www.s2is.org
International Journal on Smart Sensing and Intelligent Systems
ISSN 1178-5608

Spatial-temporal Collaborative Sequential Monte Carlo for Mobile Robot Localization in Distributed Intelligent Environments

Kun Qian, Xudong Ma, Xian Zhong Dai, Fang Fang
School of Automation, Southeast University
Key Laboratory of Measurement and Control of Complex Systems of Engineering, Ministry of Education
No.2 Sipailou, Nanjing, China
Emails: kqian@seu.edu.cn

Submitted: Mar. 30, 2012 ***Accepted: May 15, 2012*** ***Published: June 1, 2012***

Abstract- In this paper, a spatial-temporal collaborative sequential Monte Carlo architecture for mobile robot localization is designed to well suites intelligent environment for service robotic system. A proposed algorithm, namely Distributed Proportional Allocation-Augmented Particle Filter (DPA-APF), resolves the sensor collaboration problem by the processes of augmented sampling, inter-node resampling, inner-node resampling and particle exchange. These procedures exploit data parallelism and pipelining of resampling operations and improve the scalability of distributed particle filters (PFs). Moreover, modified visual and laser sensor perception models are also addressed to guarantee reliable and accurate robot localization in dynamic scenarios that robot coexists with people. The proposed method is applied to a home-care robotic intelligent room with distributed smart nodes, and the

experimental results validate the effectiveness of the proposed method, which is hopeful to reduce the gap that exists between PF theory and their implementation using networked hardware.

Index terms*:* spatial-temporal collaboration, mobile robot, particle filter, distributed sensor network, localization and navigation.

I INTRODUCTION

Dependable method to improve service quality for the elderly in care homes are a pressing need for the aging society[1]. Among these methods, robotic intelligent environment has been developed for supporting service mobile robot navigation and other manipulative tasks, such as Robotic Room[2], Intelligent Space [3], KDRS [4], Ubiquitous Robot [5], PEIS-Ecology [6] and so on. These types of system consist of robots and a number of smart devices (smart nodes), which are conceptually referred as sensor-actuator subsystem with rich sensing, computing capabilities and are able to interact with other nodes through network communications. The collaboration of distributed nodes to assist mobile robot's limited sensing capability in solving the localization and navigation problem is a key issue.

In the research field of intelligent environment, automatic and adaptive sensor selection methods have been proposed for distributed sensors[7] or multi-camera system[8]. In this paper, we consider the nature of the monitored mobile robot can be captured by a Markovian state-space model that involves potentially nonlinear dynamics, nonlinear observations, and non-Gaussian innovation and observation noises. It's natural to refer to the sequential Monte Carlo (SMC)[9], also known as Particle Filter (PF) method, which has shown promising advantages in addressing mobile robots probabilistic localization [10][11] and other state estimation tasks for these types of system. However, their application in real-time distributed systems is limited due to their inherent computational complexity.

To solve this, there have been some efforts to design distributed particle filter methods. These methods are divided into centralized and decentralized structures. In the centralized structure category, particle generation and weight calculation are performed in parallel by distributed nodes and resampling is carried out by the central processing node. After the resampling, a considerable amount of samples are to be transferred from the central node to other nodes, which burdens the central node's computation and communication load. In contrast, in the total decentralized structure category, inter-node communication amount is independent with the network scale, which guarantees the system scalability. Following the decentralized framework, Zhao [12] proposes a multisensory collaborative target tracking method. In this method, a leader node is selected according to the maximum expected effect value of nodes' estimation, and it maintains the target's belief distribution. Rosencrantz [13] proposes a decentralized particle filter for multi-robot multi-target tracking. In this method, a query based information sharing mechanism is proposed which can reduce the communication data between mobile robots. In the sensor network research society, distributed particle filters have also been developed [14][15][16], however, they have not yet been applied to the robot localization problem.

It can be noticed that the difficulty of distributed implementation of SMC lies in several aspects. Firstly, since the SMC algorithms are substantially more computationally demanding than more parametric alternatives, it demands an efficient distributed framework to minimize the execution time of PF and reduce the computation load of all nodes. Secondly, sensor observation failure is commonly caused by occlusions and limited sensing coverage area in typical dynamic indoor environments, thus a spatially distributed resampling algorithm is crucial to effectively utilize sensor information to avoid the samples from degrading. Thirdly, identifying the information that needs to be exchanged is also a pressing problem [15] and thus a reasonable particle exchange strategy is required for the nodes' collaboration.

In this paper, a spatial-temporal collaborative sequential Monte Carlo architecture for mobile robot localization is designed to well suites the intelligent environment for service robotic system. We consider a typical intelligent environment that consists of mobile robot and a smart camera network. Following this framework, an implementation algorithm using Augmented Particle Filter and automatic particle scheduling and routing strategy is proposed to exploit data parallelism and pipelining of resampling operations and improve the scalability of the filter architectures affected by the resampling process.

The organization of the lecture is as follows. Section II describes the principle of the designed spatial-temporal collaborative SMC architecture. Section III gives the details about the proposed distributed resampling algorithm, namely Distributed Proportional Allocation-Augmented Particle Filter (DPA-APF) algorithm. Since the environmental dynamic affects the integrality and effectiveness of sensor observation, in Section IV we proposed a modified vision perception model and laser perception model for improving the robustness of the proposed algorithm in dynamic environment. In Section V, experimental results of both simulation and real-world application are given, which illustrates the effectiveness of the proposed method in service robot application.

II Spatial-temporal Collaborative SMC Architecture

We acknowledge and address the distributed implementation of SMC problem in three major aspects: (a) the sampling algorithm in single node that computes how the particles are predicted and propagated along time, (b) inter-node scheduling that shift samples to nodes for optimally resampling in the system, (c) how samples are exchanged among nodes via network communication.

