

RFID Multi-target Tracking Using the Probability Hypothesis Density Algorithm for a Health Care Application

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Abstract. The intelligent multi-sensor system is a system for target detection, identification and information processing for human activities surveillance and ambient assisted living. This paper describes RFID multi-target tracking using the Gaussian Mixture Probability Hypothesis Density, GM-PHD, algorithm. The multi target tracking ability of the proposed solution is demonstrated in a simulation and real environment. A performance comparison of the Levenberg-Marquardt algorithm with and without the GM-PHD filter shows that the GM-PHD algorithm improves the accuracy of tracking and target position estimation significantly. This improvement is demonstrated by a simulation and by a physical experiment.

Keywords: Human Tracking, Probability Hypothesis Density, Radio Frequency Identification.

1 Introduction

The intelligent multi-sensor system, IMSS, is a high-performance autonomous distributed vision and information processing system, [1]. Fig. 1 illustrates the idea of using radio-frequency identification, RFID, sensors for person identification and localization. This is useful for medical healthcare services, security, the home help service etc., for all services that require robust tracking. One approach which has attracted particular attention is that of ambulatory wireless systems worn by elderly individuals in their own homes and designed to detect abnormalities in their motions and to report these abnormalities to a remote monitoring center for further action. The IMSS system inter alia includes vision, RFID sensors and actuators for surveillance and tracking of the human activities space. This space consists of the human beings and their surrounding environment, including robots, household appliances, and so on. An intelligent agent contains a knowledge database that includes learning and decision-making components that can be used to track, recognize, and analyze targets.

Just like the human eye, the multi vision sensor system acquires information about objects such as color, shape and position etc. in a 3D space. The accuracy of the target

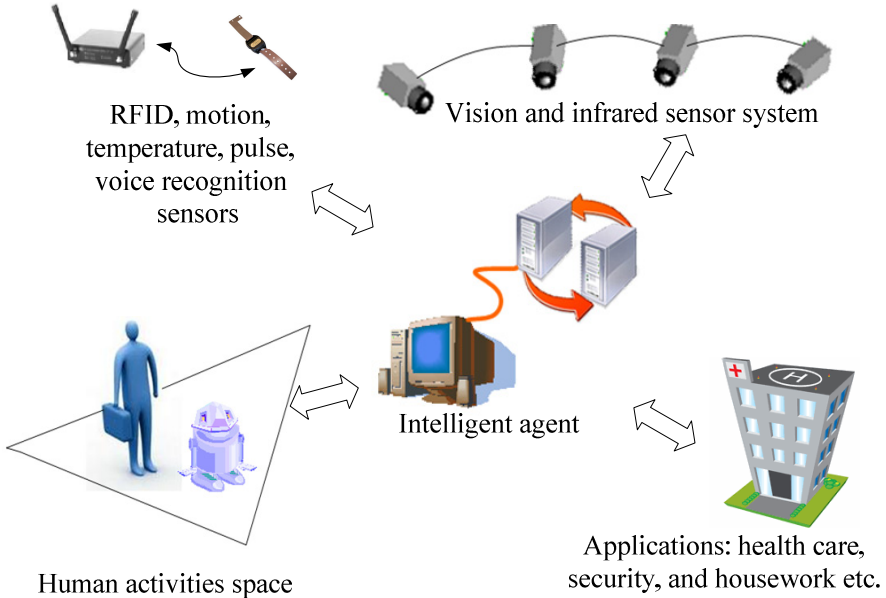


Fig. 1. Intelligent multi-sensor system

position estimation depends on many factors where the most important are: the distance between target and camera, camera focal length, stereo baseline and camera resolution, [2]. The target tracking robustness is also affected by light, obstacles, the camera’s field of view etc. The human factor can also interfere with the tracking process. RFID is a rapidly developing technology based on wireless communication used to identify the target. The RFID system consists of tags which can be very small and easily carried by a human being. The tags can also be easily equipped with emergency buttons or other sensors, such as motion, temperature, heart rate, and voice recognition sensors. The RFID reader receives data from the tags that are used to identify the target. The technology has been widely studied and used in different applications, [3-5]. For instance, the tagged target’s position can be tracked in an indoor environment by means of the tag’s radio signal strength, RSS. The advantage of the RFID tracking system is its low-cost, large coverage area, independence of light, and ability to penetrate obstacles.

