)}{\kappa_k(m_{j,t}) + D_k(m_{j,t})}\tilde{w}^i_{k|k-1}(\mathbf{x}) \tag{28}$$

in which N_c is the number of compensatory measurements $\widehat{M}_{\mathrm{k,c}}$. And then, the predicted weight of Eq. 18 can be computed as follows:

$$
\begin{aligned}
\tilde{w}_k^i &= \sum_{j=1}^{n_c} \tilde{w}_{k,c}^{i,j} + \sum_{j=1}^{n_t} \tilde{w}_{k,t}^i \\
&= \sum_{j=1}^{N_c} \frac{p_{D,k}(\tilde{\mathbf{x}}_k^i)\ell_k(m_{j,c}|\tilde{\mathbf{x}}_k^i)}{\kappa_k(m_{j,c}) + D_k(m_{j,c})} \tilde{w}_{k|k-1}^i(\mathbf{x}) + \sum_{j=1}^{N_t} \frac{p_{D,k}(\tilde{\mathbf{x}}_k^i)\ell_k(m_{j,t})}{\kappa_k(m_{j,t}) + D_k(m_{j,t})} \tilde{w}_{k|k-1}^i(\mathbf{x})
\end{aligned} \tag{29}
$$

Step 4 Target state estimations

And then, the estimations of target states are computed according to true measurements and compensatory measurements as Eq. 26,

$$
\hat{X}_k = \hat{X}_{k,t} + \hat{X}_{k,c} \tag{30}
$$

$$
\hat{X}_{k,t} = \sum_{j=1}^{n_t} \tilde{w}_{k,t}^{i,j} x_{k,t}^j \tag{31}
$$

$$
\hat{X}_{k,c} = \sum_{j=1}^{n_c} \tilde{w}_{k,c}^{i,j} x_{k,c}^j \tag{32}
$$

Mixture weights can present more valid estimators with less variance, which improve the diversity of the population of PMC algorithm. Also, the whole mixture of observations can match well with the targets than each observation separately.

At each time interval, state error can be obtained from Eq. 27 referred from [45], in which x_k^{iest} is the estimated state and x_k^i is the actual one, which are the distances between target and sensors.

$$
Te_k = \sum_{i=1}^{N_k} \frac{\left\| x_k^{iest} - x_k^i \right\|}{N_k} \tag{33}
$$

Tracking delay is also an important character in our time-critical tracking system, and we always attempt to improve the behavior of delay in order to obtain the real-time monitoring and tracking. In MC-MPMC scheme, delay contains two parts $T_k^{j(\mathrm{HTC})}$ and $T_k^{j(\mathrm{MC\text{-}MPMC})}$. The estimation of time delay in communication can be referred as [48],

$$
T_k^i = \sum_{j=1}^{i} (T_k^{j(\mathrm{HTC})} + T_k^{j(\mathrm{MC\text{-}MPMC})}) \tag{34}
$$

Tracking consumption is the most important metric in energy-constrained WSNs. Average cost can be presented in two parts $E_k^{i(\mathrm{HTC})}$ and $E_k^{i(\mathrm{MC\text{-}MPMC})}$, which refers to the cost of performing HTC scheme and MC-MPMC scheme in iteration, respectively.

$$
E_k^{N_k} = \frac{1}{N_k} \sum_{j=1}^{N_k} (E_k^{j(\mathrm{HTC})} + E_k^{j(\mathrm{PMCL})}) \tag{35}
$$

4 Simulation results

In this section, extensive simulations are presented to validate the accuracy of MC-MPMC method, which are derived based on different parameters such as detection probability P_D, anchors' ratio γ, node density λ_0, adaptive sample number N_k etc., using NS-2 simulator according to previous analyses. Simulation setup is similar to that of PMCL, following each data package exchange means as [49].

The target is assumed to move in the two-dimensional scenario $(0, 20) \times (0, 20)$ m^2 for 100 sampling period, with three true maneuvering trajectories. Target moving velocity v plays an important role in target tracking performance, and higher velocity brings performance degradation of tracking. The maximum velocity is set 6 m/s. The sensor's sampling period is set to 1 s.

And also, performance comparisons between MC-MPMC method and other tracking schemes, such as BELS [16], P-EETT [30], ITTWSN [31] and MC-SMC-PHD [37], are proposed. Communication and computation parameters for all these schemes are similarly set as shown in Table 1, and simulation scenes are set to the similar installation.

True target trajectories in this test are shown in Fig. 3, maneuvering trajectories including straight-line trajectories and crossover trajectories. It is worth noting that the relationship of N_k with the sum of N_c and N_t plays an important role in tracking behaviors. That is, if the sum of N_c and N_t is larger than N_k, there are not enough samples to participate in tracking, leading to once more iterations and then more delay or energy. While the sum of N_c and N_t is smaller than N_k, there are some remaining samples to be selected.

4.1 Target tracking error

Tracking accuracy is an important performance for obtaining the target in WSNs. As related in Sect. 3.3, tracking error in MC-MPMC is mostly related to sample number N_k in iteration k, node density λ_0, detected probability p_D, iteration period K, and anchor rate γ, which is shown in Eq. 33. With node density λ_0 increasing, tracking error decreases shown in Fig. 4a–c. All predicted locations are detected and correctly managed, and it can obtain higher tracking accuracy.