The distributed architecture of SMC is proposed as shown in Figure 1. It consists of the processing unit (PEs), a central unit (CU) and an interconnection network. In order to implement such architecture, a resampling algorithm called Distributed Proportional Allocation-Augmented Particle Filter (DPA-APF) algorithm is proposed. This algorithm replaces the traditional resampling procedure on single node by four steps executed among distributed smart nodes: Augmented Sampling (AS), inTer-node Resampling (TR), inNer-node Resampling (NR) and Particle Exchange (PE).

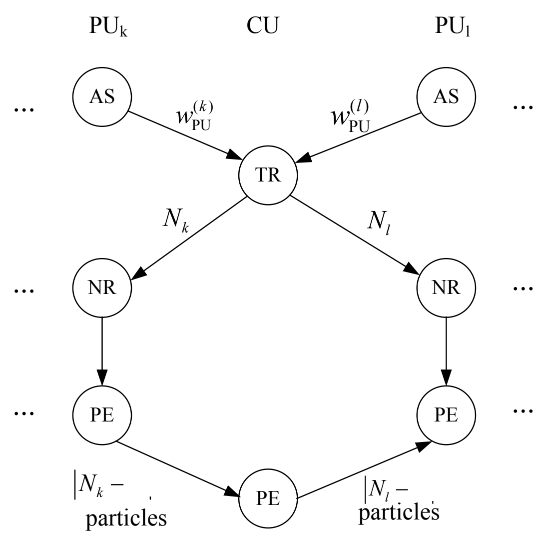


Figure 1 Spatial-temporal Collaborative SMC Architecture

According to the proposed architecture, collaboration between nodes is achieved via a strategy of sample allocation among distributed smart nodes in both temporal and spatial dimensions. In the temporal perspective, samples are generated and evaluated within one node according to the standard prediction and update processes in the PF scheme. Since the sampling/importance Resampling (SIR) [17] method is known not so robust to outliers for two different reasons: sampling efficiency and the unreliability of the empirical prediction density in the tails of the distribution, we apply Auxiliary Particle Filters (APFs) [18][19] in the augmented sampling step, which can be coped with by a sensor node with reasonable processing power and memory. Since there are no data dependencies during the particle generation and evaluation, these steps can be easily parallelized and pipelined, maintaining N particles in K PUs, each carries N_k particles. In the spatial perspective, particles are re-allocated among nodes to guarantees that nodes with better observation can be assigned with more samples to be propagated closer towards the true posterior. In each node, the TR step computes in CU the number of samples to be kept and the NR step achieves the required number of samples using importance resampling based technique. After that, the PE step exchanges particles among nodes to make sure that each node maintains the same number of particles for the next iteration period.

III THE DPA-APF ALGORITHM

a) Augmented sampling

From a *Bayesian* perspective [20], the problem of robot localization is to recursively evaluate distribution $bel(\boldsymbol{x}_t)$ of the robot's pose:

$$bel(\boldsymbol{x}_t) = \quad \boldsymbol{x} \quad \boldsymbol{z} \quad \boldsymbol{u} \quad = \int \quad \boldsymbol{z} \quad \boldsymbol{x} \quad \boldsymbol{x} \mid \boldsymbol{x}_{-} \quad \boldsymbol{u}_{-}) \, p(\boldsymbol{x}_{-} \mid \boldsymbol{z}_{-} \quad \boldsymbol{u}_{-}) \, d\boldsymbol{x}_{-} \,, \tag{1}$$

in which $\boldsymbol{u}_{1:t-}$ is the motion control, η is a normalizer, $p(\boldsymbol{x}_t \mid \boldsymbol{x}_{t-} \quad \boldsymbol{u}_{-})$ is the robot's motion model, $p(\boldsymbol{z}_t \mid \boldsymbol{x}_t)$ is the sensor perception model. The Sequential Monte Carlo (SMC) methodology uses a set of random samples $x_t^{(i)}\Big|_{i=}$ to approximately represent the distribution $bel(\boldsymbol{x}_t)$:

$$bel(\boldsymbol{x}_t) \approx \frac{1}{N} \sum_{i=} \quad _{x} \quad \boldsymbol{x} \quad , \tag{2}$$

In which N is the number of samples, and $\delta_{x_t^{(i)}} \bullet$ denotes the Delta-Dirac function at sample $\boldsymbol{x}_t^{(i)}$. Crisan and Doucet [21] concluded that SIR almost sure convergence in their research work.

In the *kth* node (denoted as PU_k) , after initially drawing N uniformity distributed samples from the initial distribution $p(\boldsymbol{r}_0)$, following steps are performed each time when $(z_t, \boldsymbol{u}_{t-}$ is available.

Step1: sampling $\boldsymbol{\mu}_t^i \sim p(\boldsymbol{x}_t \mid \boldsymbol{x}_{t-}^i$ to draw the one-step-ahead prediction $\boldsymbol{\mu}_t^i$, where $i =$;

Step2: when $\boldsymbol{\mu}_t^i$, $i =$ is obtained, compute the new index $Index(i)$ of sample i , $i =$, i.e., $Index(i) \sim p(i \mid z_t) \propto$ z $\boldsymbol{\mu}_t^i)$. The corresponding sample indexed with $Index(i)$ is to be propagated from $t-$ to t;

Step 3: using robot motion model to draw samples based on the newly indexed samples $\boldsymbol{x}_{t-}^{Index(i)}$, i.e., $\boldsymbol{x}_t^i \sim p(\boldsymbol{x}_t \mid \boldsymbol{x}_{t-}^{Index(i)}$, $i =$. Essentially, these two steps obtain a new sample set $\boldsymbol{x}_t^i$ through sampling from the prior distribution, i.e., $\boldsymbol{x}_t^i \sim p(\boldsymbol{x}_t)$;