This paper proposes the use of the GM-PHD algorithm to track multi RFID targets. The estimated position of a RFID target can be then used by a vision sensor to identify the region of interest or the target’s’ initial position. Further, this information can be valuable when determining the tracking cameras’ position, orientation, movement speed, focal length and baseline length [1], [2]. In the case when the vision system is on standby due to occlusions, darkness or due to personal reasons, the RFID can still track the individual with a certain accuracy.

2 Related Works

The tracking of a specific target can be achieved by using different positioning systems like the Global Positioning System, GPS, ultrasonic, infrared and radio frequency signals. GPS can be used for an accurate outdoor localization while technologies like artificial vision, ultrasonic, infrared and radio frequency signals can be employed for indoor localization [6-8]. The localization technique used in RFID relies mostly on an accurate estimation of the distance between the reader and the tag.

In a positioning system that uses ultrasonic or sonic signals, there is a need to initially deploy and distribute networked reference points within the tracking environment. The reference points form the reference space [9]. Within the location where the system is used, special detectors are located to detect the tags' unique ultrasonic identification signals. As the monitored object is moving within the observed area, the location of the object is being tracked and captured by the computer application (middleware) [10]. The position of the object is calculated with respect to the reference points. The integration of multi-sensor architecture for indoor navigation was introduced in [11].

The GM-PHD algorithm was proposed by Vo and Ma [12]. Clark, Panta and Vo [13] suggested that the algorithm could be used for tracking multiple targets in a high clutter density. The comparison between the algorithm and the Multiple Hypothesis Tracker, MHT, shows that the former is better in areas of high clutter density and that it estimates the number of targets and their trajectories more accurately. Further, the performance of the GM-PHD algorithm for multi-target tracking in vision systems has been evaluated by Chen *et al.* [14].

The work of Sidenbladh discusses a particle PHD filter implementation for tracking multiple vehicles in terrain, [15]. The result shows the robustness of the method when tracking a varying number of targets.

3 Problem Statement and Main Contributions

The IMSS should instantly locate the multiple targets' initial positions when the system starts up. When the vision system is on standby or the targets are obscured by obstacles, the IMSS can still track the targets' motion by using the RFID system. The paper investigates the robustness of the RFID system when tracking multiple targets. The tracking improvement is accomplished by the application of the Levenberg-Marquardt, LM, algorithm with the GM-PHD filter.

The main contributions of the paper can be summarized as follows:

- Use of a minimization algorithm to estimate the propagation factor in the radio propagation channel model;
- Implementation of the GM-PHD filter on the LM algorithm for multi-target tracking using RFID technology;
- Verification of the GM-PHD algorithm for multi-target tracking in simulated and real environments.

4 Modelling

Radio propagation in an indoor environment is affected by reflections, diffractions and scatterings. The average radio signal power is decreased log-normally with the distance for indoor wireless channels. In this section, the radio propagation channel model is discussed. The estimation of the propagation factor using the minimum square error algorithm is proposed, and the LM algorithm with the GM-PHD filter is suggested to be used to track the multiple targets.

4.1 Radio Propagation Channel Model

In wireless communication systems, the interaction between electromagnetic waves and the environment reduces the received signal strength. The path loss between two antennas strongly depends on the propagation environment. The power transfer ratio for a pair of lossless antennas in free space with optimum orientation is given by:

$$\frac{P_r}{P_t} = G_t G_r \left(\frac{\lambda}{4\pi d} \right)^2, \tag{1}$$

where λ is the wavelength; P_r is the received power; P_t is the transmitted power; G_r is the receiver antenna gain; G_t is the transmitter antenna gain; and d is the distance between antennas.

In equation (1) the factor $\left(\frac{\lambda}{4\pi d} \right)^2$, if separated from the effect of transmitter and receiver antenna gains, is referred to as the free space path loss. This is a path loss that occurs in a physical building and takes into account reflection, path obstruction, absorption and other attenuation effects introduced by the presence of objects inside the building [16].

The in-building path loss propagation model used to depict the effect of obstructions is given by:

$$PL(d) = PL(d_o) + 10\alpha_p \log\left(\frac{d}{d_o}\right) + AWGN \text{ [dB]}, \tag{2}$$

where d_o is an arbitrary reference distance away; α_p is a propagation factor, i.e., the path loss exponent which depends on the surroundings and the building types; d is the transmitter-receiver separation distance; $PL(d_o)$ is the in-building path loss at an arbitrary reference distance away, which can be derived empirically; $AWGN$ is additive white Gaussian noise with a zero-mean and the standard deviation σ .

