# Development of Tracking Filter for the Location Awareness of Moving Objects in Ubiquitous Computing

**Yang-Weon Lee**, *Member, KIMICS*

***Abstract*—** In this paper, I have presented a new approach which can track moving objects in unknown environments. This scheme is important in providing a computationally feasible alternative to complete enumeration of JPDA which is intractable. I have proved that given an artificial measurement and track's configuration, proposed scheme converges to a proper plot in a finite number of iterations. In this light, even if the performance is enhanced by using the relaxation, we also note that the difficulty in tuning the parameters of the relaxation scheme is critical aspect of this suggestion.

***Index Terms*—**Ubiquitous, Tracking, Association, Awareness.

## I. INTRODUCTION

The purpose of location awareness of moving objects is to provide an accurate position and velocity from the observed data in a desired ubiquitous environment. The performance of this tracking capability is inherently limited by the measurement inaccuracy and source uncertainty caused by the presence of missed detection, false alarms, emergence of new objects into the observed region and disappearance of existing objects from the observed region. Therefore, it is difficult to determine precisely which object corresponds to each of the closely spaced measured objects. An example of measurement ambiguity is shown in Figure 1.

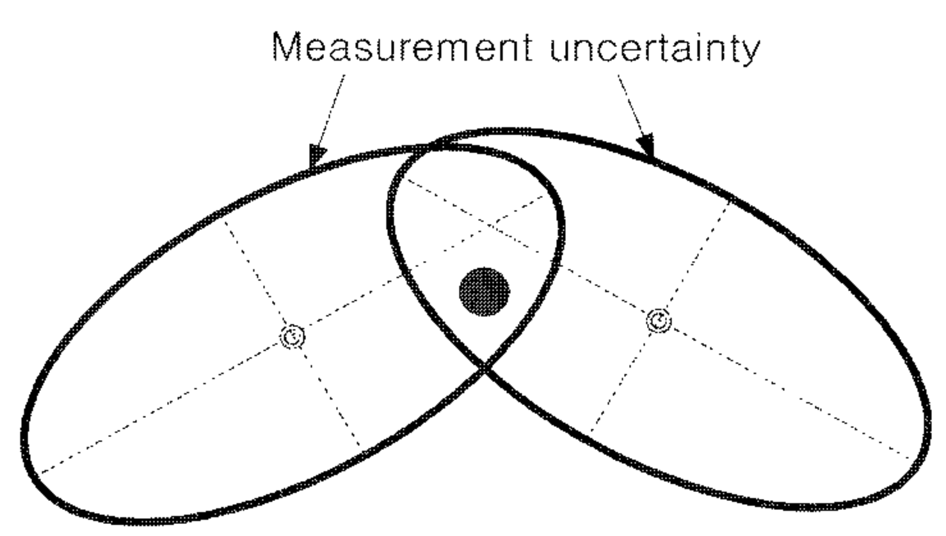


Fig. 1 Measurement uncertainty between nearby observation.

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Yang-Weon Lee is with the Department of Information and Communication Engineering, Honam University, Kwangju, 506-714, Korea (Tel: +82-62-940-5572, Fax: +82-62-945-9030, Email: ywlee@hohnam.ac.kr)

Generally, there are three approaches in data association for location awareness: non-Bayesian approach based on likelihood function [1], Bayesian approach [2], and neural network approach [3]. The major difference of the first two approaches is how to treat the false alarms. The non-Bayesian approach calculates all the likelihood functions of all the possible tracks with given measurements and selects the track which gives the maximum value of the likelihood function. Meanwhile, the tracking filter using Bayesian approach predicts the location of interest using *a posteriori* probability. The two approaches are inadequate for real time applications such as ubiquitous computing environment because the computational complexity is overwhelming even for relatively large objects and measurements and a computationally efficient substitute based on a careful understanding of its properties is lacking.

The outline of his paper is as follows. In Section II, the problem is defined and briefly derived the energy function. Then the relaxation scheme is proposed for the development of tracking filter for the location awareness of moving objects in ubiquitous computing. Finally we present our simulation results in section IV, and conclusions in section V .

## II. Derivation of Object and Observation Relationship

### *A. Problem Definition*

Fig. 2 shows the overall scheme. This system consists of three blocks: acquisition, association, and prediction. The purpose of the acquisition is to determine the initial starting position of the object tracking. After this stage, the association and prediction interactively determine the tracks. Our primary concern is the association part that must determine the actual measurement and object pairs, given the measurements and the predicted gate centers.