Step 4: using multisensory perception update to computes the weight w_t^i of the sample $\boldsymbol{x}_t^i$ according to $w_t^i =$ z $\boldsymbol{x}$ $)/p(z_t \mid \boldsymbol{\mu}_t^i)$, and then normalized the weight according to $\pi = \sum_{i=}$. As a results, the augmented sampling procedure in PU_k obtains N new samples $\{\boldsymbol{x}_t^i\}_{i=}^N$, each sample is endowed with a weight of π . The perception model $p(z_t \mid \boldsymbol{x}_t)$ reflects the correspondence of the sample after motion update with current observations, and is a probabilistic model determined by the type of sensor, which will be discussed in Section IV.

b) Inter-node Resampling

To evaluate to effectiveness of the *kth* node sensor observation about the current robot's position, we propose a concept of *particle cluster* and its weight value. After the augmented sampling procedure within the *kth* node, the average weight value is computed as the weight of the *particle cluster*:

$$w_{\mathrm{PE},t}^{(k)} = \frac{1}{N_k} \sum_{i=} \quad , \; k = \quad . \tag{3}$$

The inter-node Resampling procedure treats the sample set of *kth* node as one single particle cluster. The systematic resampling method is employed to determine the number of sample to be kept within the *kth* node for further resampling in the next period.

Firstly, the sample weights sum of the kth node is computed as $C^{(k)} = \sum_{l=}$. Then a new variable $U^{(k)}$ is computed and compared with $U^{(k)}$, $k =$. $U^{(0)}$ is draw from the uniform distribution $\mathcal{U}$, and the equation $U^{(k)} = \quad + \quad$ is used to calculate other $U^{(k)}$ for $k =$. As show in Figure 2, this method divides the vertical axis of the coordinate into K equal parts.

The number of times that the kth particle cluster should be copied is computed according to $w_{\mathrm{PE},t}^{(k)}$ as # $w_{\mathrm{PE},t}^{(k)} \in \lfloor \quad \rceil$, i.e., the frequency that $w_{\mathrm{PE},t}^{(k)}$ falls between $\lceil \quad \rceil$. Since the sample set of the kth node is treated as a single *particle cluster*, the number of samples to be kept within this node is $N_k =$ $\in \lfloor \quad \rfloor$, where M is the total number of samples maintained in the whole system.

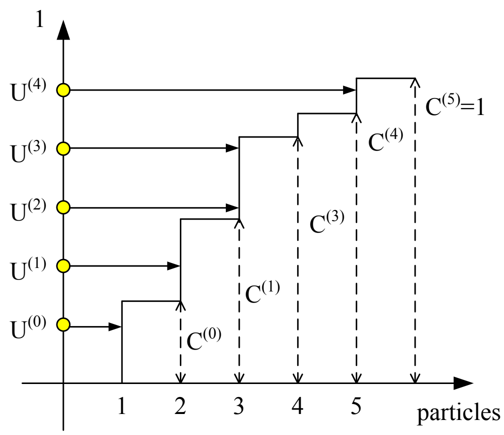


Figure 2 Systematic resampling

c) Inner-node resampling

After N_k ($k =$), the number of samples to be maintained at each node is determined, parallel inner-node resampling is performed in all K nodes simultaneously. Since the perception update cannot guarantee samples to approach the true distribution, therefore two validations are applied to introduce different resampling processes in this step for improving the robustness of resampling. Over-convergence validation process is implemented with entropy of normalized sample distribution and effective sample size. Uniformity validation is implemented through summation of sample weight of non-normalized sample distribution. More details about the two validations process can be found at our previous work [22].

Since the particle cluster weight of each node differs, it represents that node's observation is of different effectiveness about robot's current position. The inter-node resampling and inner-node resampling processes make sure that nodes with better observation can receive higher evaluation and thus produce more copy of its "good" samples.

d) Particle exchange

In this process, the system will adjust the allocation of samples in all nodes to ensure that the number of samples on each node is equally $N =$, getting prepared for the AS step of the next period.

After the above process, those nodes with the sample number $N_k \leq$ are called *lacking nodes* because the node's current observation is more highly evaluated and require more samples for improving the approximation to the true distribution. These nodes will need to recruit a number of $|N_k -$ new samples from other nodes. Meanwhile, those nodes with the sample number $N_k \geq$ are called *surplus nodes*, and a number of $|N -$ samples will be disseminated to other nodes. This particle exchange process allows the highly evaluated samples to be transferred to those nodes that lack effective samples, so that the distribution in the receiving nodes will more easily approximate the true posterior in the next period.

IV IMPROVED SENSOR PERCEPTION MODELING

The perception model $p(\boldsymbol{z}_t \mid \boldsymbol{x}_t)$ characterizes the probability of receiving sensor measurement $\boldsymbol{z}_t$ given a robot pose $\boldsymbol{x}_t$. In this system, sensor in one node can be either global camera or onboard laser range finder. Their perception models are denoted as $p(\boldsymbol{z}_t^{Cam} \mid \boldsymbol{x}_t)$ and $p(\boldsymbol{z}_t^{laser} \mid \boldsymbol{x}_t)$, respectively.

a) Visual perception model

Five stationary CCD cameras (Panasonic WV-CP240) were mounted on each side of the room above head level as shown in Figure 3 and Figure 4. Each camera detects the robot's color marker (Figure 5) and gives an observation of robot's ground position $\boldsymbol{x}$ as a Gaussian random variable $\boldsymbol{x} \sim \quad \Sigma$. The vision measurement can be considered as "detection driven", i.e., this model is valid only when the robot is visible in vision subsystem. Thus η_i is introduced to denote whether target is visible ($\eta_i =$ or not ($\eta_i =$ by the *ith* camera:

$$\eta_i = \begin{cases} & \text{detected} \\ & \text{otherwise} \end{cases} \tag{4}$$

