2008 IEEE/RSJ International Conference on Intelligent Robots and Systems
Acropolis Convention Center
Nice, France, Sept, 22-26, 2008

Target Tracking Using SIR and MCMC Particle Filters by Multiple Cameras and Laser Range Finders

Ryo Kurazume, Hiroyuki Yamada, Kouji Murakami, Yumi Iwashita, and Tsutomu Hasegawa

Abstract— **This paper presents a sensor network system consisting of distributed cameras and laser range finders for multiple objects tracking. Sensory information from cameras is processed by the Level Set Method in real time and integrated with range data obtained by laser range finders in a probabilistic manner using novel SIR/MCMC combined particle filters. Though the conventional SIR particle filter is a popular technique for object tracking, it has been pointed out that the conventional particle filter has some disadvantages in practical applications such as its low tracking performance for multiple targets due to the degeneracy problem. In this paper, the new combined particle filters consisting of a low-resolution MCMC particle filter and a high-resolution SIR particle filter is proposed. Simultaneous tracking experiments for multiple moving targets are successfully carried out and it is verified that the combined particle filters has higher performance than the conventional particle filters in terms of the number of particles, the processing speed, and the tracking performance for multiple targets.**

I. INTRODUCTION

Demand for service robots which coexist with human and provide various services in daily life is expected to increase more and more in next decades. However, since the daily environment is complex and unpredictable, these robots must have a sufficient ability to sense the change of the environment and cope with a variety of situation. One of the promising approaches for the robots to coexist with human is the utilization of IT technology such as a distributed sensor network and network robotics. The basic idea of this approach is that robots provide a variety of services according to environmental information from not only on-board sensors but also sensor networks structured in the environment. As an empirical example of the above approach, we have been conducting a research project named "Robot Town Project". The aim of this research project is to develop a distributed sensor network system covering a town-size area in which there are many houses, buildings, and roads, and manage robot services by monitoring whole events occurred in the town. The events sensed are notified to the "Town Management System, TMS", and each robot receives appropriate information of surroundings and instructions for proper services. We have already developed the prototype of the TMS and demonstrated some applications for human-robot cooperation according to several practical scenarios.

R. Kurazume, K. Murakami, Y. Iwashita and T. Hasegawa are with Graduate Faculty of Infomation Sciencen and Electrical Engineering, Kyushu University, 744 Motooka, Nishi-ku, Fukuoka, Japan kurazume@is.kyushu-u.ac.jp

H. Yamada is with Graduate School of Infomation Sciencen and Electrical Engineering, Kyushu University, 744 Motooka, Nishi-ku, Fukuoka, 819-0395, Japan

In this project, detection, tracking, and management of position information of both human and robots in the town are important functions of the TMS. For tracking moving objects by cameras, we have developed the vision-based tracking system using Level Set Method named Level Set Tracking [1], [2]. However, several small and handy Laser Range Finders (LRFs) have been developed and are available at a low price in recent years, and a distributed LRF system is becoming a practical candidate of a sensor network system in terms of cost and performance.

On the other hand, statistical time-series approach such as kalman filter or particle filter [3] has been attracting wide attention as a robust tracking system of moving objects, and a lot of literatures have been presented. Especially, the particle filter is becoming a popular technique with the increase of computer performance. In this method, a number of candidates (particles) are prepared and optimum solutions are searched in a parallel way based on the Bayesian estimation theory. Once a proper likelihood function of each sensor is defined, it is easy to integrate observation information from various sensors in a probabilistic manner even if a number of heterogeneous sensors are used. However, though the particle filter is a powerful tool for the robust tracking of a moving target, it has been pointed out that the conventional particle filter has some disadvantages in practical applications such as low tracking performance for multiple targets in case that the number of particles is insufficient or there are too many targets.

In this paper, we present the integrated system of vision-based and LRF-based multi-target tracking using novel SIR/MCMC combined particle filters. Sensory information from cameras is processed by the Level Set Tracking and integrated with range data obtained by LRFs in a probabilistic manner using two kinds of particle filters with different space resolutions, that is, a low-resolution MCMC (Markov Chain Monte Carlo) particle filter [4] and a high-resolution SIR (Sequential Importance Resampling) particle filter. The proposed system makes it possible to track multiple targets robustly against inherent sensor noise, missed detection, and mutual occlusions. Simultaneous tracking experiments for multiple moving targets are successfully carried out and it is verified that the combined particle filters has higher performance than the conventional particle filters in terms of the number of particles, the processing speed, and the tracking performance for multiple targets.

978-1-4244-2058-2/08/$25.00 ©2008 IEEE.

