International Journal of Navigation and Port Research
Vol.28, No.7 pp. 635~640, 2004 (ISSN-1598-7701)

A Tracking Algorithm for Autonomous Navigation of AGVs: Federated Information Filter

Yong-Shik Kim · Keum-Shik Hong***

**School of Mechanical Engineering, Pusan National University, Busan 609-735, Korea*
***Dept. of Mechanical and Intelligent Systems Engineering, Pusan National University, Busan 609-735, Korea*

Abstract : *In this paper, a tracking algorithm for autonomous navigation of automated guided vehicles (AGVs) operating in container terminals is presented. The developed navigation algorithm takes the form of a federated information filter used to detect other AGVs and avoid obstacles using fused information from multiple sensors. Being equivalent to the Kalman filter (KF) algebraically, the information filter is extended to N-sensor distributed dynamic systems. In multi-sensor environments, the information-based filter is easier to decentralize, initialize, and fuse than a KF-based filter. It is proved that the information state and the information matrix of the suggested filter, which are weighted in terms of an information sharing factor, are equal to those of a centralized information filter under the regular conditions. Numerical examples using Monte Carlo simulation are provided to compare the centralized information filter and the proposed one.*

Key words : *State estimation, Kalman filter, information filter, sensor fusion, federated filter, automated guided vehicle*

1. Introduction

Recent advances in electronics, sensors, information technologies, and automation have made the operation of a fully automated container terminal technically realizable. In container terminals, automated guided vehicles (AGVs) are used to replace the manually driven trucks that transport containers within the terminal. Fig. 1 shows an AGV, with a load, in the ECT (Europe Container Terminal) in Rotterdam. The port of Rotterdam operates a fully automated container terminal, ECT, using AGVs and automated yard cranes to handle containers.

An AGV system consists of a vehicle, an onboard controller, a management system, a communication system, and a navigation system. The navigation system provides guidance and navigation to the AGVs in the operating yard. The effectiveness of a navigation system depends on the interpretation of the information arriving from sensors, which provide details of the surrounding environment and obstacles.

Many studies on the autonomous navigation and localization of AGVs have appeared in the literature. Adam et al. (1999) presented a method of determining the position and orientation of an AGV by fusing odometry with the information provided by a vision system. Park et al. (2002) proposed a path-generation algorithm that uses the sensor scanning method. The scanning algorithm is used to recognize the ambient environment surrounding the AGV. In Lim and Kang (2002), a technique for the localization of a mobile robot by using sonar sensors was investigated. Kim et al. (2001) developed a sensor system measuring locations of a vehicle to localize a mobile robot while it moves on the track. Madhavan and Durrant-Whyte (2004) utilized a natural landmark navigation algorithm for autonomous vehicles operating in relatively unstructured environments.

In order to detect other AGVs or avoid obstacles using the object information obtained from multiple sensors, tracking techniques based on the Bayesian approach are usually used (Bar-Shalom et al., 2001). One method for designing such systems is to employ a number of sensors and to fuse the information from all of these sensors in a central processor. However, in case the data of multi-sensor systems should be processed in real-time, the centralized KF has the disadvantage that the estimation performance is degraded.

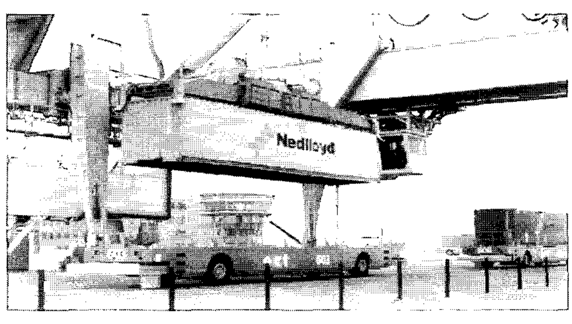

Fig. 1 An AGV in an automated container terminal: ECT at Rotterdam

* Corresponding Author : Keum-Shik Hong, kshong@pusan.ac.kr 051)510-2454
** immpdaf@pusan.ac.kr 051)510-1481

As an alternative method to improve the track fusion, the information filter (IF) (Bar-Shalom et al., 2001; Mutambara, 1998), which is claimed algebraically equivalent to the KF, was developed. The IF is essentially a KF expressed in terms of measures of information about state estimates and their associated covariance matrices. In Carelli and Freire (2003), a state variables estimation structure was proposed that fuses sonar and odometric information by using a decentralized version of the IF (DIF) (Mutambara, 1998).