The radio propagation properties can be estimated by the identification procedure. For instance, the optimized propagation factor, α_p , can be estimated by applying the minimum square error algorithm:

$$\min_{\alpha_p} \sum_{i=1}^I \left(PL_{RSS}(d_i) - PL(\alpha_p, d_i) \right)^2, \tag{3}$$

where PL_{RSS} is the measured path loss from RSS for the corresponding distance d_i from a reader to tag. The theoretical path loss, $PL(\alpha_p, d_i)$, is calculated from equation (2). I is the number of samples.

4.2 Target Tracking Using the GM-PHD Algorithm

Using the wireless wave propagation model (2), we can estimate the distances from a tag to the multiple base stations, the RFID readers, using RSS with AWGN. For each reader as a center, a sphere can be formed with a radius equal to the distance from the station to the tag found from the RSS. The straightforward approach uses a geometric method to find the intersection point of the spheres around each reader. This point determines the tag position.

In practice, however, the calculated distances from a tag to the readers are contaminated by noise. The estimated spheres may not even have an intersection that allows the tag position to be found. In this case, one can apply the Levenberg-Marquardt, LM, algorithm to estimate the tag position, $\zeta(x, y, z)$, [17].

The distances, D_l , from a tag position, $\zeta(x, y, z)$, to the l -th reader's position, $\beta(x_l, y_l, z_l)$, can be described as:

$$D_l = \sqrt{(x - x_l)^2 + (y - y_l)^2 + (z - z_l)^2} \quad \forall l = 1, \dots, L, \quad (4)$$

where L is the number of readers.

The LM algorithm is an iterative technique that locates the minimum of a function expressed as:

$$\min_{\zeta(x, y, z)} \sum_{l=1}^L (D_l(\zeta) - d_l)^2, \quad (5)$$

where the distance from tag to readers d_l is calculated from (2) according to the RSS received by the l -th reader and where L is a number of readers.

In the framework of the multi-target tracker, the state of the multi-target position can be described by the Random Finite Set, RFS. The state can be represented as a discrete time k set \mathbf{X}_k defined as:

$$\mathbf{X}_k = \{\chi_{k,i} : i = 1, \dots, M_{\chi}(k)\}, \quad (6)$$

where $M_{\chi}(k)$ is the number of targets in the space in the time k , and i is the index variable.

Firstly, according to (5) the state of the multi-target position can be estimated using the LM algorithm from the RSS measured by the RFID readers. Then, the multi-target measurement can be formulated as the set:

$$\mathbf{Z}_k = \{\zeta_{k,j} : j = 1, \dots, M_{\zeta}(k)\}, \quad (7)$$

where $M_{\zeta}(k)$ is the number of observations in the time k , and j is the index variable.

The PHD algorithm assumes that each target generates observations independently and the clutter RFS is a Poisson distribution independent of target-oriented

measurement, and that the predicted multi-target RFS is also a Poisson distribution. The GM-PHD filter is based on three additional assumptions compared to the PHD algorithm, [12]:

(i) Each target and the sensor follow the linear Gaussian model which can be described by:

$$\begin{aligned} f_{k|k-1}(\mathcal{X}|\zeta) &= N(\mathcal{X}; \mathbf{F}_{k-1}\zeta; \mathbf{Q}_{k-1}) \quad , \\ g_k(\zeta|\mathcal{X}) &= N(\zeta; \mathbf{H}_k\mathcal{X}; \mathbf{R}_k) \quad , \end{aligned} \quad (8)$$

where N is the normal or Gaussian distribution operator and $N(\cdot, m, \Psi)$ denotes a Gaussian density with the mean m and the covariance Ψ ,

\mathbf{F}_{k-1} is the state transition matrix,

\mathbf{Q}_{k-1} is the process noise covariance matrix,

\mathbf{H}_k is the observation matrix, and

\mathbf{R}_k is the observation noise covariance matrix.

(ii) The survival and detection probabilities, p_S and p_D respectively, are state independent,

(iii) The intensity of the birth RFS is a Gaussian mixture.