II. Related works

LRF-based tracking systems of moving objects can be categorized into two groups: stationary LRFs in an environment [5]–[9] and on-board LRFs on mobile robot platforms [10]–[14].

For pedestrian tracking using stationary LRFs, Nakamura et al. proposed a distributed sensor system consisting of six LRFs (Sick LSM200) [5]. In this system, the ankle position of pedestrians is detected by slit-like laser light and stable tracking of individuals is performed using the kalman filter which is designed to adjust estimated motion to natural and periodic walking motion. Other than these methods, many tracking systems were proposed such as occupancy grid based tracking system [6], tracking of knee position by kalman filter and particle filter [7], estimation of height and position of a pedestrian using kalman filter [8], and a reception system using a LRF and a video camera [9].

Meanwhile, several systems which utilize on-board LRFs for the construction of an environmental map, obstacle avoidance, and target tracking have been proposed, for example, obstacle avoidance by a wheeled chair [10], pedestrian tracking using particle filter [11], [12] and with an omnidirectional image sensor [14].

This paper proposes the new tracking system using distributed image sensors and stationary LRFs in an environment, In this system, all the observation information from vision and range sensors are integrated in a probabilistic manner using two types of particle filters with different structures, MCMC/SIR particle filters.

III. Level Set Tracking

Level Set Tracking is a technique for tracking closed regions in image sequences by the Level Set Method. The Level Set Method, introduced by S. Osher and J. A. Sethian [15] , has attracted much attention as a method that realizes a topology free active contour modeling. This method utilizes an implicit representation of a contour to be tracked, and is able to handle the topological change of the contour intrinsically. Various applications based on the Level Set Method have been presented including motion tracking, 3D geometric modeling, and simulation of crystallization or semiconductor growth. However, the calculation cost of reinitialization and updating of the implicit function is considerably expensive as compared with the cost of conventional active contour models such as "Snakes". On the other hand, we have proposed an efficient calculation algorithm for the Level Set Method named the Fast Level Set Method (FLSM), and demonstrated real time tracking on video images [1] or three dimensional motion capture system [2].

By applying FLSM to target tracking problem in 2D image sequences, multiple closed regions, extracted by background subtraction for example, can be tracked quite robustly against spike noise in sensor data. Even if separate regions are overlapped temporarily, these regions are merged to a single region and separated again quite naturally. An example of Level Set Tracking for two pedestrians is shown in Fig.1. The image size and the processing speed are 320 $\times$ 240 pixels and 60 Hz, respectively. In this example, two closed contours are merged to a single closed contour by the overlap of two people, and after a short period, the single closed contour is separated into two closed contours again. This indicates that the Level Set Tracking can handle the topological change caused by the overlap of multiple regions.

Fig. 1. Level Set Tracking

IV. Tracking system using distributed video cameras and LRFs

Though the Level Set Tracking enables to track moving objects in video images robustly for sensor noise and mutual occlusion, the precise estimation of 3D position and the correct separation of occluded objects are difficult problems for a monocular camera. On the other hand, slit scanning type LRFs (Sick LMS200, Hokuyo URG04LX) can acquire the distance information from the sensor to the target directly. The slit scanning type LRF exposes slit-like projection light by a one-axis mirror, and measures the distance from the sensor to the object in a 2D plane. Therefore, by integrating range data and tracking information by the Level Set Tracking in video images, the robust motion tracking system which estimates the relative position of occluded objects correctly can be developed. In this section, we introduce the proposed tracking system using the vision and range sensors.

A. System configuration

Figure 2 shows the configulation of the tracking system. A sensor unit consisting of a video camera and a LRF is connected to a local computer and distributed in an environment as a sensor node. The video camera and the LRF are installed

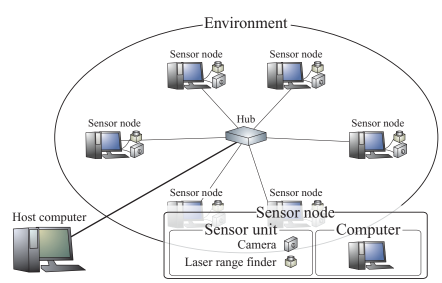


Fig. 2. Tracking system using distributed sensor units

to a base unit so that the optical axis of the camera is parallel to the slit-like laser light of the LRF (Fig.3). The position of the sensor unit in the environment is calibrated precisely beforehand. The local computers are connected to a host computer via Internet and sensory information is integrated using two types of particle filters (a low-resolution MCMC particle filter and a high-resolution SIR particle filter) in the host computer. Figure 4 shows the basic concept of data fusion of camera images and range data. Solid and dashed lines indicate the range data from the LRF and silhouette regions in the camera image, respectively. By fusing two kinds of sensor data, sensor noise in both sensors, especially unstable range data around occluding edges, is suppressed as shown in Fig.5.