Carlson and Berarducci (1994) and Paik and Oh (2000) considered a federated structure as another method for data fusion. Nebot and Durrant-Whyte (1999) presented the design of a high-integrity navigation system for use in large autonomous mobile vehicles. A decentralized estimation architecture was also presented for the fusion of information from different asynchronous sources.

This paper describes the design of a tracking algorithm for the autonomous navigation of an AGV to transport cargo containers in a port environment. As a tracking algorithm for detecting other AGVs and avoiding collisions, a federated information filter (FIF) is derived.

The contributions of this paper are as follows: First, in an automated container terminal, the FIF algorithm is provided as a navigation algorithm for AGVs in navigating autonomously in multi-sensor environments. Second, in this study, unlike the federated KF, there are no gain or innovation covariance matrices, and the maximum dimension of a matrix to be inverted is the state dimension. In multi-sensor systems the state dimension is generally smaller than the observation dimension, hence it is preferable to employ the IF and invert smaller information matrices than use the KF and invert larger innovation covariance matrices. Third, it is shown that, in terms of an information sharing factor, the FIF is equal to the centralized IF (CIF). Fourth, by introducing a federated structure to the DIF, the suggested filter improves the capability to detect, isolate, and recover from sensor faults, which, a sub-optimal performance is demonstrated.

This paper is organized as follows: In Section 2, the CIF algorithm and the DIF algorithm are reviewed. A FIF for the navigation of AGVs in multi-sensor environments is derived in Section 3. In Section 4, we evaluate the performance of the suggested filter and the CIF algorithms using Monte Carlo simulation. Section 5 concludes the paper.

2. IF in Multi-Sensor Environments

A system comprising N sensors with a composite observation model is considered. The dynamic system and observation equations are given as

$$x(k) = F(k-1)x(k-1) + w(k-1),\ k = 1,2,\cdots, \quad (1)$$

$$z_i(k) = H_i(k)x(k) + v_i(k),\ i = 1,\cdots,N \quad (2)$$

where $x(k) \in \mathbb{R}^n$ is the state vector of the target at time k, $F(k) \in \mathbb{R}^{n\times n}$ is the system matrix, $w(k) \in \mathbb{R}^n$ is the process noise, $z_i(k) \in \mathbb{R}^{m_i}$ is the observation vector at ith local sensor, $H_i(k) \in \mathbb{R}^{m_i \times n}$ is the observation matrix, $v_i(k) \in \mathbb{R}^{m_i}$ is the observation noise, $m_1 + \cdots + m_N = m$, and N is the number of sensors.

To compare performances of the centralized and decentralized estimation algorithms, the stacked global observation is written as

$$z(k) = H(k)x(k) + v(k) \quad (3)$$

where

$$z(k) = [z_1'(k),\cdots,z_N'(k)]',$$
$$H(k) = [H_1'(k),\cdots,H_N'(k)]',$$
$$v(k) = [v_1'(k),\cdots,v_N'(k)]',$$

and the covariance of the observation noise $v(k)$ is given by $E[v(k)v'(j)] = R\delta(k-j) = diag[R_1(k),\cdots,R_N(k)]$. In these equations, the prime denotes transpose.

2.1 Centralized IF Equations

Denote the information matrix as $Y(k|k) \equiv P^{-1}(k|k)$ and information state as $\hat{y}(k|k) \equiv P^{-1}(k|k)\hat{x}(k|k)$, where $P(k|k)$ and $\hat{x}(k|k)$ are the covariance matrix and state estimates of the centralized KF, respectively. Then, at the master filter, assimilation equations to produce global information state and information matrix with all the sensor data are given as (Mutambara, 1998)

i) Time update (prediction)

$$\hat{y}(k|k-1) = L(k|k-1)\hat{y}(k-1|k-1),$$
$$Y(k|k-1) = [F(k-1)Y^{-1}(k-1|k-1)F'(k-1) + Q(k-1)]^{-1}, \quad (4)$$

ii) Measurement update

$$\hat{y}(k|k) = \hat{y}(k|k-1) + H'(k)R^{-1}(k)z(k),$$
$$Y(k|k) = Y(k|k-1) + H'(k)R^{-1}(k)H(k) \quad (5)$$

where the information prediction coefficient $L(k|k-1)$ is given by

$$L(k|k-1) = Y(k|k-1)F(k-1)Y^{-1}(k-1|k-1). \quad (6)$$

Remark 1: The primary limitations of a typical centralized architecture, when it is applied to multi-sensor systems with embedded local filters, are (i) heavy computational loads, (ii) poor fault-tolerance, and (iii) inability to correctly process pre-filtered data in a cascaded filter structure.