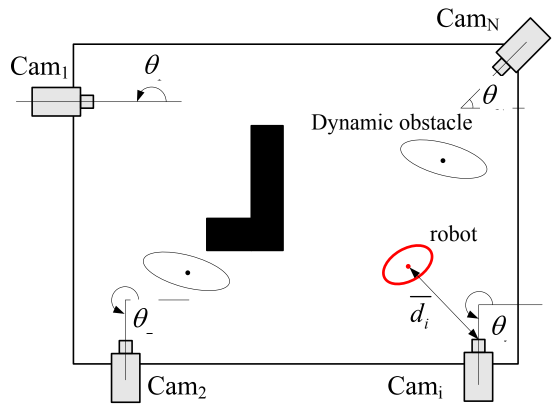


Figure 3 The camera network configuration

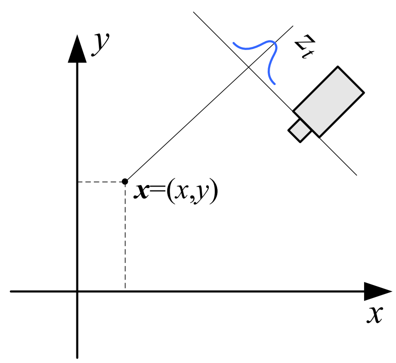


Figure 4 Camera measurement illustration

Firstly, in situations that the occlusion is ignored, the camera observation model can be modeled as:

$$\boldsymbol{z} = \boldsymbol{A}\boldsymbol{x} + \boldsymbol{v}. \tag{5}$$

In the visual perception system with K networked cameras, the matrix $\boldsymbol{A}$ can be written as:

$$\boldsymbol{A} = \begin{pmatrix} & \\ & \\ \vdots & \vdots \\ & \end{pmatrix}. \tag{6}$$

Secondly, we consider the most common situations with occlusion, the visual observation equation of Cam_i is:

$$z_i = \quad \boldsymbol{a} \quad \boldsymbol{x} - \boldsymbol{\mu} + \boldsymbol{v} \quad + \boldsymbol{a} \quad \boldsymbol{\mu},\ i = \qquad . \tag{7}$$

in which $\boldsymbol{a}_i^T = - \qquad \theta$, $\boldsymbol{v}_i$ is the observation error of Cam_i that satisfies $\boldsymbol{v}_i \sim \qquad \Sigma$

and $\Sigma \qquad + \qquad (1,1)$ where σ is the positional covariance of the occluding object and $\overline{d_i}$ is the distance between Cam_i to the center $\boldsymbol{\mu}$ of the occluding object. Hence the vision model when the camera detects the object is

$$z_i = \boldsymbol{a} \ \boldsymbol{x} + \boldsymbol{v} \ , \tag{8}$$

and if the camera fails to detect the object, it will consider that the object is located at its average position.

$$z_i = \boldsymbol{a} \ \boldsymbol{\mu} \ . \tag{9}$$

In cases that the occluding aspect is considered, the covariance of $\boldsymbol{x}$, Σ is:

$$\Sigma \qquad \boldsymbol{x} - \quad \boldsymbol{x} \quad \boldsymbol{x} - \quad \boldsymbol{x} \qquad = \qquad , \tag{10}$$

in which . We assume that Σ can be written as:

$$\Sigma \qquad \qquad \alpha \tag{11}$$

Now we compute Σ , the variance of z, according to the variance of $\boldsymbol{x}$. For simplicity, we characterize the linear relation between z and $\boldsymbol{x}$ as $z = \boldsymbol{Hx} + \boldsymbol{V}$. As a result, we will have

$$\begin{aligned} \Sigma \qquad & z - \quad z \quad z - \quad z \\ = \quad & \boldsymbol{Hx} + \boldsymbol{V} - \boldsymbol{H} \quad \boldsymbol{x} - \quad \boldsymbol{V} \quad \boldsymbol{x} \ \boldsymbol{H} \quad + \boldsymbol{V} \ - \quad \boldsymbol{x} \quad \boldsymbol{H} \ - \ \boldsymbol{V} \\ = \quad & \left[\boldsymbol{H} \ \boldsymbol{x} \quad \boldsymbol{x} \ \boldsymbol{x} \quad \boldsymbol{x} \ \ \boldsymbol{H} \right] \quad \boldsymbol{VV} \quad \boldsymbol{HPH} \qquad \left[\boldsymbol{VV} \ \right] \end{aligned} \tag{12}$$

We replace $H = \ \boldsymbol{a}$ and $V = \ \boldsymbol{v} + \boldsymbol{a} \ \boldsymbol{\mu} - \eta \boldsymbol{a} \ \boldsymbol{\mu}$ to Equation 12 to get:

$$\begin{aligned} \Sigma \qquad & \boldsymbol{a} + \ \left[\ \boldsymbol{v}\boldsymbol{v} \ \right] \ \boldsymbol{a} \ \boldsymbol{\mu}\boldsymbol{\mu} \quad - \quad \boldsymbol{a} \\ = \ \boldsymbol{a} \quad & \boldsymbol{a} + \ \Sigma \qquad - \quad \boldsymbol{a} \end{aligned} \tag{13}$$

$\boldsymbol{x}_i \in \mathbb{R}$, , ,$\Sigma \qquad \Sigma \qquad \Sigma$.