Fig. 3. Sensor unit

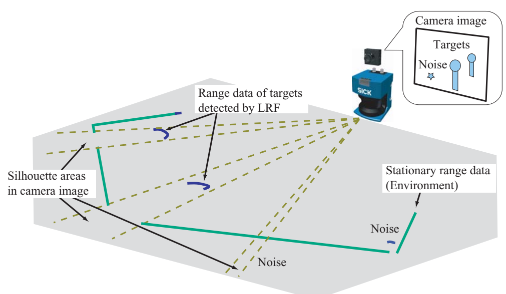


Fig. 4. Information fusion of range data and camera images

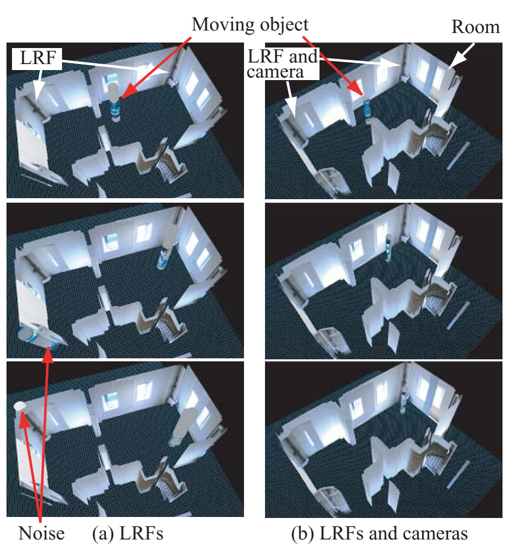


Fig. 5. Suppression effect of noise by fusing camera images and range data

B. Processing flow of the proposed system

In this section, we explain the processing flows of the proposed system in the sensor unit and the host computer, separately. We assume that the number of moving objects is unknown and each particle of both particle filters has the status about position and velocity of a single target.

1) Processing flow in the sensor unit: At first, the sensor unit i measures the environment in which there is no moving target, and obtains the information concerning the static environment. The obtained information of the static environment is a background image from the camera $I_s^i(u,v)$ and static range data $Z_s^i = \{\mathbf{z}_{s1}, \ldots, \mathbf{z}_{sM}\}$ from the LRF to stationary objects such as walls, doors, or furnitures.

Moving objects at time t are detected through the following two steps.

1) Apply the Level Set Tracking for detected regions obtained by the background subtraction for the captured image $I_t^i(u,v)$ using the background image $I_s^i(u,v)$. Find the left and right coordinates u_l and u_r of the jth detected contour and calculate the azimuth angles $\theta_{tj} = \{\theta_l, \theta_r\}$ of the contour j in which the jth target is involved as shown in Fig.6. If multiple regions are detected, the azimuth angles are obtained as $\Theta_t^i = \{\theta_{t1}, \theta_{t2}, \ldots \theta_{tm}\}$, where m is the number of the detected regions.
2) Extract discrete points $\tilde{Z}_t^i$ from range data Z_t^i at time t which are separated T_r away from the static range data Z_s^i.

$$\tilde{Z}_t^i = Z_t^i, \quad (\| \mathbf{z}_{sj} - \mathbf{z}_{tj} \| > T_r;\ j = 1 \sim M) \qquad (1)$$

The above tasks are repeated independently in each sensor unit, and provide the most recent information to the host computer according to the demand command.

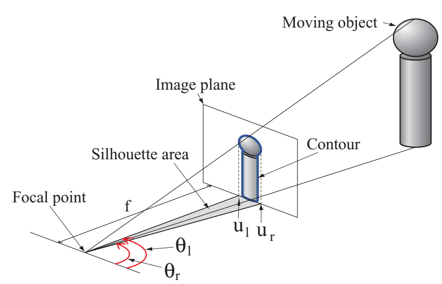


Fig. 6. Existing region of a target

2) Processing flow in the host computer: The host computer integrates the information from the sensor units and estimates the positions of the moving objects. The details are as follows:

1) Send demand commands to the sensor units sequentially and obtain the sensor data Θ_t^i and $\tilde{Z}_t^i$. Then, integrate the sensor data from sensor units as $\Theta_t = \{\Theta_t^i\}$, $\tilde{Z}_t = \{\tilde{Z}_t^i\}$. Θ_t consists of the sets of the area of objects in all images. On the other hand, $\tilde{Z}_t$ consists of all the range data detected by the sensor units. We do not consider which sensor the range data is obtained from.