Like other smoothing filters, the GM-PHD filter consists of two steps: prediction and update. The prediction equation is defined as:

$$v_{k|k-1}(\mathcal{X}) = \gamma_k(\mathcal{X}) + p_{S,k} \sum_{j=1}^{J_{k-1}} w_{k-1}^{(j)} N(\mathcal{X}; m_{k-1}^{(j)}, \Psi_{k|k-1}^{(j)}) \quad , \quad (9)$$

where γ is the birth intensity and w is the weight parameter.

After the object detection has been finished and Z_k is available, the state is updated according to:

$$v_k(\mathcal{X}) = (1 - p_{D,k}) v_{k|k-1}(\mathcal{X}) + \sum_{\zeta \in Z_k} \sum_{j=1}^{J_{k|k-1}} w_k^{(j)}(\zeta) N(\mathcal{X}; m_{k|k}^{(j)}, \Psi_{k|k}^{(j)}) \quad , \quad (10)$$

where v is the intensity function.

5 Implementation and Validation

In this section, simulation results are shown to validate that the GM-PHD algorithm implemented in Matlab, can track multiple RFID targets. The performances of the LM algorithm with and without GM-PHD are analyzed and compared. Further, the measurements of the RFID system used in real environments verify the model and the simulation results. To assess the uncertainty of the estimated target position by the algorithm, we use the Euclidean distance between the actual location of the target and the estimated location.

5.1 Method Validation by the Simulation Results

The models introduced in the previous chapter were implemented in Matlab and the validation scenario was then applied in a simulated space corresponding to a 3D indoor environment. This space was covered by signal receiving ranges of three RFID readers in order to determine the tag position. The simulation environment considered a regular room of the size $9\text{ m} \times 6.5\text{ m} \times 3\text{ m}$ as shown in Fig. 2. In order to simplify the analysis of the tracking process, the targets were represented as points in the 3D space and located at same height as the three readers. The readers were located at $A(0, 0, 1.5)\text{ m}$, $B(9, 0, 1.5)\text{ m}$, and $C(9, 6.5, 1.5)\text{ m}$ positions respectively. The propagation factor, α_p , was set as 3.00, which is consistent with the physical measurement shown the next section.

The model validation was carried out in a noisy environment. The RSS was simulated from the radio propagation path loss channel model (2) as a function of the distance between the tag and the reader, and contaminated by the AWGN. The noise takes input disturbances into account. In this simulation, the Gaussian noise distribution with the standard deviation 1.5 and the mean 0 was added.

To validate the GM-PHD algorithm implemented in Matlab and applied for RFID multi-target tracking, the trajectories of two targets in a form of circular motion and straight line motion respectively were used. The RFID tags' positions were first estimated by the LM algorithm (5) according to the distance from the tags to the different readers, where the distance was estimated using the path loss radio propagation channel model (2). Then, the GM-PHD algorithm was applied. In Fig. 2, the tag circular and straight line motion are illustrated as a red dash line and green solid line respectively, and the prediction positions from the GM-PHD algorithm are shown as red

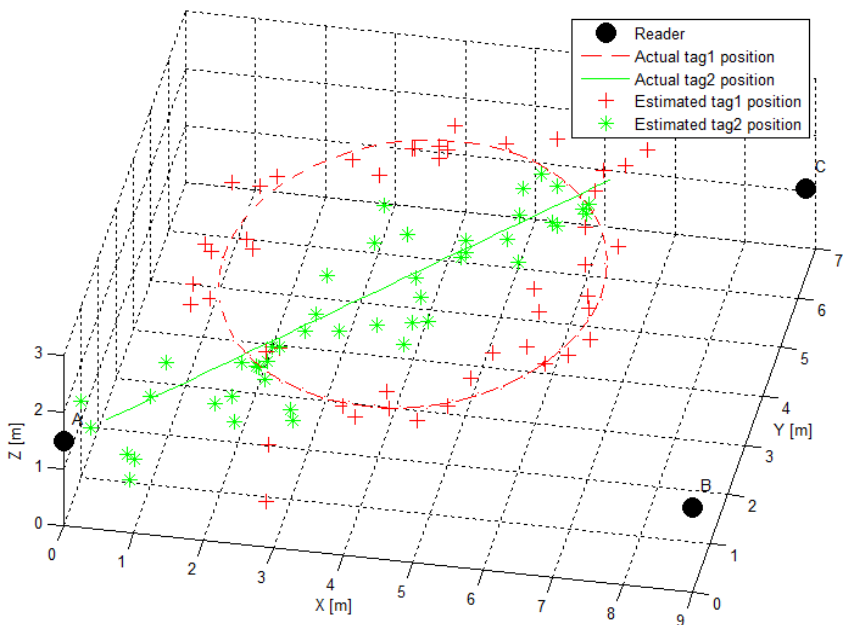


Fig. 2. The schematic diagram of the two targets motion paths in space simulation