Nodes, concluding anchors and target, are assumed to locate randomly uniformly over indoor room according to Poisson distribution with a density of λ_0, and all nodes can move in maneuvering mode. The number of N_k is less than the sum of N_c and N_t, which leads to tracking participated samples less than the sum of true samples and compensation samples. And so, actual samples are not enough to exact tracking the target, which leads to much error such as $N_k = 30$ and $N_k = 50$ in Fig. 4d–f. With the increasing of

Table 1 Parameter set

Symbol	Value set	Symbol	Value set
K	100 s	N_c	30
R	20 m	γ	20%
T	1 s	v_{max}	6 m/s
S	20×20	σ_x	0.01
N_t	30	σ_y	0.001

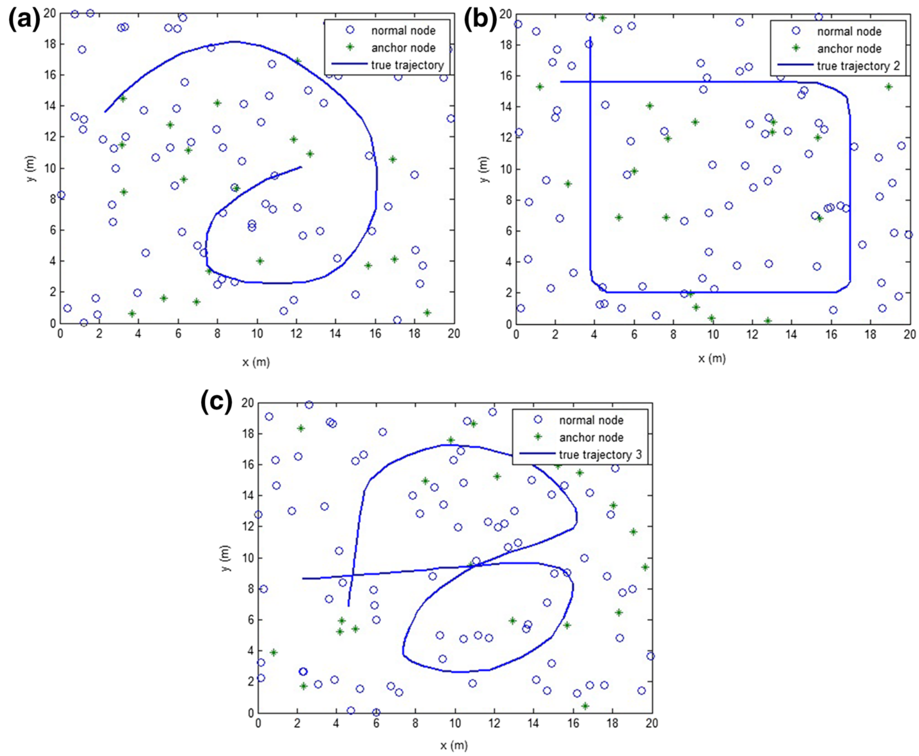

Fig. 3 True target trajectories. **a** A single target moves in a maneuvering trajectory without any intersection; **b** a single target moves in a maneuvering trajectory with one intersection and straight-line part; **c** a single target moves in a maneuvering trajectory with two intersections

p_{D}, error decreases much. And with normal nodes increasing, the samples observed by known anchors increases, leading to more accuracy shown in Fig. 4a, b. And when $\lambda > 0.06$, error can reach stable values.

Tracking error for line part of trajectory 2 is less than that of maneuvering trajectory for predicted computation increasing, as shown in Fig. 4a–f. With the increasing of iteration, the error decreases. Proposal generating distribution for each iteration follows Poisson process, and λ_k of iteration period k is adaptive with each other.

4.2 Localization delay

Delay is also an important character in tracking system, especially for our time-critical system. And we always attempt to improve the behavior of delay in order to obtain the real-time monitoring.

With node density λ_0 increasing, tracking delay decreases as shown in Fig. 5a–c. With the number of normal nodes increasing, the target can contact its 1-hop and 2-hop neighbors with higher probability to establish HTL which contains tracking samples. And also, the target needs to redetect the relative location when p_{D} is low, which consumes much time such as $p_{\mathrm{D}} = 0.8$ and $p_{\mathrm{D}} = 0.9$. With the increasing of λ_0, delay decreases for $p_{\mathrm{D}} = 0.8$ and $p_{\mathrm{D}} = 0.9$, while delay increases for $p_{\mathrm{D}} = 0.96$ and $p_D = 1$ when $\lambda_0 > 0.06$, especially for trajectory 2 and trajectory 3 shown in Fig. 5b, c. Detected samples carry enough information for tracking the target, and lots of remained samples