2) The target positions are estimated using the combined particle filters. Details of the combined particle filters are shown in the next section.

C. Data integration using MCMC/SIR combined particle filters

In the host computer, the tracking information by the Level Set Tracking and range data are integrated in a probabilistic manner using two types of particle filters, the low-resolution MCMC particle filter and the high-resolution SIR particle filter.

The SIR particle filter is a popular technique which has been used in many tracking applications. As is well known, the SIR particle filter is robust for missed detection and easy to integrate tracking information from multiple sensors. However, there is a well-known problem in case of multiple target tracking. If there are multiple targets in the scene but plenty of particles are not used, particles concentrate to a few targets and tracking of other targets fails. This problem is known as "Degeneracy problem" [3] (Fig.7), and an inherent problem of the SIR particle filter which generates new particles around the particles having large weights intensively. To avoid this problem, some extensions of the particle filter

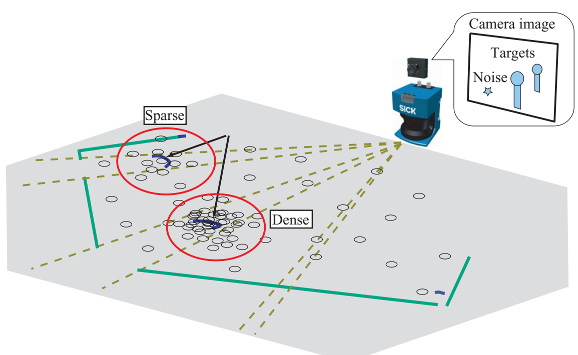


Fig. 7. Degeneracy problem

algorithm have been proposed, for example, Resampling move method [16] which utilizes the state transition based on MCMC and SIR sampling recursively, Regularized particle filter [17], the use of Gibbs sampler [18], and the Mixture particle filter [19]. However, the convergence speed of these techniques is low or the number of particle filters must be changed according to the number of targets. Therefore, it is difficult to apply these techniques for real time applications or the algorithm becomes complex if objects leave and enter the scene.

Meanwhile, the MCMC particle filter [4] is based on the Metropolis-Hastings which is a weak resampling technique, and thus, the convergence speed to concentrate particles around the target posterior is lower than the SIR particle filter which is based on the importance resampling. No particles are killed and reproduced. However, the MCMC particle filter shows good performance for tracking of multiple targets since it converges to all the targets uniformly thanks to the random sampling.

Taking these features into acount, we propose the combined system of these two particle filters which are defined in different space resolutions. The basic idea is as follows: new particles of the SIR particle filter are generated around not only the particles having large weight but also the particles of the MCMC particle filter. In addition, we set that the resolution of the tracking space of the MCMC particle filter is lower than the one of the SIR particle filter since the MCMC particle filter cannot handle objects moving at high speed in high resolution space. The convergent process of the MCMC particle filter is repeated from initial particle positions distributed uniformly at every update time of the SIR particle filter. The idea of the combined particle filter explained above is illustrated in Fig.8. The proposed

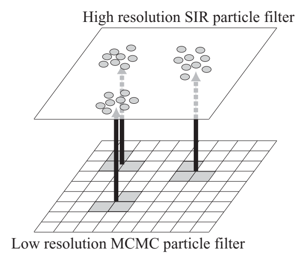


Fig. 8. The combined particle filter

combined particle filter has both features of high tracking accuracy by the SIR particle filter and good performance for the simultaneous tracking of multiple targets without undetected targets by the MCMC particle filter. Therefore, the proposed filter can track multiple targets with a small number of particles robustly even if the number of targets is unknown and changed during the tracking. In addition, since the number of particles can be reduced, the processing speed is also improved as shown in the following experiments.

The details of the combined particle filters are discribed follow. The event X_t indicates that the moving object is located in position $\mathbf{x_t}$ at time t. In both particle filters, each particle has a hypothesis and its likelihood. The posterior probability $p(X_t|\Theta_t, \tilde{Z}_t)$ after obtaining the observation Θ_t and $\tilde{Z}_t$ can be estimated recursively using particles. Here, Θ_t and $\tilde{Z}_t$ indicate the events that sensory data Θ_t and $\tilde{Z}_t$ are obtained from the video camera and the LRF, respectively. The difference of the MCMC and the SIR particle filters is the way to choose particles at next time $t+1$ according to the current likelihood.

1) SIR particle filter: The procedure of the SIR particle filter is as follows:

(1) Generation of initial particles

Generate N particles $s_0^{(n)} = \{\mathbf{x}_0^{(n)}, \mathbf{v}_0^{(n)}, w_0^{(n)}\}$ $(n = 1 \sim N)$. Here, $\mathbf{x}_t^{(n)}$, $\mathbf{v}_t^{(n)}$, $w_t^{(n)}$ are the position vector, the velocity vector, and the weight at time t, respectively.