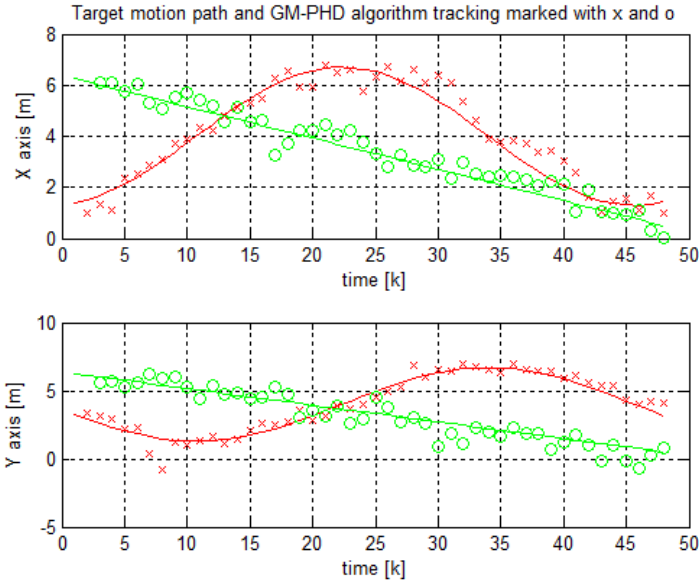


Fig. 3. The target motion paths in space from Fig. 2 in the x and y coordinates; for different target the ground truths are marked as the solid lines and the predictions by the GM-PHD are marked as crosses and circles respectively

crosses and green asterisks respectively. Fig. 3 indicates the tracking manner of the GM-PHD algorithm in the x and y directions in respect to the time k . The same two truth trajectories as in Fig. 2 are presented as solid red and green lines, respectively. The GM-PHD predictions of each of the two targets are marked as the red crosses and green circles respectively. The algorithm tracks the targets' movement successfully which confirms the GM-PHD algorithm's ability to track the multiple targets. The estimation uncertainties of the LM algorithm with and without GM-PHD are shown in Table 1. Applying the GM-PHD algorithm reduces the mean and standard deviation of the distance estimation uncertainty by 30% and 33%, respectively.

5.2 Physical Experiment

The active RFID system for target tracking consists of active tags and readers. The active tag used was a Wavetrend TG100-A, which is generally used for personnel tagging. The RFID reader was a Wavetrend RX-900 with an AN100 whip antenna, where the fronted side of the reader orients to the tag. The reader radio signal coverage was greater than 15 meters and at a working frequency of 433.92 MHz. The environment is considered as a free space of the size $9\text{ m} \times 6.5\text{ m} \times 3\text{ m}$. The tag was mounted on a tripod and moved in the room without any obstacles and the tag antenna was kept in the vertical direction. The gross error was removed from the measurement of the radio signal strength, [18].

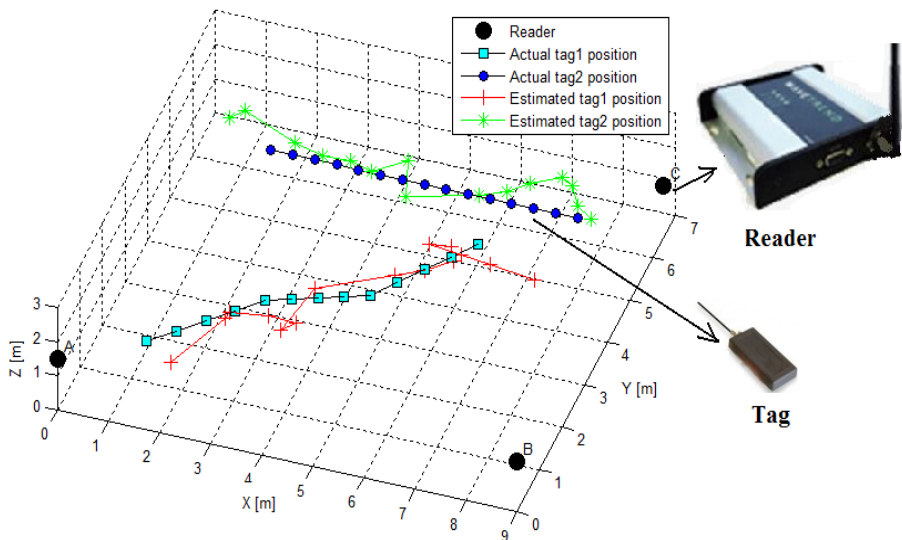
Table 1. The distance estimation uncertainty of the LM algorithm with and without the GM-PHD filter for the simulation and the physical experiment