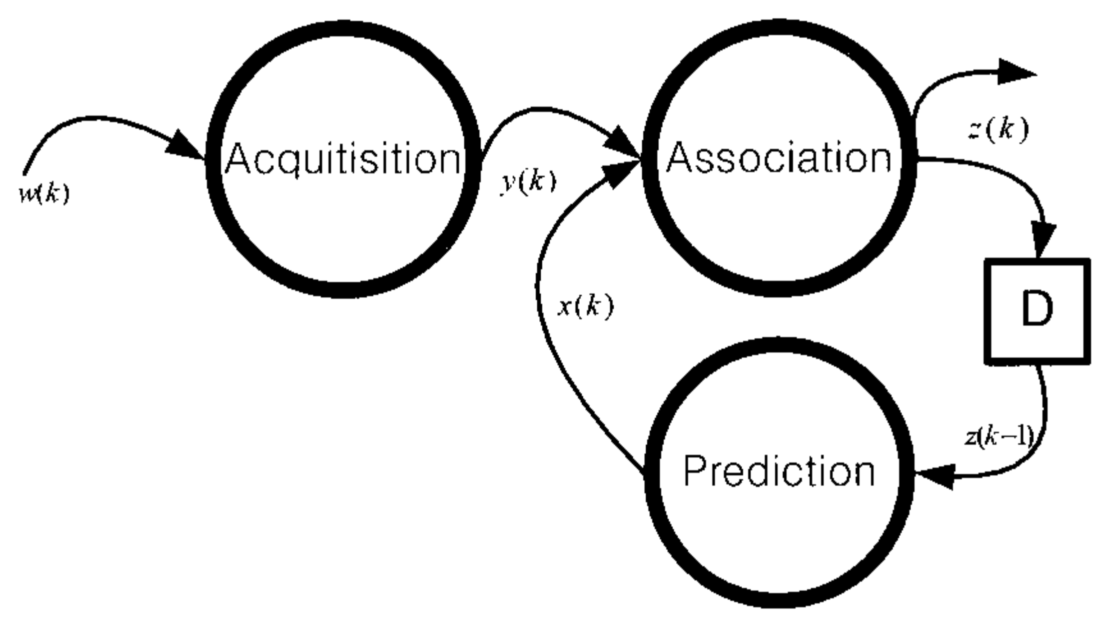


Fig. 2 An overall scheme of object tracking

Let $m$ and $n$ be the number of measurements and objects, respectively, in an observed area. Then, the relationships between the objects and measurements are efficiently represented by the validation matrix $w$ :

$$\omega = \{\omega_{jt} | j \in [1, m], t \in [0, t \tag{1}$$

Where the first column denotes noise and always $\omega_{j0} =$. For the other columns, $\omega_{jt} = 1(j \in [1, m], t \in [1, r$, if the validation gate of object t contains the measurement j and $\omega_{jt} =$, otherwise.

Based on the validation matrix, we must find hypothesis matrix $\hat{\Omega} = \{\omega_{jt} | j \in [1, m], t \in [0, t$ that must obey the data association hypothesis:

$$\begin{cases} \Sigma_{t=0}^{n} \hat{w}_{jt} = 1 & for \quad (j \in [1, m]) \\ \Sigma_{t=0}^{n} \hat{w}_{jt} = 1 & for \quad (t \in [1, n]) \end{cases} \tag{2}$$

Here, $w_{jt} =$ only if the measurement $j$ is associated with noise (t=0) or object ( $t =$). Generating all the hypothesis matrices leads to a combinatorial problem, where the number of data association hypothesis increases exponentially with the number of objects and measurements.