(2) State transition

Apply the motion model $p(X_t|X_{t-1})$ to the particles and move them to the next status. In this paper, we utilize the linear uniform motion as the motion model described as

$$\mathbf{x}_t^{(n)} = \mathbf{x}_{t-1}^{(n)} + \mathbf{v}_{t-1}^{(n)} T_s \quad (2)$$

where T_s is a sampling interval and w .

(3) Likelihood calculation

Calculate likelihood $p(\Theta, \tilde{Z}|X_t)$ for each particle according to the following equation.

$$p(\Theta_t, \tilde{Z}_t|X_t) = p(\Theta|X_t)p(\tilde{Z}|X_t) \quad (3)$$

where

$$p(\Theta_t|X_t) = f(\mathbf{x}_t^{(n)}) \quad (4)$$

$$p(\tilde{Z}_t|X_t) = exp(-d^2/2\sigma_s^2)/\sqrt{2\pi}\sigma_s \quad (5)$$

and σ_s is a position error, d is minimum Euclidean distance between $\mathbf{x}_t^{(n)}$ and $\tilde{Z}_t$.

$$d = \min_i \ \| \mathbf{x}_t^{(n)} - \mathbf{z}_{ti} \| \quad (6)$$

$f(\mathbf{x}_t^{(n)})$ is a function which returns the constant value S $(0 \leq S \leq 1)$ if the azimuth angle to $\mathbf{x}_t^{(n)}$ is in the area of Θ_t, and $1 - S$ if it is not. Instead of this simple function $f(\mathbf{x}_t^{(n)})$, we can utilize some statistical functions such as a Gaussian kernel. In this paper, we choose the simplest function explained above in order to obtain the constant value if occlusion occurs. This point will be discussed later.

From Eqs.(3) to (6), we determine the weight of each particle as

$$w_t^{(n)} = p(\Theta_t, \tilde{Z}_t|X_t) \quad (7)$$

Then, the sum of the weight of all particles $w_t^{(all)} = \sum_{n=0}^{N} w_t^{(n)}$ is calculated.

(5) Resampling

Choose NP $(0 < P < 1)$ particles $s_t^{(n)}$ from the N particles according to the probability $w_t^{(n)}/w_t^{(all)}$, and generate new particles $s_{t+1}^{(n)}$ by adding random noise. $N(1-P)$ particles are newly generated around the estimated target positions by the following MCMC particle filter.

(6) Position estimation

Estimate the positions of the moving objects based on the distribution of particles. At first, all the particles are divided into several groups by k-means clustering algorithm. If the number of particles in one group is larger than the threshold, the position of the moving object is estimated as the weighted mean of the positions of particles in the group.

2) MCMC particle filter: The MCMC particle filter is quite similar to the SIR particle filter. The only thing that is different is the resampling procedure in step (5).

(5) Resampling

Choose NP $(0 < P < 1)$ particles $s_t^{(n)}$ from the N particles randomly and generate candidates of new particles $s_{t+1}^{(n)\prime}$. Then, the weight $w_t^{(n)\prime}$ of each candidate is calculated according to the Eq.(7). Next, by applying the Metropolis-Hastings using the weight ratio $w_t^{(n)\prime}/w_t^{(n)}$, new particles $s_{t+1}^{(n)}$ are generated. $w_t^{(n)}$ is the weight before applying the state transition in step (2). On the other hand, $N(1-P)$ particles are generated uniformly in the whole space so that new targets can be detected and tracked.

As for the occlusion problem, since range data from different sensors are all processed without distinction of sensor units in 2D plane, the tracking performance is not affected seriously if the range data of the object is obtained sufficiently from the other sensors which can see the object. In addition, even if the object is occluded by front objects in camera images, the likelihood calculated in Eq.(4) is unchanged since the occluded object is also in the region of the area of the occluding objects in images. The performance of the proposed system for the occlusion problem is verified through the tracking experiments with a number of pedestrians in section V.

V. Experiments

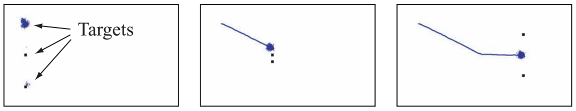
This section introduces the experimental results using the propose distributed sensor system and the combined particle filters. The performance of the proposed combined particle filters is evaluated by computer simulations and the simultaneous tracking experiments of multiple targets in actual environments, respectively.

