다중표적추적용 데이터 결합을 위한 홉필드 신경망 기법 연구

이양원

A Study on the Hopfield Neural Scheme for Data Association in Multi-Target Tracking

Yang-Weon Lee

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요 약

본 논문에서는 다중표적 추적을 위한 데이터 결합 기법중에서 MHDA 스킴을 제안하였다. 이 구조는 기본의 JPDA보다 계산면에서 단축이 가능하여 실제 응용에 많은 적용이 기대된다. 인위적인 측정값과 표적을 이용하여 시뮬레이션을 수행한 결과 MHDA는 기존의 JPDA보다 성능도 비슷한 특성을 보이는 것을 확인하였다.

ABSTRACT

In this paper, we have developed the MHDA scheme for data association. This scheme is important in providing a computationally feasible alternative to complete enumeration of JPDA which is intractable. We have proved that given an artificial measurement and track's configuration, MHDA scheme converges to a proper plot in a finite number of iterations. Also, a proper plot which is not the global solution can be corrected by re-initializing one or more times. In this light, even if the performance is enhanced by using the MHDA, we also note that the difficulty in tuning the parameters of the MHDA is critical aspect of this scheme. The difficulty can, however, be overcome by developing suitable automatic instruments that will iteratively verify convergence as the network parameters vary.

키워드

Neural Netwrok, Hopfield, Multi-target tracking, Data association

Ⅰ. Introduction

Generally, there are three approaches in data association for MTT(Multi-target tracking): 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 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.

*호남대학교 정보통신공학과

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These two approaches are inadequate for real time applications because the computational complexity is tremendous.

As an alternative approach, Sengupta and Iltis[3] suggested a Hopfield neural network probabilistic data association (HNPDA) to approximately compute a posteriori probability β_j^t for the joint probabilities data association filter (JPDAF) [4] as a constrained minimization problem.

This technique based on the use of neural networks was also started by comparison with the traveling salesman problem (TSP).

In fact β_j^t is approximated by the output voltage X_j^t of a neuron in an (m + 1) × n array of neurons, where m is the number of measurements and n is the number of targets.

Sengupta and Iltis[3] claimed that the performance of the HNPDA was close to that of the JPDAF in situations where the numbers of measurements and targets were in the ranges of 3 to 20 and 2 to 6, respectively.

The success of the HNPDA in their examples was credited to the accurate emulation of all the properties of the JPDAF by the HNPDA.

However, the neural network developed in [3] has been shown the two problems.

First, the neural network developed in [3] has been shown to have improper energy functions.

Second, heuristic choices of the constant parameters in the energy function in [3] didn't guarantee the optimal data association.

II. Energy Function in the HNPDA

Suppose there are n targets and m measurements. The energy function used in [3] is reproduced below

$$
\begin{aligned}
E_{DAP} = {} & \frac{A}{2}\sum_{j=0}^{m}\sum_{t=1}^{n}\sum_{\tau=1,\tau\neq t}^{n} X_j^t X_j^\tau + \frac{B}{2}\sum_{t=1}^{n}\sum_{j=0}^{m} X_j^t X_l^t \\
& + \frac{C}{2}\sum_{t=1}^{n}\Big(\sum_{j=0}^{m} X_j^t - 1\Big)^2 + \frac{D}{2}\sum_{j=0}^{m}\sum_{t=1}^{n}\big(X_j^t - \rho_j^t\big)^2 \\
& + \frac{E}{2}\sum_{j=0}^{m}\sum_{t=1}^{n}\sum_{\tau=1,\tau\neq t}^{n}\Big(X_j^\tau - \sum_{l=0,l\neq j}^{m} \rho_l^\tau\Big)^2
\end{aligned} \tag{1}
$$

in [3], X_j^t is the output voltage of a neuron in an (m + 1) × n array of neurons and is the approximation to the *a posteriori* probability β_j^t in the JPDAF[4]. This *a posteriori* probability, in the special case of the PDAF when the probability P_G that the correct measurement falls inside the validation gate is unity, is denoted by ρ_j^t. Actually, P_G is very close to unity when the validation gate size is adequate. In (1), A,B,C,D, and E are constants.