### *B. MAP Estimates for Data Association*

The ultimate goal of this problem is to find the hypothesis matrix, $\hat{\Omega} = \{\omega_{jt} | j \in [1, m], t \in [0, r$ given the observation $y$ and $x$, which must satisfy (2). From now on, let's associate the realizations the gate center $x$, the measurement $y$, the validation matrix , and to the random processes-$X$, $Y$, , and . Next, consider that is a parameter space and $(\Omega, Y$ is an observation space. Then, *a posteriori* can be derived by the Bayes rule:

$$P(\hat{\Omega} | \omega, y, x) = \frac{P(\omega|\hat{\Omega})P(y,x|\hat{\Omega})P(\hat{\Omega})}{P(\omega, y, x)} \tag{3}$$

Here, we assumed that $P(\omega, y, x|\hat{\Omega}) = P(\omega|\hat{\Omega})P(y, x|\hat{\Omega})$ since the two variables and (x,y) are separately observed. This assumption makes the problem more tractable as we shall see later. Given the parameter, and $(X,$ are observed. If the conditional probabilities describing the relationships between the parameter space and the observation spaces are available, one can obtain the Relaxation scheme estimator:

$$\omega^* = \arg\max_{\hat{\Omega}} P(\hat{\Omega} | \omega, y, \tag{4}$$

### *C. Representing Constraints by Energy Function*

As a system model, we assume that the conditional probabilities are all Gibbs distributions:

$$\begin{cases} P(y, x|\hat{\Omega}) \triangleq \frac{1}{Z_1} \exp\{-E(y, x| \\ P(\omega|\hat{\Omega}) \triangleq \frac{1}{Z_2} \exp\{-E(\omega|\hat{\Omega} \\ P(\hat{\Omega}) \triangleq \frac{1}{Z_3} \exp\{-E(\hat{\Omega})\} \end{cases} \tag{5}$$

where $Z_s(s \in [1, 2, 3$ is called partition function:

$$Z_s = \int_{\hat{\Omega}} \exp\{-E(\hat{\Omega})\} d \tag{6}$$

Here, denotes the energy function. Substituting (5) into (3),(4) becomes

$$\omega^* = \arg\max_{\hat{\Omega}} [E(y, x|\hat{\Omega}) + E(\omega|\hat{\Omega}) + E(\hat{\Omega} \tag{7}$$

Since the optimization is executed with respect to , the denominator in (3) is independent of and therefore irrelevant for its minimization. The energy functions are realizations of the constraints both for the object trajectories and the measurement-object relationships. For instance, the first term in (7) represents the distance between measurement and object and could be minimized approximately using the constraints. The second term intends to suppress the measurements which are uncorrelated with the valid measurements. The third term denotes constraints of the validation matrix and it can be designed to represent the two restrictions as shown in (2). The energy equations of each term are defined respectively:

$$\begin{cases} E(y, x|\hat{\Omega}) \triangleq \Sigma_{t=1}^{n} \Sigma_{j=1}^{m} r_{jt} \hat{\Omega}_{jt} \\ E(\omega|\hat{\Omega}) \triangleq \Sigma_{t=1}^{n} \Sigma_{j=1}^{m} (\hat{\Omega}_{jt} - \omega_{jt})^2 \\ E(\hat{\Omega}) \triangleq \Sigma_{t=1}^{n} (\Sigma_{j=1}^{m} \omega_{jt} - 1) + \Sigma_{j=1}^{m} (\hat{\Omega}_{jt} - \end{cases} \tag{8}$$

Putting (8) into (7), one gets

$$\omega^* = \arg\max_{\hat{\Omega}} [\alpha \sum_{t=1}^{n} \sum_{j=1}^{m} r_{jt}^* \hat{\Omega}_{jt} - \frac{\beta}{2} \sum_{t=1}^{n} \sum_{j=1}^{m} (\hat{\Omega}_{jt} - \omega_{jt})^2 + \sum_{t=1}^{n} (\sum_{j=1}^{m} \hat{\Omega}_{jt} - 1) + \sum_{j=1}^{m} (\sum_{t=1}^{n} \hat{\Omega}_{jt} - 1)] \tag{9}$$

Where and are a coefficient of the weighted distance measure and the matching term respectively. Using this scheme, the optimal solution is obtained by assigning observations to tracks in order to minimize the weighted total summed distance from all observations to the tracks to which they are assigned. This is thought of as a version of the well-known assignment problem for which optimal solutions have been developed with constraints [12],[16].