A. Simulation experiments

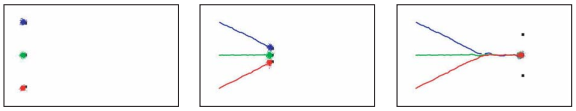
Firstly, we tested the performance of three types of particle filters in the case that three targets begin to move, overlap each others, and separate again on a 2D plane. The particle filters tested are a) the conventional SIR particle filter, b) the Mixture particle filter [19] for the tracking of multiple targets, and c) the proposed MCMC/SIR particle filter.

Figure 9 shows the experimental results. Three objects begin to move from the different initial positions toward the same target position simultaneously. The numbers of particles are, a) 900 for the SIR particle filter, b) 900 (300 $\times$ 3) for the Mixture particle filter, and c) 600 (300 for MCMC and 300 for SIR) for the proposed MCMC/SIR particle filter. In the experiment, the number and initial positions of the objects are assumed to be unknown except the Mixture particle filter. Only for the Mixture particle filter, we assign the initial 300 particles uniformly for each object, respectively, before stating the simulation.

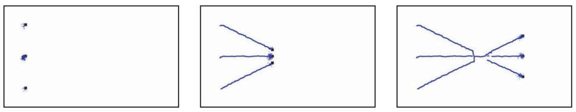
As shown in Fig.9, a) all the particles of the conventional SIR particle filter converged to the single object just after stating the simulation. As for b) the Mixture particle filter, each object was tracked separately by each particle filter until the objects crossed each other. However, after the overlap and separation, all the particles were converged to the single object and other objects could not be tracked appropriately. On the other hand, the proposed MCMC/SIR particle filter with the least number of particles was able to keep tracking all the target stably even after they overlapped and separated.



(a) SIR particle filter (Number of particles is 900)



(b) Mixture particle filter (Number of particles is 300×3)

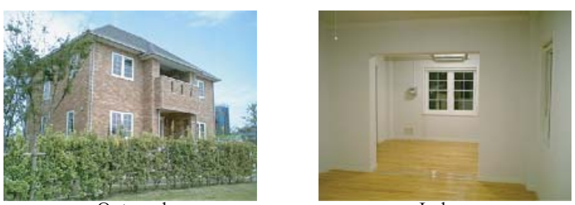


(c) SIR/MCMC particle filter (Number of particles is 300× 2)

Fig. 9. Simulation experiments for multiple targets

B. Tracking experiment in real environment

Next, we conducted the tracking experiment in an actual house shown in Fig.10. Four sensor units (Dragonfly2x4, LMS200x4) are placed in four rooms on the first floor of the house (Fig.11). In the experiment, up to five people waking around the first floor are tracked simultaneously. The numbers of particles of the SIR and MCMC particle filters are 2000 and 1000, respectively. Figure 12 shows the experimental results. Left, middle, and right columns indicate the camera images, tracking results from the same viewpoint, and tracking results from the top view. From this experiment, it is verified that all the people including the one sitting on the chair can be tracked appropriately using the proposed distributed sensor system.



Outward Indoor

Fig. 10. Experimental house for the robot town project

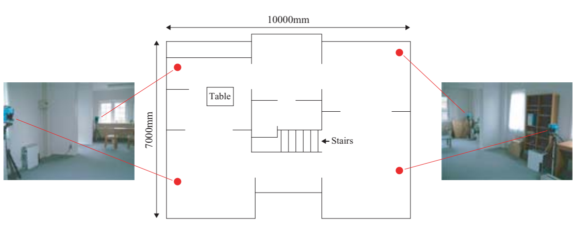


Fig. 11. Sensor positions in the house

C. Tracking experiment for a number of moving objects

Next, we placed four sensor units (Dragonfly2x4, LMS200x4) in a same room of $14[m] \times 10[m]$, and tracked up to 11 people simultaneously. The numbers of particles of the SIR and MCMC particle filters are 2000 and 1000, respectively. Figure 13 shows the walking paths of 11 people,