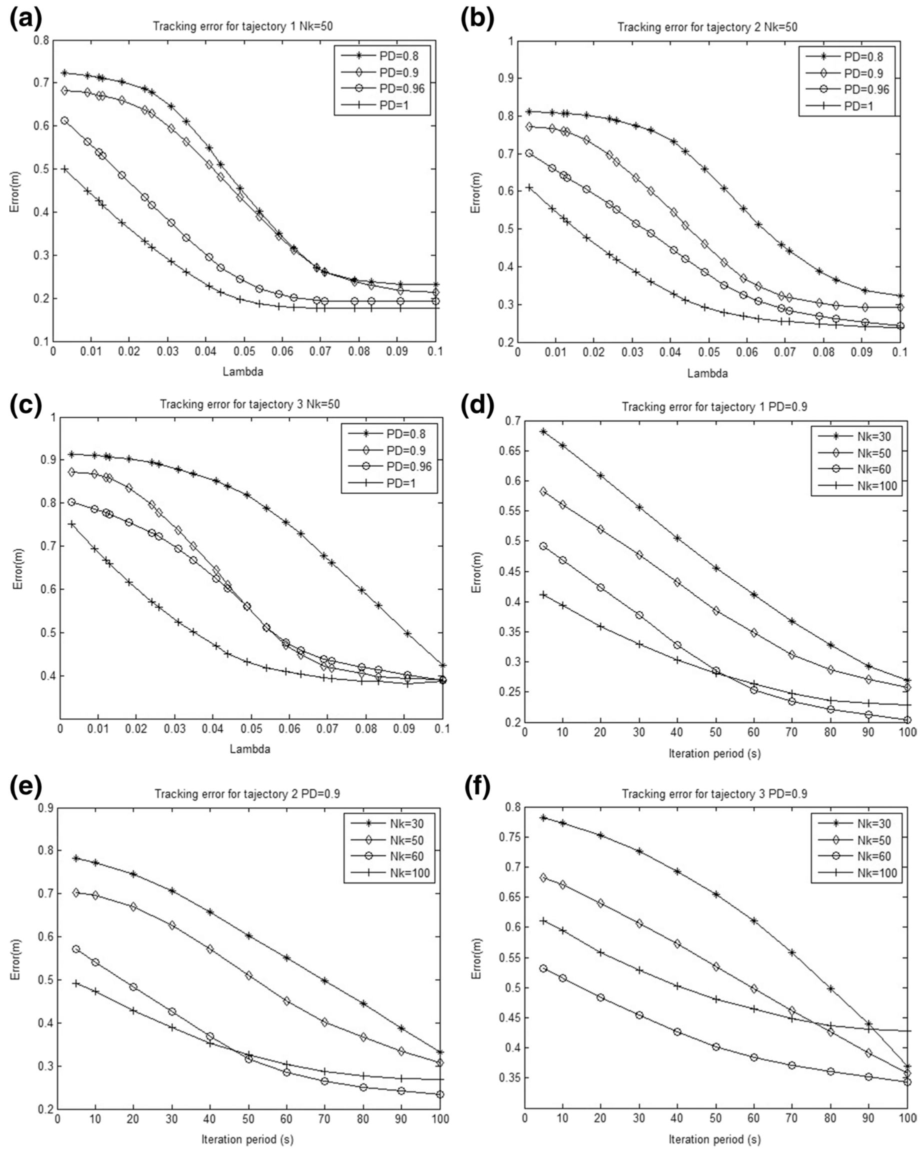

Fig. 4 **a**–**c** Tracking error related to detected probabilityp_D based on node densityλ_0. **a** Trajectory 1; **b** Trajectory 2; **c** Trajectory 3; **d**–**f** Tracking error related to samplesN_k based on iteration periods. **d** Trajectory 1; **e** Trajectory 2; **f** Trajectory 3

are required to be processed, which consumes much extra time. More valid samples of target states exchange sensed target location and moving information, more time consumes.

With the iteration increasing at $k \leq 60$, delay increases sharply while increases slowly for $k > 60$. Delay maintains at a relatively high stable value at iteration 80 when N_k is more than 60. The preset of N_k is higher, delay will be lower as regular, but delay is higher at $N_k > 60$ when iteration period is higher than 80, as shown in Fig. 5d–f.

4.3 Localization consumptions

In most analyses of tracking consumption, computational cost and communication cost are both taken into account for energy-limited WSNs [50, 51], which include energy