## III. Relaxation Scheme

The optimal solution for (9) is hard to find by any deterministic method. So, we convert the present constrained optimization problem to an unconstrained problem by introducing the Lagrange multipliers and local dual theory [10,11]. In this case, the problem is to find $(\text{such that } \hat{\Omega}^* = \arg\min_{\hat{\Omega}} \max_{\lambda} L(\hat{\Omega}, \lambda$ where

$$L(\hat{\omega},\lambda,\varepsilon) = \alpha \sum_{t=0}^{n}\sum_{j=1}^{m} r^2_{jt}\hat{\omega}_{jt}(1-\delta_t) + \frac{\beta}{2}\sum_{t=0}^{n}\sum_{j=1}^{m}(\hat{\omega}_{jt}-\omega_{jt})^2 + \sum_{t=0}^{n}\lambda_t\left(\sum_{j=1}^{m}\hat{\omega}_{jt} - 1 - d_{mn}\delta_t\right) + \sum_{j=1}^{m}\varepsilon_j\left(\sum_{t=0}^{n}\hat{\omega}_{jt} - 1\right) \quad (10)$$

Here, and are the Lagrange multipliers. Note that (10) includes the effect of the first column of the association matrix, which represents the clutter as well as newly appearing objects. In general setting, we assume *m>n*, since most of the multi-object problem is characterized by many confusing measurements that exceed far over the number of original objects. Let's modify (10) so that each term has equal elements:

$$L(\hat{\omega},\lambda,\varepsilon) = \alpha \sum_{t=0}^{n}\sum_{j=1}^{m} r^2_{jt}\hat{\omega}_{jt}(1-\delta_t) + \frac{\beta}{2}\sum_{t=0}^{n}\sum_{j=1}^{m}(\hat{\omega}_{jt}-\omega_{jt})^2 + \sum_{t=0}^{n}\lambda_t\left\{\sum_{j=1}^{m}\hat{\omega}_{jt} - 1 - d_{mn}\right\} + \sum_{j=1}^{m}\varepsilon_j\left(\sum_{t=0}^{n}\hat{\omega}_{jt} - 1\right) \quad (11)$$

Where $d_{mn} = m - n -$ . We now look for a dynamical system of ordinary differential equations. The state of this system is defined by $\hat{\omega} = \{\hat{\omega}$ and the energy equation is continuously differentiable with respect to $\hat{\omega}_{jt}(j = 1,\ldots,t$ and $t = 0,\ldots$. Since we are dealing with a continuous state problem, it is logical to use the Lagrange multipliers in the differential approach:

$$\begin{cases} \frac{d\hat{\omega}_{jt}}{dt} \triangleq -\eta(\hat{\omega})\frac{\partial L(\hat{\omega},\lambda,\varepsilon)}{\partial\hat{\omega}_{jt}} \\ \frac{d\lambda_t}{dt} \triangleq \frac{\partial L(\hat{\omega},\lambda,\varepsilon)}{\partial\lambda_t} \\ \frac{d\varepsilon_j}{dt} \triangleq \frac{\partial L(\hat{\omega},\lambda,\varepsilon)}{\partial\varepsilon_j} \end{cases} \quad (12)$$

where $\eta($ is a modulation function that ensures that the trajectories of (12) are in a state space contained in Euclidean *nm*-space. Performing gradient ascent on and have been shown [16] to be very effective in the resolution of constrained optimization problems.

To find a minimum of this equation by iterative calculations, we can use the gradient descent method:

$$\begin{cases} \hat{\omega}^{n+1} = \hat{\omega}^{n} - \eta(\hat{\omega})\nabla_{\hat{\omega}}L(\hat{\omega},\lambda,\varepsilon) \\ \lambda^{n+1} = \lambda^{n} + \nabla_{\lambda}L(\hat{\omega},\lambda,\varepsilon)\Delta t \\ \varepsilon^{n+1} = \varepsilon^{n} + \nabla_{\varepsilon}L(\hat{\omega},\lambda,\varepsilon)\Delta t \end{cases} \quad (13)$$

where $\hat{\omega}^0, \lambda^0$ and are initial states, is the unit step size for each iteration, and $\nabla_{\hat{\omega}}, \nabla_{\lambda}$, are gradients. The trajectory of this dynamical equation is chosen in such a way that the energy $L(\hat{\omega},\lambda,$ decreases steadily along the path. Hence, $L(\hat{\omega},\lambda,$ is a *Lyapunov* function for this dynamical equation. Note that this algorithm converges to a minimum point nearest to the initial state. In general, the gradient search method has the property of converging to one of the local minima depending on the initial states. We assume that the energy is analytic and also that the energy is bounded below, *i.e.,* $L \geq$. A complete form of the relaxation equations are given by (14) and its overall computational flow structure is shown in Figure 3.