2.2 Decentralized IF Equations

For a local estimate by jth sensor, the decentralized estimation equations are given by (Mutambara, 1998)

i) Time update (prediction)

$$\hat{y}_j(k|k-1) = L_j(k|k-1)\hat{y}_j(k-1|k-1),$$

$$Y_j(k|k-1) = [F(k-1)Y_j^{-1}(k-1|k-1)F'(k-1)+Q(k-1)]^{-1}, \quad (7)$$

ii) Measurement update

$$\tilde{y}_j(k|k) = \hat{y}_j(k|k-1) + H_j'(k)R_j^{-1}(k)z_j(k),$$

$$\tilde{Y}_j(k|k) = Y_j(k|k-1) + H_j'(k)R_j^{-1}(k)H_j(k) \quad (8)$$

where $L_j(k|k-1)$ is given by

$$L_j(k|k-1) = Y_j(k|k-1)F(k-1)Y_j^{-1}(k-1|k-1), \quad (9)$$

and $\tilde{y}_j(k|k)$ and $\tilde{Y}_j(k|k)$ denote the partial information state and its information matrix based only on the jth sensor's own observation. Then, assimilation equations to produce global information estimates are as follows:

$$\hat{y}(k|k) = \hat{y}(k|k-1) + \sum_{j=1}^{N}\{\tilde{y}_j(k|k) - \hat{y}_j(k|k-1)\}, \quad (10)$$

$$Y(k|k) = Y(k|k) + \sum_{j=1}^{N}\{\tilde{Y}_j(k|k) - Y_j(k|k-1)\}. \quad (11)$$

Remark 2: As above, the decentralized estimation algorithm has the same form as the centralized estimation algorithm in real-time implementation. Although the decentralized filtering technique has been recognized as an effective method to reduce the typically high computational load in standard centralized filtering, its potentially high fault-tolerance performance capability has not been widely investigated.

3. IF Fusion with Federated Structure

A federated KF can be considered a special form of decentralized KF (Carlson and Berarducci, 1994). The federated filter can obtain the globally optimal estimate by applying the information-sharing principle to each local filter and then fusing the estimates of these local filters. This provides a great variety of possibilities for improving the computational efficiency as well as the fault-tolerance performance. For the system of a local filter structure such as Eqs. (7) and (8), the global information state and information matrix equations are as follows:

$$Y_{master}(k) = Y_1(k) + \cdots + Y_N(k), \quad (13)$$

$$\hat{y}_{master}(k) = \sum_{i=1}^{N}\hat{y}_i(k). \quad (14)$$

Theorem 1. For system Eqs. (1)-(2), and the local filter structure Eqs. (7)-(8), the solution of the FIF, Eqs. (13) and (14), is equal to the solution of the CIF, Eqs. (4) and (5), if the conditions a) - c) are satisfied.

a) The initial value of the information matrix, initial information state, and process noise covariance are distributed to the local filters as follows:

$$Y_i(0) = \frac{1}{\gamma_i}Y(0), \qquad i = 1,\cdots,N, \quad (15)$$

$$\hat{y}_i(0) = \hat{y}(0), \qquad i = 1,\cdots,N, \quad (16)$$

$$Q_i(k) = \gamma_i Q(k), \qquad i = 1,\cdots,N. \quad (17)$$

b) The information state and its information matrix, which are calculated using Eqs. (13) and (14), are distributed to the local filters as follows:

$$Y_i(k) = \frac{1}{\gamma_i}Y_{master}(k), \qquad i = 1,\cdots,N, \quad (18)$$

$$\hat{y}_i(k) = \hat{y}_{master}(k), \qquad i = 1,\cdots,N. \quad (19)$$

c) An information-sharing factor is defined as follows:

$$\sum_{i=1}^{N}\frac{1}{\gamma_i} = 1, \; 0 \le \frac{1}{\gamma_i} \le 1. \quad (20)$$