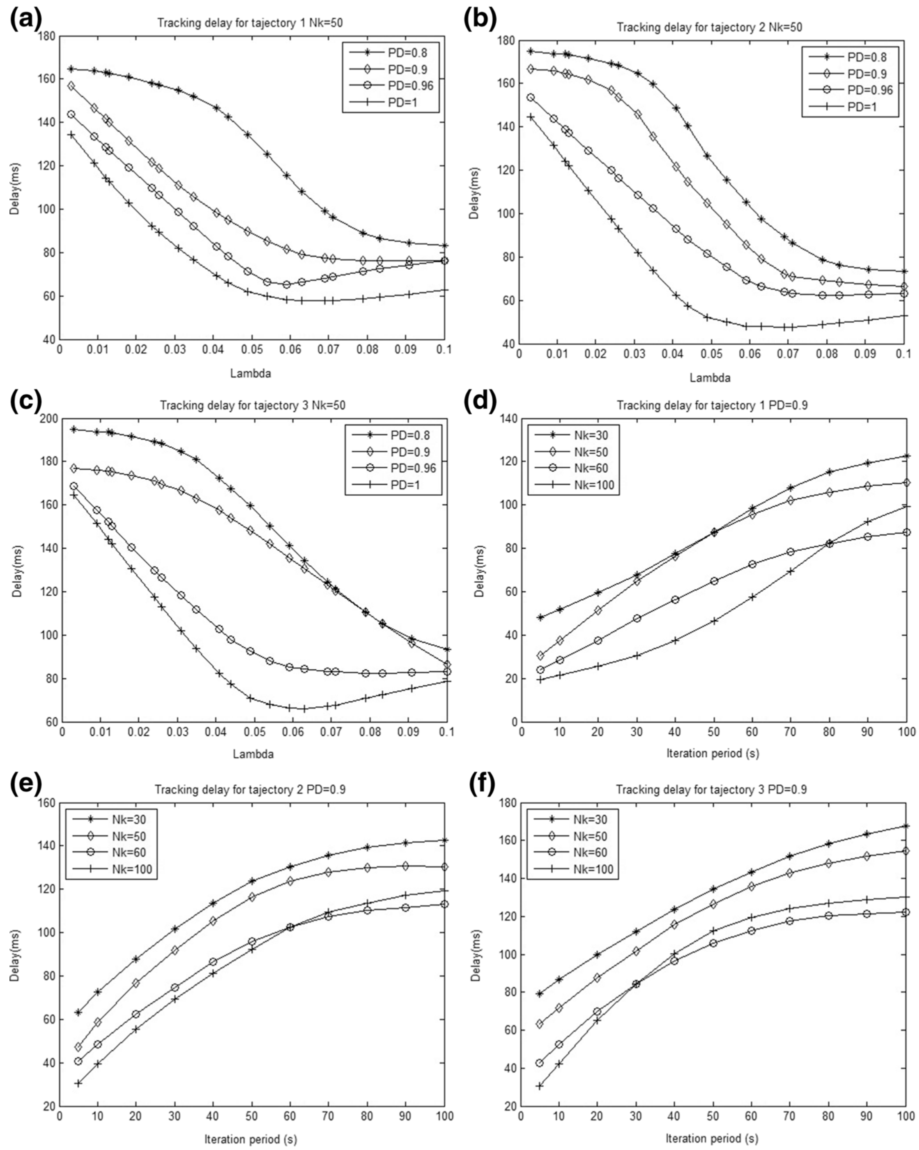

Fig. 5 **a**–**c** Tracking delay related to detected probabilityp_D based on node densityλ_0. **a** Trajectory 1; **b** Trajectory 2; **c** Trajectory 3; **d**–**f** Tracking delay related to samplesN_k based on iteration periods. **d** Trajectory 1; **e** Trajectory 2; **f** Trajectory 3

consumption for performing HTC scheme and MC-MPMC scheme. Nodes obtain their HTLs through transmitting small packages of HTC Pair Request, HTC Information Exchange, HTC Information Notification and HTC information Confirmation. These small package exchanges can consume some relatively low energy. Besides these small package exchanging, MC-MPMC cost small computational energy for its computation of missing detection and its correction.

With node density λ increasing, localization consumption decreases shown in Fig. 6a–f. Cost is a stable value for anchor rate $\lambda_0 > 0.07$ for trajectory 1, while increases again for $\lambda_0 > 0.06$ as trajectory 2 and 3 shown in Fig. 6a–c. Maneuvering mode involves the randomly turn, which brings nodes much sensing energy and identifying energy.