$$\begin{cases} \hat{\omega}_{jt}^{n+1} = \hat{\omega}_{jt}^{n} - \Delta_t\left[\alpha r_{jt}^2(1-\delta_t) + \beta(\hat{\omega}_{jt}^{n} - \omega_{jt})\right] \\ \lambda_t^{n+1} = \lambda_t^{n} + \Delta t\left[\sum_{j=1}^{m}\hat{\omega}_{jt}^{n} - 1 - d_{mn}\delta_t\right] \quad (1 \\ \varepsilon_j^{n+1} = \varepsilon_j^{n} + \Delta t\left[\sum_{t=0}^{n}\hat{\omega}_{jt}^{n} - 1\right] \end{cases}$$

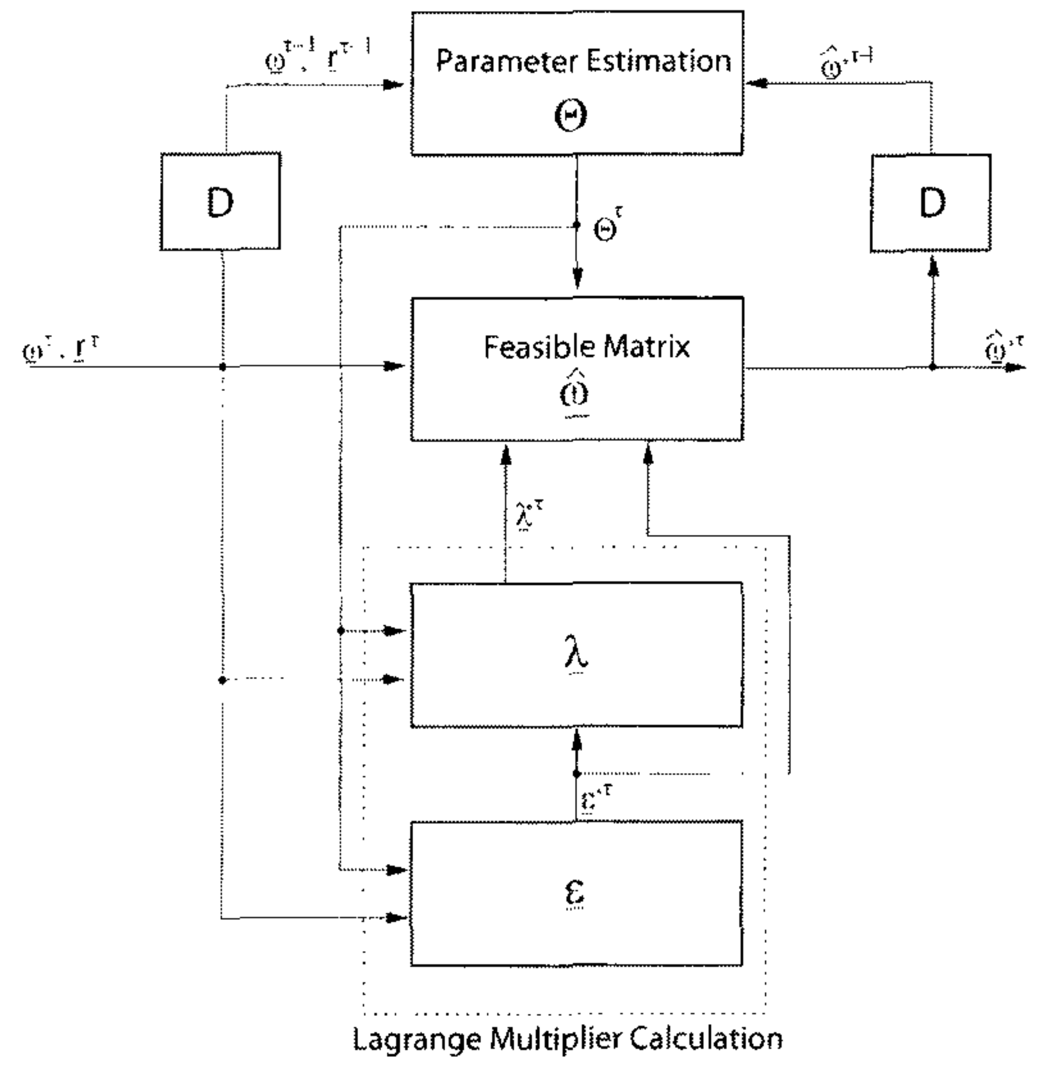


Fig. 3 Overall flow diagram of RA association

This equation can be computed by an array processor. A processing element in this array stores and updates the states by using information coming from nearby processors, together with their previous states. To terminate the iteration, we can define in advance either the maximum number of iterations or a lower bound of the change of $\hat{\omega}, \lambda$ anc in successive steps.