Proof: we shall prove this hypothesis using a mathematical induction. First, we assume that at k-1 time epoch, the information state and information matrix of the master filter is identical to those of the CIF as follows:

$$Y_{master}(k-1|k-1) = Y^*(k-1|k-1), \; i = 1,\cdots,N, \quad (21)$$

$$\hat{y}_{master}(k-1|k-1) = \hat{y}^*(k-1|k-1), \; i = 1,\cdots,N \quad (22)$$

where $\hat{y}^*$ and Y^* are the information state and its information matrix of the CIF, respectively. The fused information state and its information matrix are sent to the local filters as follows:

$$Y_i(k-1|k-1) = \frac{1}{\gamma_i}Y_{master}, \quad (23)$$

$$\hat{y}_i(k-1|k-1) = \hat{y}_{master}(k-1|k-1). \tag{24}$$

The prediction procedure at each local filter is rewritten as follows:

$$\begin{aligned} Y_i(k|k-1) &= [F(k-1)(Y_i^{-1}(k-1|k-1)F'(k-1)+Q_i(k-1)]^{-1} \\ &= [F(k-1)\{\frac{1}{\gamma_i}Y_{master}(k-1|k-1)\}^{-1}F'(k-1)+\gamma_i Q(k-1)]^{-1} \\ &= \frac{1}{\gamma_i}[F(k-1)Y_{master}^{-1}(k-1|k-1)F'(k-1)+Q(k-1)]^{-1} \\ &= \frac{1}{\gamma_i}[F(k-1)Y^{-1*}(k-1|k-1)F'(k-1)+Q(k-1)]^{-1} \\ &= \frac{1}{\gamma_i}Y^*(k|k-1), \qquad i=1,\cdots,N, \end{aligned} \tag{25}$$

$$\begin{aligned} \hat{y}_i(k|k-1) &= L_i(k|k-1)\hat{y}_i(k-1|k-1) \\ &= L_i(k|k-1)\hat{y}_{master}(k-1|k-1) \\ &= L_i(k|k-1)\hat{y}^*(k-1|k-1) \\ &= \hat{y}^*(k|k-1). \end{aligned} \tag{26}$$

The measurement update of the information matrix at each local filter can be obtained as follows:

$$\begin{aligned} Y_i(k|k) &= Y_i(k|k-1) + H_i'(k)R_i^{-1}(k)H_i(k) \\ &= \frac{1}{\gamma_i}Y_{master}(k|k-1) + H_i'(k)R_i^{-1}(k)H_i(k). \end{aligned} \tag{27}$$

Hence, the assimilation equation in the master filter is expressed as follows:

$$\begin{aligned} Y_{master}(k|k) &= \sum_{i=1}^{N} Y_i(k|k) \\ &= \sum_{i=1}^{N}\frac{1}{\gamma_i}Y_{master}(k|k-1) + \sum_{i=1}^{N}H_i'(k)R_i^{-1}(k)H_i(k) \\ &= Y(k|k-1) + \sum_{i=1}^{N}H_i'(k)R_i^{-1}(k)H_i(k) \\ &= Y(k|k). \end{aligned} \tag{28}$$

The measurement update of the information state at the local filters can be written as

$$\hat{y}_i(k|k) = \hat{y}_i(k|k-1) + H_i'(k)R_i^{-1}(k)z_i(k). \tag{29}$$

Therefore, the assimilation equation in the master filter is given by

$$\begin{aligned} \hat{y}_{master} &= \hat{y}_1 + \cdots + \hat{y}_N = \sum_{i=1}^{N}\hat{y}_i(k|k) \\ &= \sum_{i=1}^{N}[\hat{y}_i(k|k-1) + H_i'(k)R_i^{-1}(k)z_i(k)] \\ &= \hat{y}^*(k|k-1) + \sum_{i=1}^{N}H_i'(k)R_i^{-1}(k)z_i(k) \\ &= \hat{y}^*(k|k). \end{aligned} \tag{30}$$

Remark 3: According to Eqs. (15) and (17) of the suggested filtering scheme, the system process information is distributed among the master and local filters in given proportion of $1/\gamma_i$. The issue in the suggested filter design is to determine how the total information is to be divided among the individual filters to achieve a higher fault-tolerance performance and improvement in throughput and efficiency. In the suggested filter, contrary to other decentralized filters, the master filter combines the only filtered information state and its information matrix of local filters. Therefore, the number of variables transmitted from the local filters to the master filter is diminished. The FIF structure is shown in Fig. 2.