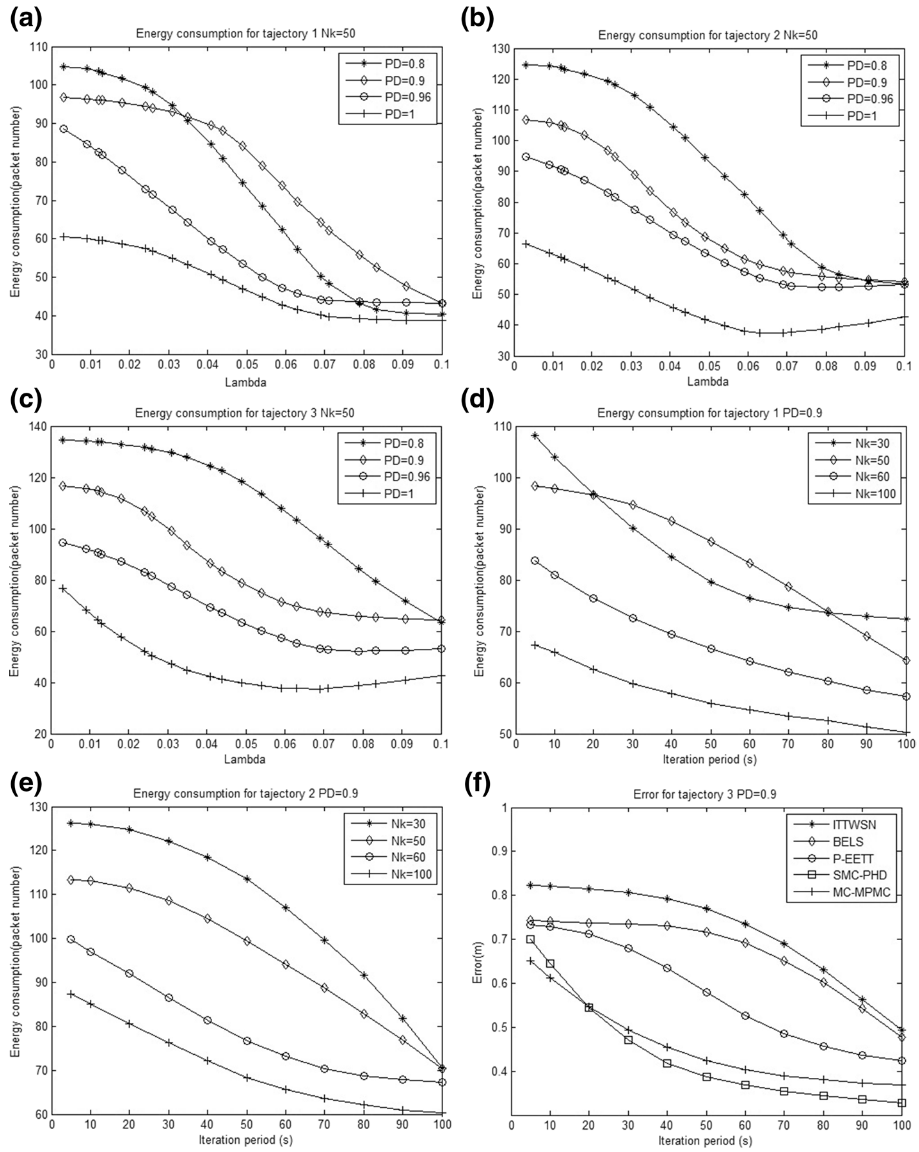

Fig. 6 **a**–**c** Tracking energy consumption related to detected probabilityp_D based on node densityλ_0. **a** Trajectory 1; **b** Trajectory 2; **c** Trajectory 3; **d**–**f** Tracking energy consumption related to samplesN_k based on iteration periods; **d** Trajectory 1; **e** Trajectory 2; **f** Trajectory 3

And also, localization consumption decreases with the iteration N_k increasing. Energy consumed for $N_k = 30$ is lower than that of $N_k = 50$. Similar to delay, energy consumption decreases for $p_D = 0.8$ and $p_D = 0.9$ the increasing of λ_0, while energy consumption increases for $p_D = 0.96$ and $p_D = 1$ when $\lambda_0 > 0.06$, especially for trajectory 2 and trajectory 3, as shown in Fig. 6b, c.

Tracking performance such as accuracy, delay and consumption depends on the network parameters such as detection probability p_D and samples N_k for a great extent, and node density λ_0 and anchor rate γ likewise. With increasing detection probability p_D, the target identification probability increases. And also, the increasing number of nodes including anchors can bring about more samples, avoiding low weighted samples fading away. But too many nodes or too many samples can also lead to inferior performance for too much information sensed by samples need to be fused and exchanged, leading to much energy and delay cost.

4.4 Performance comparisons

Experiment results shown above are comprehensive for applications, and we can present that MC-MPMC scheme can bring about expectant behaviors for our target tracking. And also, we can compare the performance metrics of MC-MPMC mechanism with those of other target tracking schemes, such as BELS [16], P-EETT [30], ITTWSN [31] and MC-SMC-PHD [37].

BELS [16] is based on improved Bayesian scheme and enhanced least-square (CLS) algorithm. Sub-range probability is obtained based on target predictive location, forming a range joint probability matrix which is updated in a dormant state in order to save energy in WSNs. The main energy-saving strategies in BELS scheme conclude that it introduces a geometric model to localize and track the target and fuses the distribution and true attributes of the measurement data to form a range joint probability matrix. BELS improves the tracking performance of delay and energy.

P-EETT [30] adopts particle swarm optimization, comprising of estimation and prediction phase. It is a clustering-based target tracking scheme, which performs clustering by adopting the maximum entropy method. P-EETT scheme costs much energy on clustering.

An IMM based target tracking in WSN ITTWSN is proposed in [31], which adopts multiple models (velocity and acceleration) to handle both maneuvering and non-maneuvering targets and multiple sensors to detect and identify the targets. This tracking scheme overcomes the problem of location error and missing detection, and saves much energy.

MC-SMC-PHD scheme [37], SMC-PHD denoted in simulation Figs. 7, 8 and 9, develops a compensatory measurement generating mechanism and presents a novel measurement compensation-based SMC-PHD filter to track target, avoiding unreliable clustering. This is a high-efficiency target tracking scheme, not applying to track the target for WSNs. We can attempt to apply this scheme in WSNs, and derive that this tracking scheme has the same high-efficiency tracking.

MC-MPMC scheme is used for time-critical, low mobile velocity monitoring and detection application, in which minimized delay is the most important target, and localization accuracy likewise. Delay performance metrics of MC-MPMC scheme accompanying with HTC algorithm are improved over other schemes, while error and energy efficiency are improved over others on the conditions of more node density and more iterations.

Through tracking comparisons as shown in Fig. 7a–c, we can obtain that these tracking schemes can exactly track the target. Some errors appear when tracking the beginning. Most tracking positions of tracking schemes are in accordance with target true positions, and the most error within 5.1%-11.5%.

Tracking error comparisons are shown in Fig. 8a–f. With node density λ_0 increasing, tracking error decreases. And tracking error of SMC-PHD is higher than that of MC-MPLC when $\lambda_0 > 0.03$ for trajectory 1, $\lambda_0 > 0.04$ for trajectory 2. With iteration periods increasing, tracking error decreases.