The Relaxation scheme estimate adaptive data association scheme's computational complexities of basic routine per iteration require $O(m$ computations. When we assume the average iteration number as , the total data association calculations require $O(km$ computations. Therefore, even if the tracks and measurements are increased, the required computations are not increasing exponentially. However JPDAF as estimated in [4] requires the computational complexity $O(2^m$, so its computational complexity increases exponentially depending on the number of tracks and measurements.

## IV. Experimental Results

In this section, we present some results of the experiments comparing the performance of the proposed MAP estimate adaptive data association (RA) with that of the JPDA [6]. We just used the standard Kalman filter[15] for the estimation part once feasible matrix is computed. The performance of the RA is tested in two separate cases in the simulation. In the first case, we consider two crossing and parallel objects for testing the track maintenance and accuracy in view of clutter density. In the second case, all the objects as listed in Table 1 are used for testing the multi-object tracking performance. The dynamic models for the objects have been used by the Singer model developed in [14].

Table 1 Initial Position and Velocity of 8 Objects

| Object i | Position(m) | | Velocity(m/s) | |
|---|---|---|---|---|
| | x | y | $\dot{x}$ | $\dot{y}$ |
| 1 | -40 | 10 | 2 | -0.5 |
| 2 | -40 | 10 | 2 | -0.5 |
| 3 | -60 | -50 | 0 | 3 |
| 4 | -55 | -50 | 0 | 3 |
| 5 | 80 | -70 | -3 | 0 |
| 6 | -80 | -80 | 3 | 0 |
| 7 | -50 | 89 | 2.5 | 0 |
| 8 | -50 | 89 | 2.5 | 0 |

The crossing and parallel objects whose initial parameters are taken from object 1,2,3 and 4, respectively in Table 1 are tested. The rms estimation errors and standard deviation value from the filtering based on the crossing and parallel objects are shown in Figure 4. We note that the performance of the RA is better than that of the JPDA in view of both tracking accuracy.