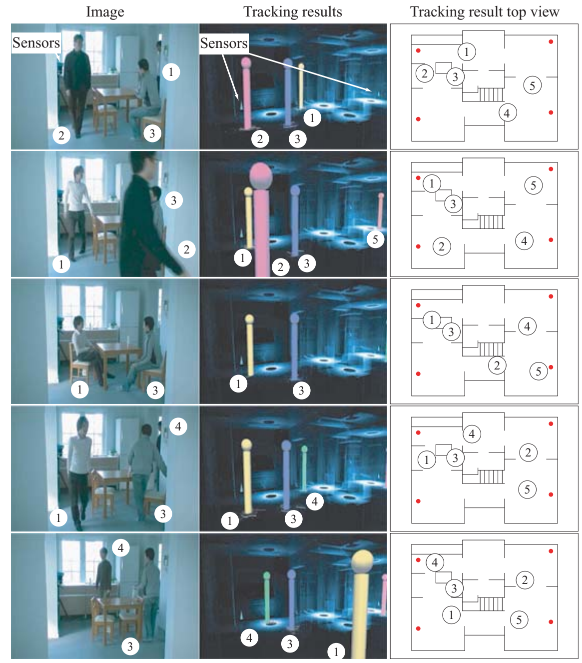


Fig. 12. Tracking results in the house

and Fig.14 shows the images of the experiments (left column) and tracking results (right column). By comparing the true positions measured by the total station (TOPCON, GTS-825A) and hand-held corner cubes, the average error and the standard deviation of these paths were 86.9 [mm] and 59.7 [mm], respectively. The processing time for the tracking of 11 people was 32.6 [ms] in the case that the MCMC and SIR particle filters are updated 10 times and 1 time, respectively.

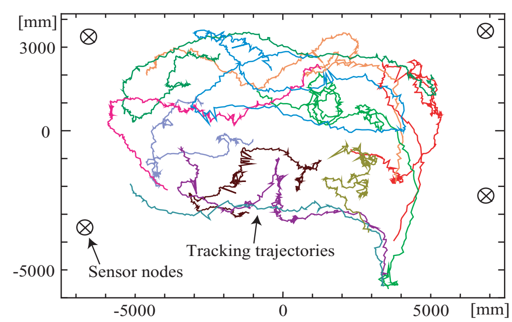


Fig. 13. Paths of 11 targets

Figure 15 shows the comparison experiments of the SIR particle filter, the Mixture particle filter, and the proposed SIR/MCMC particle filter. The numbers of particles of the SIR, the Mixture, and the proposed SIR/MCMC particle filters are 6000, 6000 (=2000x3), and 3000(2000 for SIR and 1000 for MCMC), respectively. Three objects appeared from different positions sequentially, got together, and separated and disappeared. Figure 15 shows that only the proposed combined particle filters could track the objects even after they dispersed. The processing time for the SIR and the Mixture particle filters were 19.8 [ms] and 19.6 [ms], respectively. On the other hand, the processing time of the proposed MCMC/SIR particle filter was 17.1 [ms].

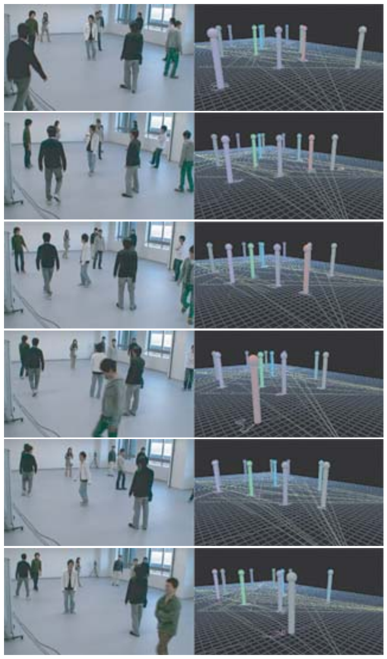


Fig. 14. Tracking results of 11 targets by SIR/MCMC particle filters

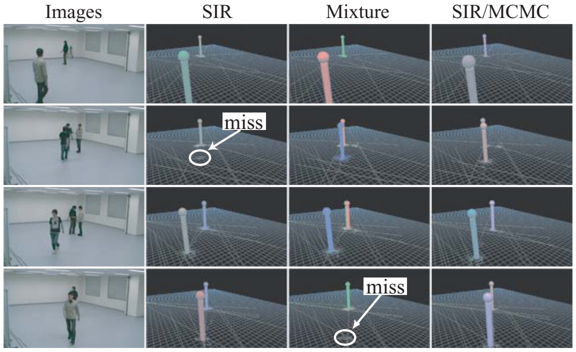


Fig. 15. Experimental results of SIR, Mixture and SIR/MCMC particle filters

From all the experiments explained above, it was verified that a set of combined particle filters is able to keep tracking the unknown number of people who appear and disappear at unknown positions, appropriately.

VI. Conclusion

This paper proposed a new tracking system of multiple moving objects using Level Set Tracking and multiple laser range finders. Sensory information from distributed sensor system is integrated by the combined particle filters consisting of the low-resolution MCMC particle filter and the high-resolution SIR particle filter, sequentially. Simultaneous tracking experiments for multiple moving targets are successfully carried out and it is verified that the combined particle filters has higher performance than the conventional particle filter in terms of the number of particles, the processing speed, and the tracking performance for multiple targets.