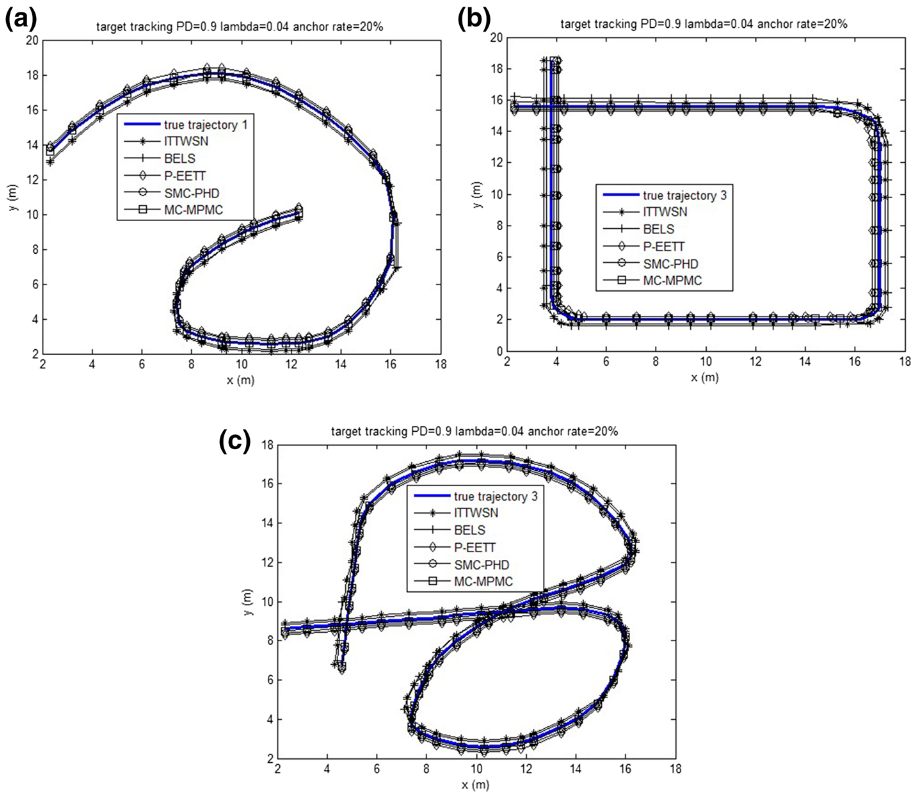

Fig. 7 Maneuvering trajectory tracking comparisons for a single target moving.

Tracking delay comparisons are shown in Fig. 9a–f. With node density λ_0 increasing, tracking delay decreases. But delay increases for MC-MPMC scheme when $\lambda_0 > 0.06$ shown in Fig. 9a, for much valid information sensed by nodes including anchors exchanges. Valid samples are enough to predict the states of target, and redundant samples sensing can consume much energy and time. With iteration periods increasing, tracking delay increases.

Tracking energy consumption comparisons are shown in Fig. 10a–f. With node density λ_0 increasing, tracking consumption decreases. But energy consumption increases for MC-MPMC scheme when $\lambda_0 > 0.06$ shown in Fig. 10a–c, for the same reason of delay increasing as Fig. 9a. With iteration periods increasing, tracking error decreases.

5 Results and discussion

In this paper, we have presented a prediction-based target tracking scheme MC-MPMC for mobile sensor networks, accompanied by an HTC algorithm. At first, the original statistical PMC scheme is denoted briefly. Then, an improved location-based tracking scheme adopted MPMC scheme is elaborately proposed, combined with a measurement compensation strategy to resolve the problem of missing detection or false measurement. Firstly, the mixture weighted method used for proposal generating is introduced to avoid sample degeneracy and maintain the diversity of samples. Secondly, inspired