The visual observation model $p(z_t^{Cam_i} \mid \boldsymbol{x}_t)$ characterizes the probability that Cam_i obtains the observation z_t when the robot is positioned at $\boldsymbol{x}_t$. As a result, the visual observation probability distribution is computed as:

$$p(z_t^{Cam_i} \mid x_t) = \frac{1}{\sqrt{2\pi}\ \Sigma_{-i}} \quad -\frac{1}{2}\ z - x \quad \Sigma_{-i} \quad \cdot x \tag{14}$$

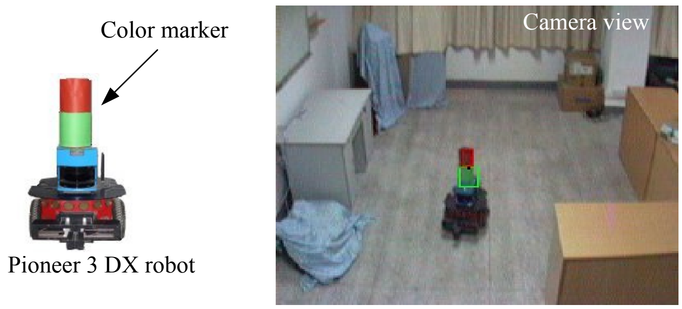


Figure 5 The robot and camera's view image

b) Laser perception model

To calculate $p(z_t^{laser} \mid x_t)$, the Likelihood Field Model models three types of noise sources:

$$p(z_t^{laser} \mid x_t, M) = \quad + \quad _{rand} \quad + \quad . \tag{15}$$

Measurement noise: p_{hit} captures the sensor noise by a zero-mean Gaussian. The p_{hit} model of the α th laser beam is computed as

$$p_{\text{hit}}(z_{t,\alpha} \mid x) = \quad \propto \quad \frac{1}{\sqrt{2\pi\sigma}} \cdot \quad -\frac{1}{2\sigma} \tag{16}$$

where d_α is the Euclidean distance between the α th laser point (after transformed to the x-y coordinate frame) and the nearest obstacle in the local grid map obtained by the laser ray-tracing. Obstacle candidates can be either mapped objects or people hypothesis.

Failures: The possible failures of the max-range readings are modeled by a point-mass distribution $p_{\max}$.

Unexplained random measurement: The random noise of laser sensors is modeled by a uniform distribution p_{rand}.

For an entire laser scan, the probability $p(z_t^{laser} \mid x_t, M)$ amounts to Equation 17 under an independent assumption among the readings of each laser beam.

$$p(z_t^{laser} \mid r_t, M) = \sum_{\alpha=}^{N} \quad z \quad x \quad M). \tag{17}$$

V EXPERIMENTAL RESULTS

a) Filters simulation performance

We firstly use a simulated model to evaluate the performance of AS using auxiliary particle filtering in each sensor nodes. Assume that the target motion is modeled by non-linear dynamic equation and non-linear observation equation:

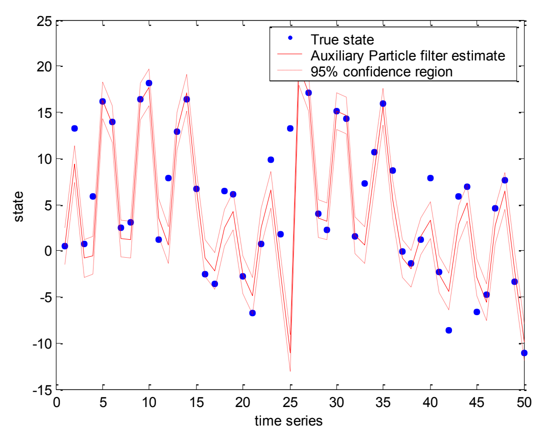
$$x_k = \quad + \frac{20x}{1+} + \quad - \quad + \quad , \tag{18}$$

$$z_k = \frac{x^2}{10} + \quad . \tag{19}$$

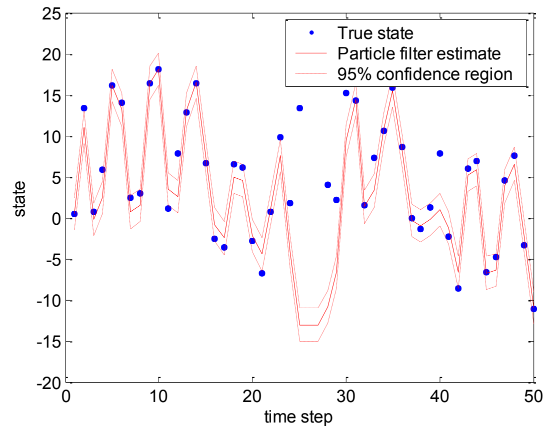
In which w_k and v_k are zero-mean Guassian white noises with $Var(w_k) =$ and $Var(v_k) =$. In the simulation, the number of samples was chosen 500 and the time step was 50. As can be seen from Figure 6, the augmented particle filter outperforms traditional particle filter in that the posterior distribution can better approximate the target distribution. The tracking error RMS is computed according to Equ.20.

$$RMS = \sqrt{\frac{1}{tf}\sum_{t=}} \quad . \tag{20}$$

The result in Figure 6 shows that the APF method is capable of keeping closer track of the system movement and achieving smaller RMS error.