Experiment	Distance estimation uncertainty	With GM-PHD	Without GM-PHD
		Simulation	Mean [m]
	Standard Deviation [m]	0.4	0.6
Physical	Mean [m]	1.0	1.4
	Standard Deviation [m]	0.6	0.9

The propagation factor α_p was found using the optimization algorithm (3) for 20 samples when the tag moved away from the reader by a distance of 1 meter to 20 meters with an interval of 1 meter. Each sample was calculated as a mean value of three RSS measurements taken from each position of the tag. The propagation factor, α_p , was found to be 3.00.

Fig. 4 shows the schematic diagram of the experiment. Three readers were located at the $A(0, 0, 1.5)$ m, $B(9, 0, 1.5)$ m and $C(9, 6.5, 1.5)$ m positions respectively. Two tags were used in the real experiment and their trajectories are depicted in the figure as blue circles and turquoise squares respectively. The positions estimated by GM-PHD algorithm are marked as red crosses and green asterisks, respectively. Fig. 5 indicates the tracking manner of the GM-PHD algorithm in the x and y directions in the real environment in respect to the time k . The result verifies the GM-PHD algorithm ability to track a multi-target.

The estimation uncertainties when tracking real RFID tags using the LM algorithm with and without the GM-PHD filter are shown in Table 1. Applying the GM-PHD algorithm reduces the mean and standard deviation of the distance estimation uncertainty with about 29% and 33% respectively, which validates the similar simulation results.

**Fig. 4.** The schematic diagram of the physical experiment

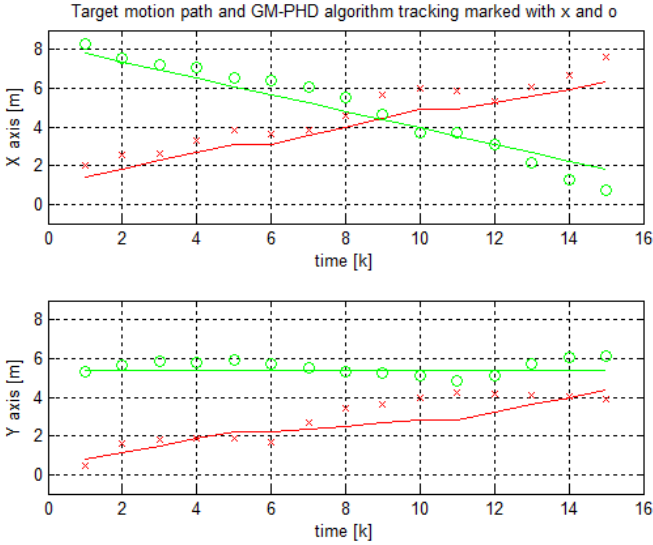


Fig. 5. The target motion paths in physical experiment environment in the x and y coordinates; for different targets the ground truths are marked as the red and green solid lines respectively and the predictions by the GM-PHD are marked as red crosses and green circles respectively

6 Conclusions

The paper proposes the LM algorithm with the GM-PHD filter to track multiple targets using the RFID system for ambient assisted living applications.

The propagation factor for the radio propagation model in the RFID system can be found by applying the optimal algorithm with the minimum square error. This robust and flexible method can be used to adjust the factor to different environments.

The LM algorithm with and without the GM-PHD filter has been implemented for multi-target tracking in RFID systems by Matlab. The ability of the GM-PHD algorithm for multi-target tracking is validated by simulation and real environment experiments. It is shown that the algorithm successfully tracks multiple targets while using the RSSs of each tag. The GM-PHD algorithm improves the accuracy of the target position estimation. The simulation and physical experiments show an improvement of the mean value by 30% and 29%, respectively, and an improvement of the both standard deviations by 33%, when compared to using the LM algorithm without the GM-PHD filter.