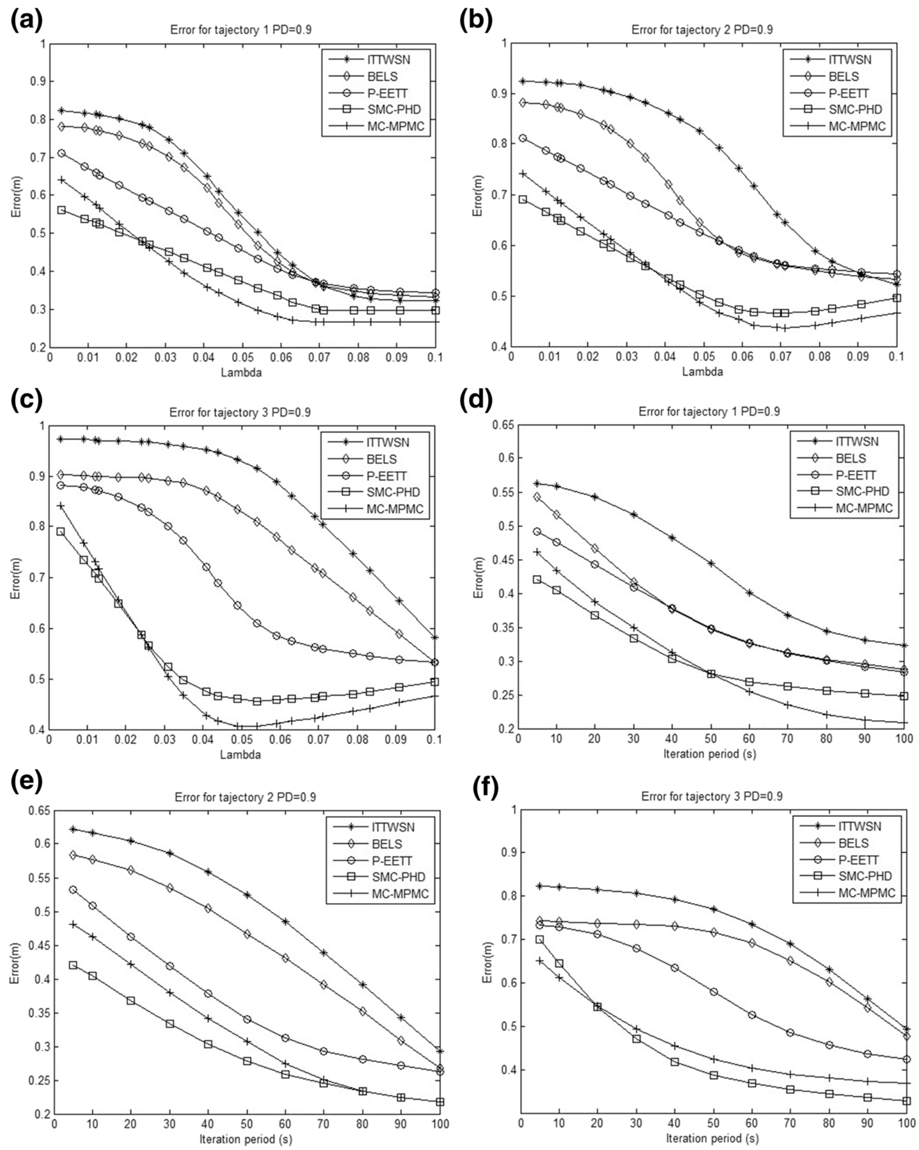

Fig. 8 **a**–**c** Tracking error comparisons related to node densityλ_0. **a** Trajectory 1; **b** Trajectory 2; **c** Trajectory 3; **d**–**f** Tracking error comparisons related to iteration periods. **d** Trajectory 1; **e** Trajectory 2; **f** Trajectory 3

by the missing detection or correction of MC-SMC-PHD scheme, a measurement compensation method is proposed to enhance the tracking performance. Thirdly, the HTC scheme is introduced to decrease the communication cost and delay for exchanging tracking information with small packages at the beginning of each iteration. Tracking performance such as tracking error, delay and consumption, especial delay, is presented based on the statistical point of view taking parameters such as anchor rate γ, node density λ_0, mixture nodes N_k and detected probability p_D into account. Comprehensive simulations are presented to verify the behaviors based on the straight-line trajectory

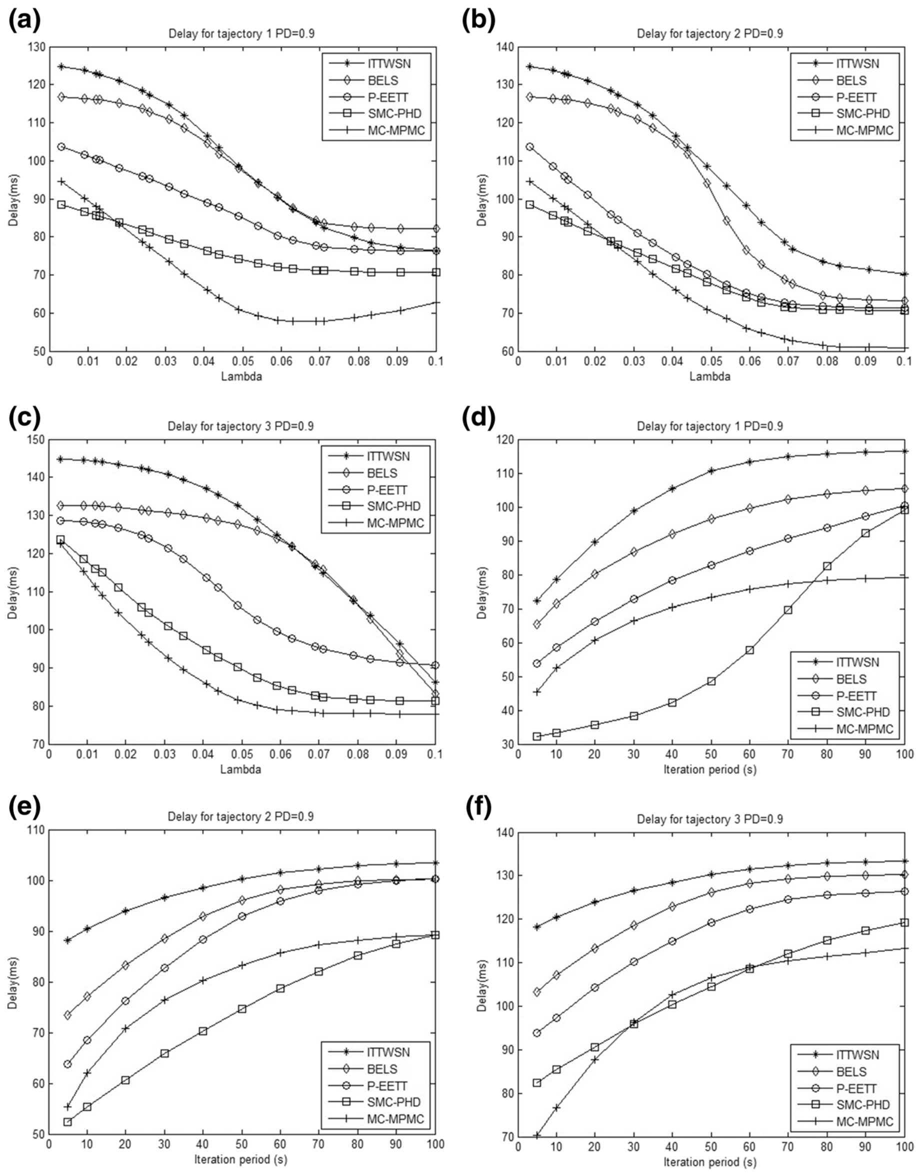

Fig. 9 **a**–**c** Tracking delay comparisons related to node densityλ_0. **a** Trajectory 1; **b** Trajectory 2; **c** Trajectory 3. **d**–**f** Tracking delay comparisons related to iteration periods. **d** Trajectory 1; **e** Trajectory 2; **f** Trajectory 3

and maneuvering trajectory. Moreover, performance comparisons between MC-MPMC algorithm and other tracking schemes are made.