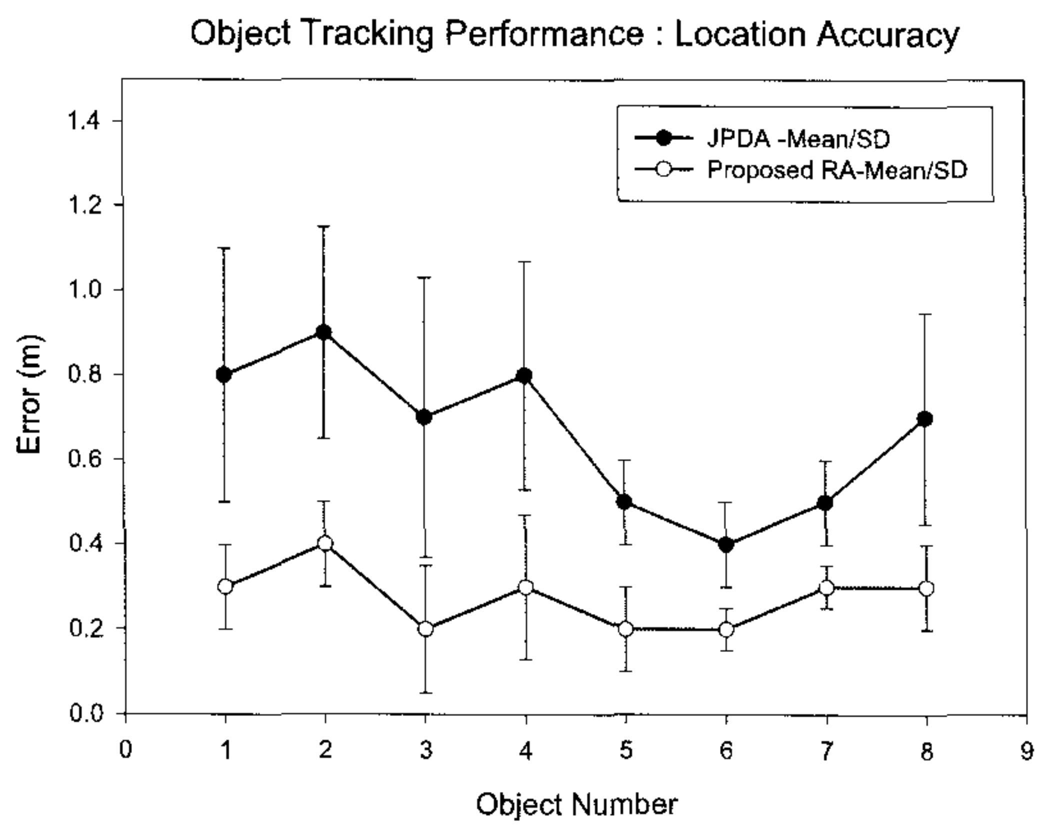


Fig. 4 Object Tracking Performance

Table 2 summarizes the rms position and velocity errors for each object in the second test. From Table 2, we note that RA's track maintenance capability is higher than JPDA. We also note that the general performance of the RA is almost better than that of JPDA. The RA appears to be an alternative to the JPDA instead of HNPDA. Also, it could replace the sequential computations required for the JPDA with a parallel scheme. But the difficulties in adjusting the parameters still exist.

## V. CONCLUSIONS

The purpose of this paper was to explore an adaptive data association method as a tool for applying location awareness for the ubiquitous environment. It was shown that it always yields consistent data association, in contrast to the JPDA, and that these associated data measurements are very effective for indoor environment tracking. Although the RA finds the convergence recursively, the RA is a general method for solving the data association problems in data association. A feature of our algorithm is that it requires only $O_1$ storage, where *m* is the number of candidate measurement associations and *n* is the number of trajectories, compared to some branch and bound techniques, where the memory requirements grow exponentially with the number of objects. The experimental results show that the RA outperforms the JPDA in terms of both rms errors and track maintenance rate. This algorithm has several applications and can be effectively used in long range object tracking systems using surveillance radar.

Table 2 RMS errors in 8 objects

| Object *i* | Pos. Err(m) | | Vel. Err(m/s) | | Track Keep(%) | |
|---|---|---|---|---|---|---|
| | JPDA | RA | JPDA | RA | JPDA | RA |
| 1 | 0.8 | 0.3 | 0.01 | 0.01 | 100 | 100 |
| 2 | 0.9 | 0.4 | 0.02 | 0.01 | 98 | 100 |
| 3 | 0.7 | 0.2 | 0.01 | 0.01 | 100 | 100 |
| 4 | 0.8 | 0.3 | 0.02 | 0.01 | 93 | 100 |
| 5 | 0.5 | 0.2 | 0.01 | 0.01 | 100 | 100 |
| 6 | 0.4 | 0.2 | 0.01 | 0.01 | 100 | 100 |
| 7 | 0.5 | 0.3 | 0.01 | 0.01 | 100 | 100 |
| 8 | 0.7 | 0.3 | 0.01 | 0.01 | 100 | 100 |

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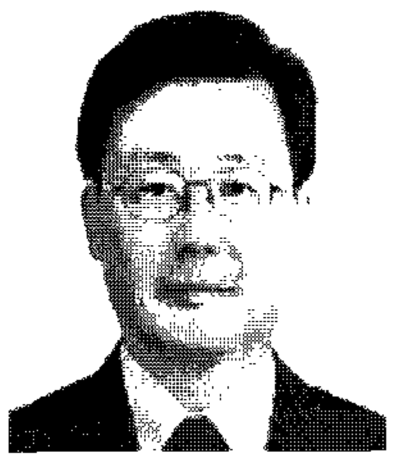

**Yang-Weon Lee**

He Received B.S degree in the Department of Electrical Engineering from Chungang University, Korea, in 1982, and the M.S. degree in the Department of Control and Measurement Engineering from Seoul National University, in 1991. In 1996, he received Ph. D. degrees in the Department of Electrical Engineering from Pohang University of Science and Technology (POSTECH), Korea. During 1982-1996, he worked for Agency for Defense Development as senior researcher. Since 1996, he has worked in the Department of Information and Communication Engineering at the Honam University, where he now works as a professor. His current research interests include ubiquitous computing, target estimation and tracking filter design, communication signal processing, and .Net application.