4. Simulations Results

For comparing the performance of the FIF and CIF algorithms, we ran Monte Carlo simulations using two sensors with different qualities. To ensure fair comparisons, all filters employed the same sensor state models for their associated sensors. The state vector in (31) includes position and velocity variables. It was assumed that two sensors were tracking an AGV whose kinematic model is

$$x(k+1) = \begin{matrix} 1 & T \\ 0 & 1 \end{matrix}\, x(k) + u(k) + \begin{matrix} T^2/2 \\ T \end{matrix}\, w(k) \tag{31}$$

where the sampling time was T = 0.1 sec and $w(k)$ was a zero-mean white Gaussian process noise with the variance Q given in Table 1. The measurement of the two sensors were modeled as

$$z_i(k) = [1 \;\; 0]x(k) + v_i(k), \;\; i = 1,2 \tag{32}$$

where the measurement noise v_i was assumed to be independent white Gaussian with zero mean with the variance R_i given in Table 1.

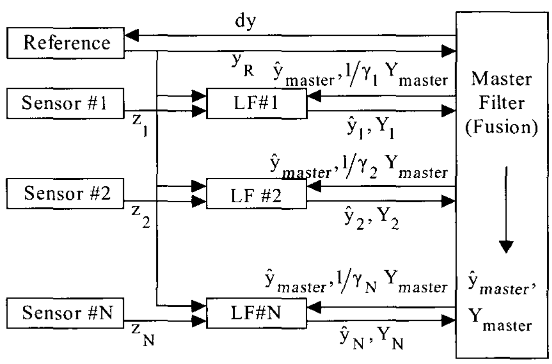

Fig. 2 Federated IF structure

Table 1 Numerical values for Monte Carlo simulation

Process noise covariance Q (m^2)	Information sharing factor		Measurement noise covariance (m^2)	
	$1/\gamma_1$	$1/\gamma_2$	Sensor 1 (R_1)	Sensor 2 (R_2)
Case 1: diag[0.01 4]	0.5	0.5	1	1
Case 2: diag[0.0225 9]	0.5	0.5	1	1
Case 3: diag[0.01 4]	1	0	1	1

Each algorithm was started with identical initial conditions for the state and information matrices and the same values of process and measurement noise covariances. Initial values of the information state and information matrix were $\hat{y}(0|0) = [0\ 0]'$ and $Y(0|0) = diag[0.01\ 0.04]'$, respectively. Simulations were performed considering 3 different cases, which can be classified by system noise covariances and information sharing factors. Numerical values of simulation conditions are represented in Table 1.

Figs. 3-5 show comparisons of the true position and the estimated ones with CIF and FIF algorithms: Case 1, Case 2, and Case 3, respectively. Figs. 3-4 show the performance of the CIF and the FIF algorithms operating in the fusion reset (FR) mode, with information-share fractions $1/\gamma_i$ for the two local filters, while Fig. 5 shows comparable results for the suggested filter operating in the no reset (NR) mode. As can be seen from these figures, except for the Case 3, the FIF algorithm produces almost the same results obtained by using the CIF algorithm. Figs. 3-4 show illustrations of the synergistic use of two sensors to increase the capabilities of systems. Also, it represents that the simulation results of Cases 1 and 2 agree with the theoretical results suggested in Theorem 1. From Fig. 5 (Case 3), it can be seen that, when Sensor 2 is broken down, there is no feedback from the master filter to the local filter at Sensor 2. Note that the FIF NR results are less accurate than these of the FR mode. However, even though the NR mode is theoretically less accurate than the FR mode, it is very useful for typical navigation systems. The estimate from a broken local filter does not affect other local filters and facilitates fault detection and isolation, since each local filter operates independently. Figs. 6-8 show the RMS estimation errors of the position, respectively. From the RMS estimation errors shown in Figs. 6-8, it can be seen that for the FR mode the accuracy of the suggested algorithm is close to that of the CIF algorithm.

5. Conclusions

In this paper, a federated information filter structure was investigated. Comparison and analysis between the centralized information filter and federated information filter have been performed based on accuracy, computational efficiency, and fault-tolerance.