Acknowledgment

This research was supported in part by the Ministry of Education, Science, Sports and Culture, through a Grant-in-Aid for Scientific Research (B) (No.19360119).

References

[1] Y. Iwashita, R. Kurazume, T. Tsuji, K. Hara, and T. Hasegawa, "Fast implementation of level set method and its realtime applications," in *Proc. IEEE International Conference on Systems, Man and Cybernetics 2004*, 2004, pp. 6302–6307.

[2] Y. Iwashita, R. Kurazume, K. Hara, and T. Hasegawa, "Robust motion capture system against target occlusion using fast level set method," in *Proc. IEEE International Conference on Robotics and Automation*, 2006, pp. 168–174.

[3] S. Arulampalam, S. Maskell, N. Gordon, and T. Clapp, "A tutorial on particle filters for on-line non-linear/non-gaussian bayesian tracking," *IEEE Transactions on Signal Processing*, vol. 50, no. 2, pp. 174–188, Feb. 2002.

[4] Z. Khan, T. Balch, and F. Dellaert, "Mcmc-based particle filtering for tracking a variable number of interacting targets," *IEEE Tranaction on Pattern Analysis and Machine Intelligence*, vol. 27, no. 11, pp. 1805–1918, November 2005.

[5] K. Nakamura, H. Zhao, R. Shibasaki, K. SAKAMOTO, T. Ohga, and N. Suzukawa, "Tracking pedestrians using multiple single-row laser range scanners and its reliability evaluation," *Systems and computers in Japan*, vol. 37, no. 7, pp. 1–11, 2006.

[6] E. Prassler, J. Scholz, and A. Elfes, "Tracking people in a railway station during rush hour," in *In H.I.Christensen, editor, Proc. Computer Vision Systems, First International Conference, ICVSf99*, 1999, pp. 162–179.

[7] A. Fod, A. Howard, and M. J. Mataric, "A laser-based people tracker," in *Proc. International Conference on Robotics and Automation 2002*, 2002, pp. 3024–3029.

[8] A. Brooks and S. Williams, "Tracking people with networks of heterogeneous sensors," in *Proc. Australasian Conference on Robotics and Automation 2003*, 2003.

[9] M. P. Michalowski and R. Simmons, "Multimodal person tracking and attention classification," in *Proc. HRIf06*, 2006.

[10] B. Kluge, C. Kohler, and E. Prassler, "Fast and robust tracking of multiple moving objects with a laser range finder," in *Proc. International Conference on Robotics and Automation 2001*, 2001, pp. 1683–1688.

[11] D. Schulz, W. Burgard, D. Fox, and A. B. Cremers, "Tracking multiple moving targets with a mobile robot using particle filters and statistical data association," in *Proc. International Conference on Robotics and Automation 2001*, 2001, pp. 1665–1670.

[12] M. Montemerlo, S. Thrun, and W. Whittaker, "Conditional particle filters for simultaneous mobile robot localization and people-tracking," in *Proc. International Conference on Robotics and Automation 2002*, 2002, pp. 695–701.

[13] M. Lindstom and J.-O. Eklundh, "Detecting and tracking moving objects from a mobile platform using a laser range scanner," in *In. Proc. of the IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS)*, 2001.

[14] M. Kobilarov, J. Hyams, P. Batavia, and G. S. Sukhatme, "People tracking and following with mobile robot using an omnidirectional camera and a laser," in *Proc. International Conference on Robotics and Automation 2006*, 2006.

[15] S. Osher and J. A. Sethian, "Fronts propagating with curvature dependent speed: Algorithm based on hamilton-javobi formation," *Journal of Computational Physics*, vol. 79, pp. 12–49, 1988.

[16] W. R. Gilks and C. Berzuini, "Following a moving target — monte carlo inference for dynamic bayesian models," *Journal of the Royal Statistical Society Series B*, vol. 63, pp. 127–146, 2001.

[17] N. Oudjane, C. Musso, and F. Legland, "Improving regularised particle filters," *A. Doucet, N. De Freitas, and N. Gordon, editors, Sequential Monte Carlo Methods in Practice*, vol. chapter 12, pp. 247–271, 2001.

[18] C. Hue, J. P. L. Cadre, and P. Perez, "Tracking multiple objects with particle filtering," *IEEE Transactions on Aerospace and Electronic Systems*, vol. 38, no. 3, pp. 791–812, 2002.

[19] J. Vermaak, A. Doucet, and P. Perez, "Maintaining multi-modality through mixture tracking," in *Proc. the International Conference on Computer Vision*, 2003, pp. 1110–1116.