In future work, the radio propagation model and the tracking algorithm should be investigated in more complex environments. The integration of the vision and RFID systems is going to be developed to use the tag position measured by the vision system as a reference to calibrate the RFID system. This lets the system automatically adjust the radio propagation factor according to changes in the environment.

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References

1. Chen, J., Khatibi, S., Kulesza, W.: Planning of a Multi Stereo Visual Sensor System for A Human Activities Space. In: Proc. of the 2nd Int. Conf. on Computer Vision Theory and Applications, pp. 480–485 (2007)
2. Kulesza, W., Chen, J., Khatibi, S.: Arrangement of a Multi Stereo Visual Sensor System for A Human Activities Space. In: Bhatti, A. (ed.) Stereo Vision, pp. 153–172. InTech Education and Publishing (2008)
3. Yao, W., Chu, C.H., Li, Z.: The Use of RFID in Healthcare: Benefits and Barriers. In: IEEE International Conference on RFID-Technology and Applications (2010)
4. Lin, C.J., Lee, T.L., Syu, S.L., Chen, B.W.: Applications of Intelligent Agent and RFID Technology for Indoor Position: Safety of Kindergarten as Example. In: Proceedings of the 9th International Conference on Machine Learning and Cybernetics (2010)
5. Ouyang, D.F.: Identification of Car Passengers with RFID for Automatic Crash Notification. Master Thesis, Blekinge Institute of Technology (2009)
6. Abdelmoula, B., Horacio, S., Mitsuji, M.: RFID Indoor Positioning Based on Probabilistic RFID Map and Kalman Filtering. In: Proceedings of 3rd IEEE International Conference on Wireless and Mobile Computing, Networking and Communications (2007)
7. Bajaj, R., Ranaweera, S.L., Agrawal, D.P.: GPS: Location Tracking Technology. E-Journal Computer 35(4), 92–94 (2002)
8. Liu, H., Darabi, H., Banerjee, P., Liu, J.: Survey of Wireless Indoor Positioning Techniques and Systems. IEEE Transactions on Systems, Man, and Cybernetics 37(6) (2007)
9. Zhao, J.H., Wang, Y.C.: Autonomous Ultrasonic Indoor Tracking System. In: Proceedings of International Symposium on Parallel and Distributed Processing with Applications, pp. 532–539 (2008)
10. O'Connor, M.C.: Testing Ultrasound to Track, Monitor Patients. RFID Journal (2006) (Online), <http://www.rfidjournal.com/article/articleprint/2199/-1/1/> (accessed January 13, 2010)
11. Amanatiadis, A., Chrysostomou, D., Koulouriotis, D., Gasteratos, A.: A Fuzzy Multi-Sensor Architecture for Indoor Navigation. In: IEEE International Conference on Imaging Systems and Techniques, pp. 452–457 (2010)
12. Vo, B., Ma, W.K.: The Gaussian Mixture Probability Hypothesis Density Filter. IEEE Transactions Signal Processing 54(11), 4091–4104 (2006)
13. Clark, D., Panta, K., Vo, B.: The GM-PHD Filter Multiple Target Tracker. In: 9th International Conference Proc. Information Fusion, pp. 1–8 (2006)
14. Chen, J., Adebomi, O.E., Olusayo, O.S., Kulesza, W.: The Evaluation of the Gaussian Mixture Probability Hypothesis Density Approach for Multi-target Tracking. In: IEEE International Conference on Imaging Systems and Techniques, pp. 182–185 (2010)
15. Sidenbladh, H.: Multi-Target Particle Filtering for the Probability Hypothesis Density. In: 6th International Conference on Information Fusion, pp. 800–806 (2003)
16. Leong, K.S., Ling, M., Cole, P.H.: Positioning Analysis of Multiple Antennas in a Dense RFID Reader Environment. In: Proceedings of International Symposium on Applications and the Internet Workshops, pp. 56–59 (2006)
17. Jorge, J.M.: The Levenberg-Marquardt Algorithm: Implementation and Theory. Numerical Analysis 630, 105–116 (1978)
18. McGhee, J., Henderson, I.A., Korczyński, M.J., Kulesza, W.: Scientific Metrology (1998) ISBN: 83-904299-9-3