(a)APF



(b)PF

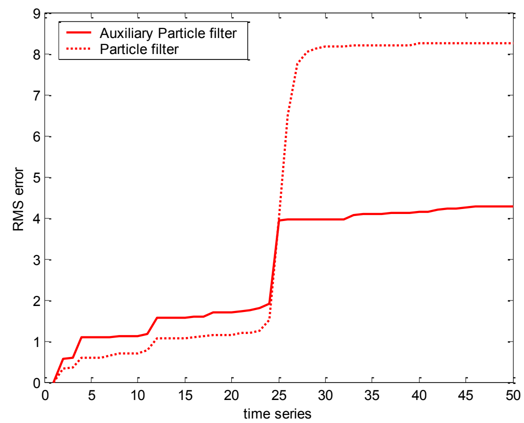


Figure 6 Tracking performance of APF and PF

b) Global localization experiment

Firstly, a simulated room environment was built in which a number of K networked cameras (as shown in Figure 7) were allocated in walls for detecting robot and other moving objects. We tested different situations when the number of sample N takes value 1000, 5000, 10000 and K takes value 1, 2, 4, 8, 16 and 32 to verify the performance of the proposed Spatial-temporal collaborative particle filter method in robot localization, and the result is shown in Figure 8. In all the experimental trials, the proposed DPA method shows significant advantages than the traditional centralized resampling method. The centralized resampling method needs to gather N samples from all nodes and disperse them after resampling via the network communication, which not only burdens the central processor but also aggravates the network transportation load. In contrast, the DPA method proposed in this paper only needs N/K times TR in CU and N_k

times TR in each node. Hence the processing burden of CU and the data communication amount in the system is greatly reduced.

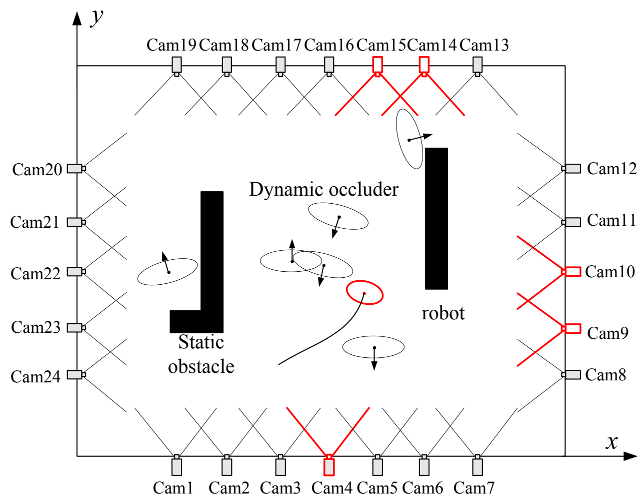


Figure 7 Simulation configuration

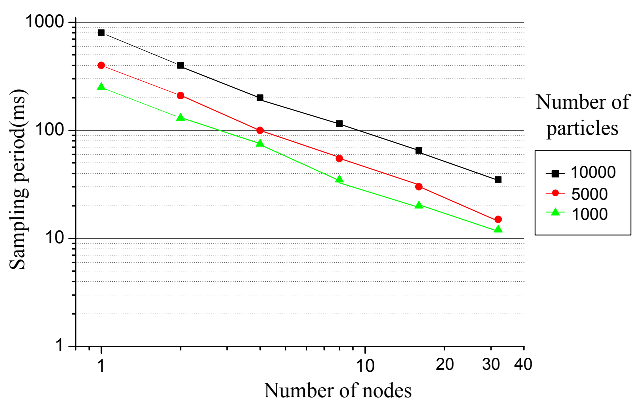


Figure 8 Parallel execution efficiency of DPA

Secondly, we conducted experimental trials in real world dynamic indoor environment designed for home-care applications in which a Pioneer 3 DX robot and moving people coexisted [23]. Figure 9 shows and example of the experiment where red dot denotes the samples and the green dot denotes the projected robot laser scan data. After a robot with unknown initial pose starts a global localization process, Figure 10 (a) shows the positional distribution just after the initialization, with particles scattered over the map. As shown from Figure 10 (b) to (d), when the robot navigated in the room and encountered moving people nearby, the people caused certain occlusion in global camera's (Cam5) view and this triggered the node collaboration process to ensure optimal arrangement of the nodes for keeping track of the robot and maintaining its pose estimation. In this case, Cam2 is selected as the most appropriate view.

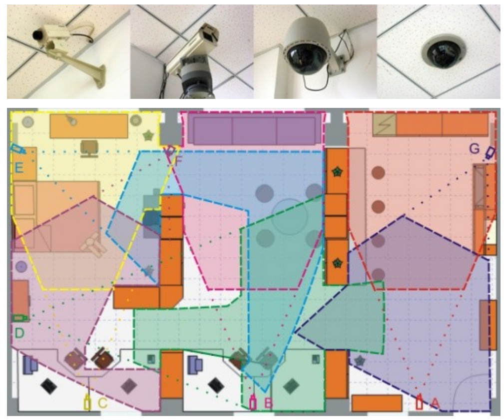
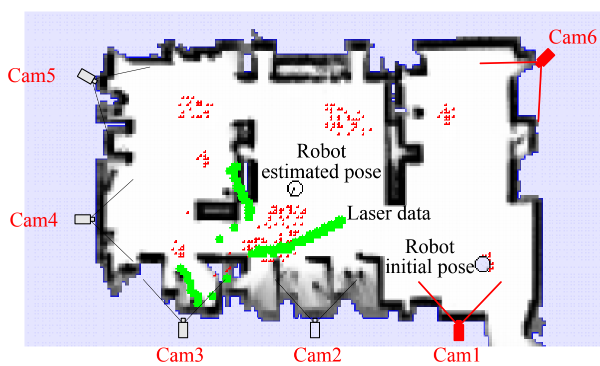
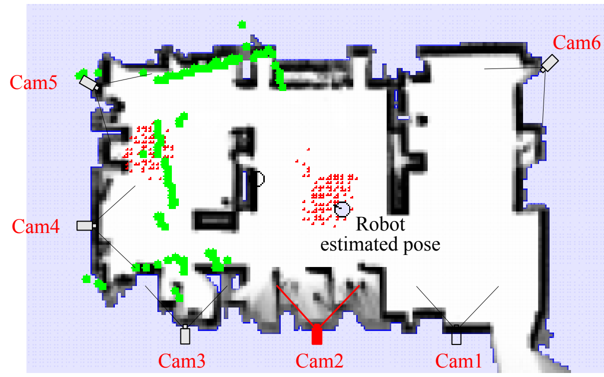