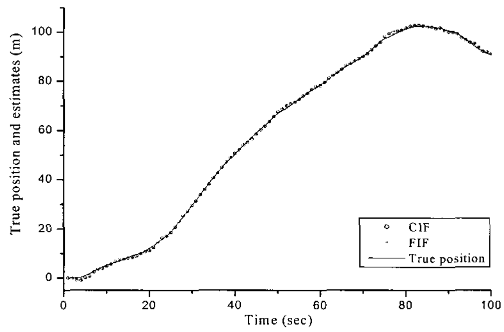

Fig. 3 Comparison of CIF with FIF: Case 1

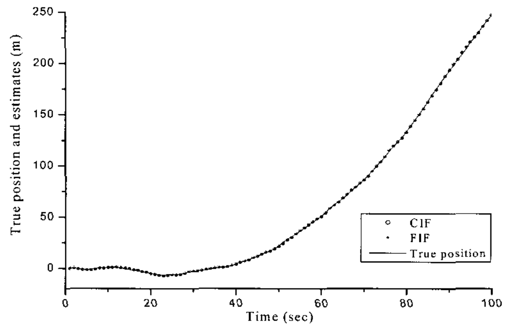

Fig. 4 Comparison of CIF with FIF: Case 2

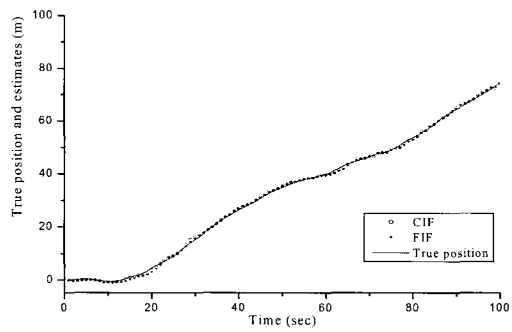

Fig. 5 Comparison of CIF with FIF: Case 3

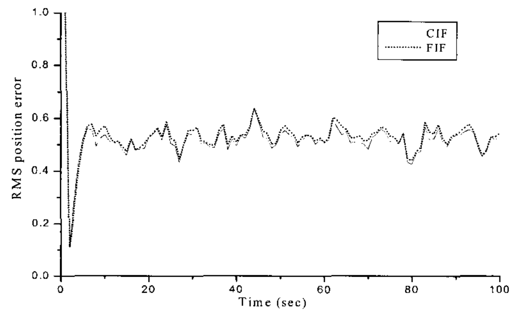

Fig. 6 RMS position errors in FR mode: Case 1

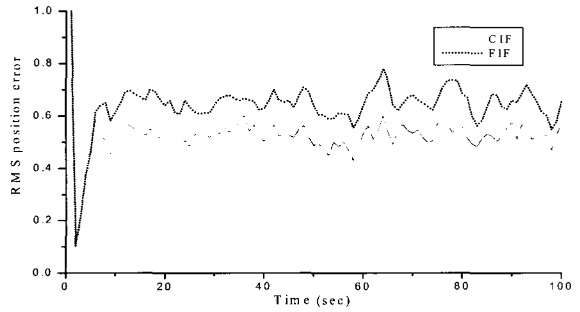

Fig. 7 RMS position errors in FR mode: Case 2

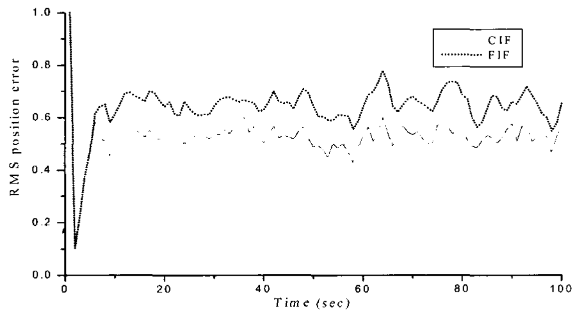

Fig. 8 RMS position errors in NR mode: Case 3

It was mathematically shown that, in view of the information sharing factor, the federated information filter is equal to the centralized information filter. For performance comparison of the centralized information filter and the suggested filter algorithms under two sensor system, an example using Monte Carlo simulations was provided.

Acknowledgements

This work was supported by the Ministry of Science and Technology of Korea under a program of the National Research Laboratory, grant number NRL M1-0302-00-0039-03-J00-00-023-10.

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Received 27 July 2004
Accepted 17 September 2004