Multiple target tracking used for large-scale crab aquaculture sensor networks is studied in the future based on the MC-MPMC scheme. In aquaculture networks, the tracking scheme can take not only the positions of objects into account as in this work, but also take the appearance of objects into account in future works [52]. We can also apply MC-MPMC tracking method to track other aquatic products underwater.

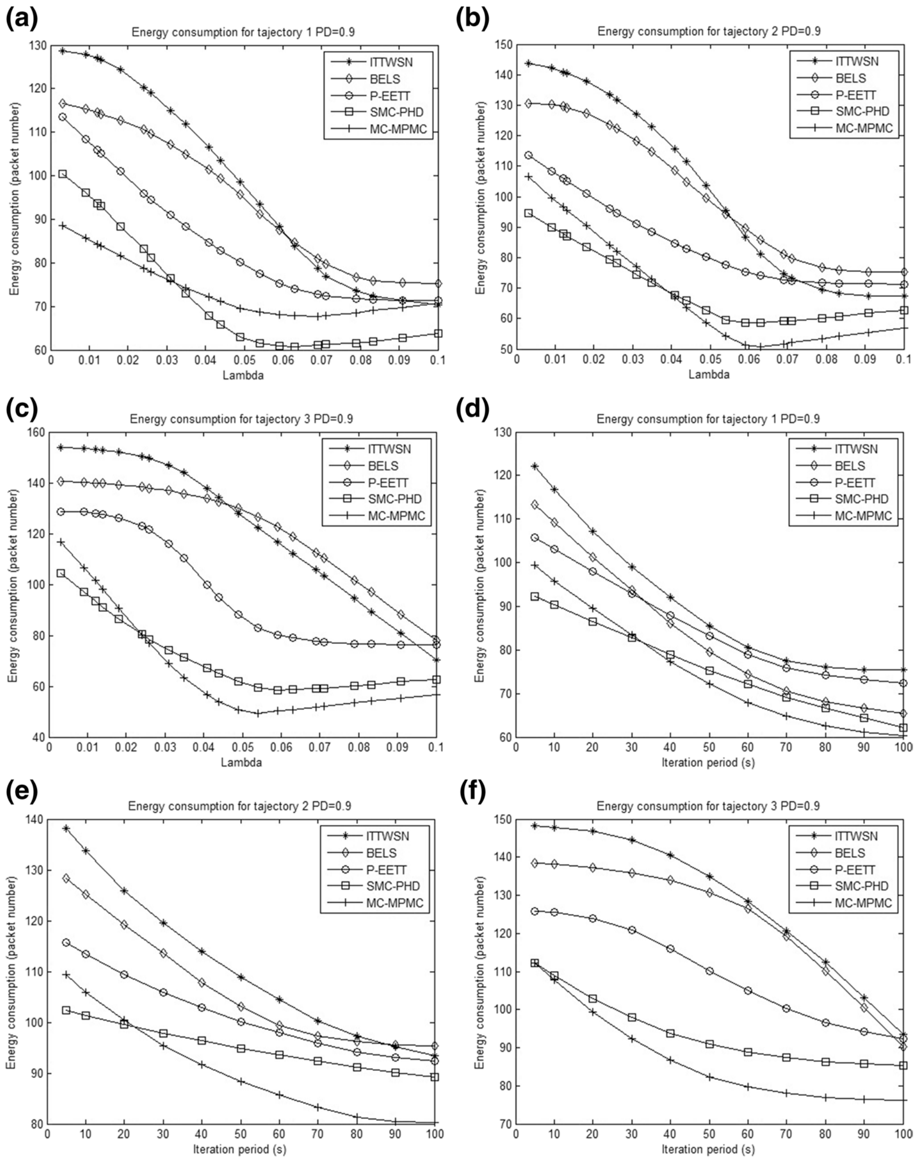

Fig. 10 **a**–**c** Tracking energy consumption comparisons related to node densityλ_0. **a** Trajectory 1; **b** Trajectory 2; **c** Trajectory 3. **d**–**f** Tracking energy consumption comparisons related to iteration periods. **d** Trajectory 1; **e** Trajectory 2; **f** Trajectory 3

Abbreviations

MC-MPMC Measurement compensation mixture population Monte Carlo
WSNs Wireless sensor networks
HTC Hidden terminal couple
UAV Unmanned aerial vehicle
UAS Unattended air system
AUV Autonomous underwater vehicle
CLS Classical least square
SHMM Semi-hidden Markov model
MDB Marginal distribution Bayes
PHD Probability hypothesis density
PLKF Pseudolinear Kalman filter
AOA Angle of arrival
TDOA Time difference of arrival
FDOA Frequency difference of arrival
IVKF Instrumental variable-based Kalman filter
P-EETT Particle energy-efficient target tracking
ITTWSN IMM-based target tracking in WSN
NPFA Novel particle filtering algorithm
BGGIW Beta gamma Gaussian inverse Wishart
PMBM Poisson multi-Bernoulli mixture
KLD Kullback–Leibler divergence
SPHD Semantic probability hypothesis density
CPHD Cardinalized probability hypothesis density

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Author contributions
CL carried out the MC-MPMC tracking scheme, accompanied by HTC transmission scheme, and helped to draft the manuscript. JZ carried out most of the simulation experiments. ZT carried out the defects of original tracking scheme and drafted the manuscript. YP took part in experimental platform establishment and project inspection throughout the work. All authors contributed to the work. All authors read and approved the final manuscript.

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Availability of data and materials
All data generated or analyzed during this study are included in this published article.

Declarations

Competing interests
The authors declare that they have no competing interests.

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