Figure 9 The robotic home-care environment and layout of the camera network

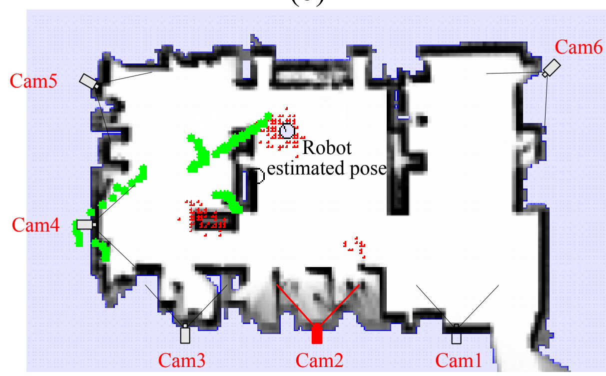
As shown in Figure 10 (d), sensor evidence eventually disambiguated between the primary hypotheses and converged on the true state of the robot. The corresponding evolution process of the global positional error of the robot is shown in Figure 11, which shows that the proposed method achieved lower error and smoother variance of the global position for the robot. The average accuracy results, recorded when the robot samples converged, indicated the mean positional errors of the robot were both less than 10cm. When the proposed method is compared with Zhao's method [12], we can find that the DPA-APF method achieved lower positioning error, as shown in Figure 12.



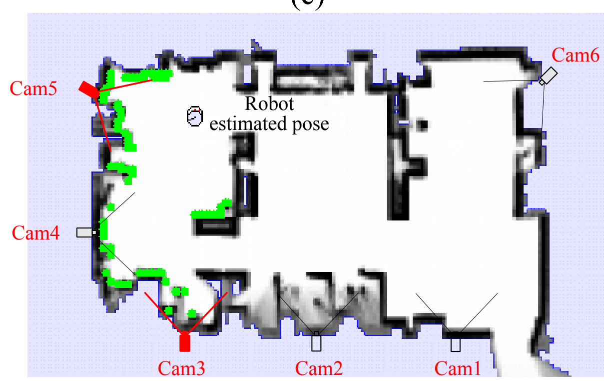
(a)



(b)

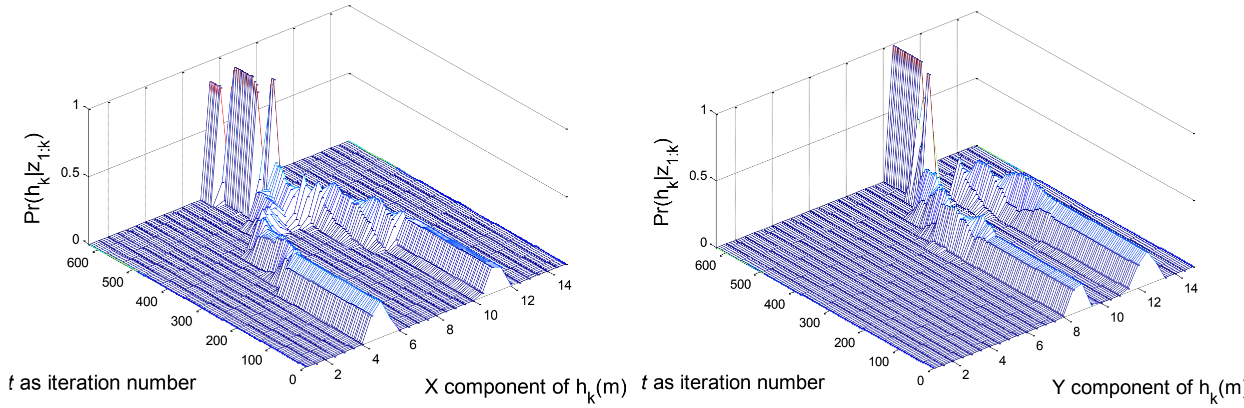


(c)



(d)

Figure 10 Mobile robot localization in dynamic environment with people coexistence



Propagation of the belief state density in the (a) X-coordinate (b) Y-coordinate

Figure 11 Evolution of the global positional uncertainty of the robot

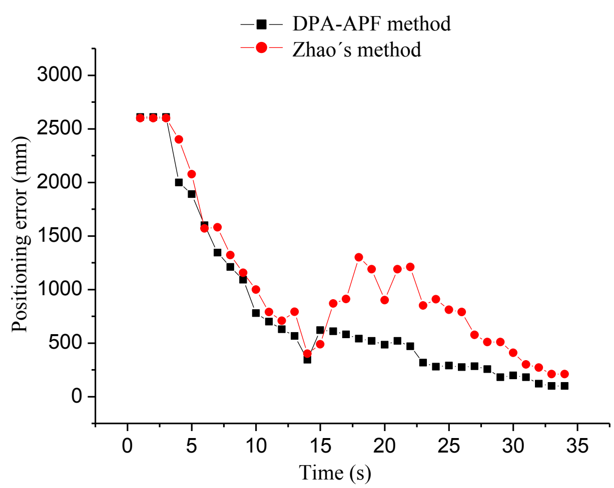


Figure 12 Localization accuracy comparison

VI. CONCLUSIONS

In this paper, a spatial-temporal collaborative sequential Monte Carlo architecture and an implementation algorithm named Distributed Proportional Allocation-Augmented Particle Filter (DPA-APF) are proposed. The proposed method exploits the parallelism and pipelining of resampling operations among distributed nodes, and thus extends the traditional particle filters to distributed implementation that is featured with high efficiency, flexibility and scalability. Application for mobile robot localization and navigation in typical intelligent environment with networked laser and camera sensors is given and the experimental results validate the effectiveness of the proposed method.

ACKNOWLEDGEMENT

This work is supported by the National Natural Science Foundation of China (Grant No. 61075090, No. 61005092, No. 61105094 and No.60805032).

REFERENCES

[1] J. Reijula, T. Rosendahl, K. Reijula, P. Roilas, H. Roilas, R. Sepponen, "New Method to Assess Service Quality in Care Homes for the Elderly", International Journal on Smart Sensing and Intelligent Systems, Vol.3, No,1, pp.14-26, 2010.

[2] T. Sato, T. Harada, T. Mori, "Environment-type robot system Robotic Room featured by behavior media, behavior contents, and behavior adaptation", IEEE/ASME Transactions on Mechatronics, Vol.9, No.3, pp.529-534, 2004.

[3] H. Hashimoto, "Intelligent interactive spaces - Integration of IT and robotics", Workshop on Advanced Robotics and its Social Impacts. Nagoya, Japan: IEEE Computer Society, pp.85-90, 2005.

[4] H. Hongu, N. Y. Chong, M. Miyazaki, et al, "An Experimental Testbed for Knowledge Distributed Robot Systems", Proc. 1st Int. Workshop on Networked Sensing Systems. Tokyo, Japan, pp.237-240, 2004.

[5] Y. Ha, J. Sohn, Y. Cho, et al, "A robotic service framework supporting automated integration of ubiquitous sensors and devices". Information Sciences, Vol.177, No.3, pp.657-679, 2007.

[6] A. Saffiotti, M. Broxvall, M. Gritti, et al, "The PEIS-ecology project: Vision and results", 2008 IEEE/RSJ International Conference on Intelligent Robots and Systems. Nice, France: Inst. of Elec. and Elec. Eng. Computer Society, pp.2329-2335, 2008.

[7] J. H. Lee, K. Morioka, N. Ando, H. Hashimoto, "Cooperation of Distributed Intelligent Sensors in Intelligent Environment", IEEE/ASME Trans. on Mechatronics,Vol.9, No.3, pp.535-543, 2004

[8] K. Morioka, S. Kovacs, J. H. Lee, P. Korondi, "A Cooperative Object Tracking System with Fuzzy-Based Adaptive Camera Selection", International Journal on Smart Sensing and Intelligent Systems, Vol.3, No,3, pp.338-358, 2010.

[9] A. Doucet, N. de Freitas, and N. Gordon, Eds., “Sequential Monte Carlo Methods in Practice”, Springer-Verlag, 2001.

[10] S. Thrun, D. Fox, W. Burgard, “Monte Carlo Localization with Mixture Proposal Distribution”, Proceedings AAAI National Conference on Artificial Intelligence, pp.859-865, 2000.

[11] S. Thrun, D. Fox, W. Burgard, F. Dellaert, “Robust Monte Carlo Localization for Mobile Robots”, Artifial Intelligence, Vol.28, pp.99-141, 2001.

[12] F. Zhao, J. Shin, J. Reich, “Information-driven dynamic sensor collaboration for tracking applications”, IEEE Signal Processing Magazine, Vol.19, pp.61-72, 2002.

[13] M. Rosencrantz, G. Gordon, S. Thrun, “Decentralized sensor fusion with distributed particle filters”, In: Proc. Conf. Uncertainty in Artificial Intelligence, Acapulco, Mexico, 2003.

[14] M. Bolic, P. M. Djuric, S. Hong, “Resampling Algorithms and Architectures for Distributed Particle Filters”, IEEE Trans. Signal Process, Vo.53, No.7, pp.2442-2450, 2004.

[15] M Coates, “Distributed Particle Filters for Sensor Networks”, In Proc. of 3nd Workshop on Information Processing in Sensor Networks, pp:99-107, 2004.

[16] H. Q. Liu, H. C. So, F. K. W. Chan, and K. W. K. Lui, “Distributed particle filter for target tracking in sensor networks”, Progress In Electromagnetics Research C, Vol.11, pp.171-182, 2009.

[17] N. J. Gordon, D. J. Salmond, A. Smith, “Novel-approach to nonlinear non-Gaussian Bayesian state estimation”, IEE Proceedings-F Radar and signal processing, Vol.140, No.2, pp.107-113, 1993.

[18] M. K. Pitt, N. Shephard, “Filtering via Simulation: Auxiliary Particle Filters”, Journal of the American Statistical Association, Vol.94, No.446, pp.590-599, 1999.

[19] N. A. Vlassis, B. Terwijn, B. Kröse, “Auxiliary Particle Filter Robot Localization from High-Dimensional Sensor Observations”, Proceedings of the 2002 IEEE International Conference on Robotics and Automation, Washington, DC, USA, pp.7-12, 2002.

[20] S. Thrun, W. Burgard, D. Fox. “Probabilistic Robotics”, London: MIT Press, 2005.

[21] D. Crisan, A. Doucet, “A survey of convergence results on particle filtering methods for practitioners”, IEEE Trans. Signal Processing, Vol.50, No.3, pp.736-746, 2002.

[22] X. D. Ma, X. Z. Dai and W. Shang, “Vision-based Extended Monte Carlo Localization for Mobile Robot”, Proceedings of the IEEE International Conference on Mechatronics and

Automation, pp:1831-1836, 2005.

[23] K. Qian, X. D. Ma, X. Z. Dai and F. Fang, "Socially Acceptable Pre-collision Safety Strategies for Human-Compliant Navigation of Service Robots", Advanced Robotics, Vol.24, No.13, pp.1813-1840, 2010.