In the HNPDA, the connection strength matrix is a symmetric matrix of order $n(m + 1)$. With the given energy function E_{DAP} in (1), the connection strength $W_{jl}^{t\tau}$ from the neuron at location (τ, l) to the neuron at location (t, j) is

$$
W_{jl}^{t\tau} = \begin{cases} -[C + D + E(n-1)] & \text{if } t = \tau,\ j = l \text{ (self feedback)} \\ -A & \text{if } t = \tau,\ j = l \text{ (row connection)} \\ -(B + C) & \text{if } t = \tau,\ j = l \text{ (column connection)} \\ 0 & \text{if } t = \tau,\ j \neq l \text{ (global connection)} \end{cases} \tag{2}
$$

The input current I_j^t to the neuron at location (t,j), for $t = 1,2,...,n, and j = 0,1,...,m, is$

$$
I_j^t = C + (D + E)\rho_j^t + E\Big(n - 1 - \sum_{\tau=1}^{n}\rho_j^\tau\Big) \tag{3}
$$

Clearly from (2)and (3), the input current I_j^t but not the connection strength $T_{jl}^{t\tau}$ depends on the ρ_j^t s, which are computed form the measurements that comprise the input data. Ironically, in the neural network for the TSP[5], only the connection strengths depend on the input data which, in this case, are the distances between pairs of cities.

In order to justify the first two terms of E_{DAP} in (1), the authors of [3] claimed that the dual assumptions of no two returns form the same target and no single return from two targets are consistent with the presence of a dominating X_j^t in each row and each column of the $(m + 1) \times n$ array of neurons. However, these assumptions are not constraints on the values of the β_j^t's in the original JPDAF. Those assumptions should be used only in the generation of the feasible data association hypotheses, as pointed out in [4].

As a matter of fact, there could be two β_j^t's of comparable magnitude in the same row and in the same column as shown in Chapter 4 of [6]. Therefore, the presence of a dominating X_j^t in each row and each column is not a property of the JPDAF.

The third term of E_{DAP} is used to constrain the sum of the X_j^t's in each column to unity *i.e.* $\sum_{j=0}^{m} X_j^t = 1$. This constraint is consistent with the requirement that $\beta_j^t = 1$ in both the JPDAF and the PDAF[7]. Therefore, this constraint, by itself, does not permit us to infer whether the β_j^t's are from the JPDAF, or from the PDAF.

The assumption used to set up the fourth term is that this term is small only if X_j^t is close to ρ_j^τ, in which case the neural network simulates more closely the PDAF for each target rather than the intended JPDAF in the multitarget scenario. Finally, the fifth term is supposed to be minimized if X_j^t is not large unless for each $\tau \neq t$ there is a unique $l \neq j$ such that ρ_l^τ is large.

Unfortunately, this constrained minimization may not be possible as shown in [6]. This is consistent with the heuristic nature of the derivation of the energy function in [3], which

could lead to the problems in the implementation of the HNPDA as discussed next.

III. Modified Scheme of HNPDA

3.1 Basic Neural Network Representation

To address data association problem within the framework of artificial neural networks, we adopt the Hopfield-Tank[18] approach. We define, instead of the feasibility matrix element variables w_{jt} of the previous section, new continuous association variables X_l^t. Each X_l^t represents the output signal of neurons. Thus, X_l^t represents the association pair for the lth return and the tth target.

The Hopfield network for MTT is a single-layer, symmetric, nonlinear, and recurrent associative network that has m by $(n+1)$ neurons,

each receiving inputs from all the others (the input that a neuron receives from itself is ignored) as shown in Fig.3.1. The states of the neurons are denoted by S_l^t, $l \in m$, $t \in n$ in $m(n + 1)$ space.

From its state through an activation function, the association pair variable is related to the neuron's state as follows:

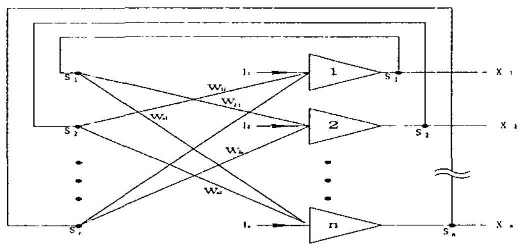

Figure 3.1 : Single layer Hopfield network

$$X_i = f(S_i) = \frac{1}{2}[1 - \tanh(S_i)]. \qquad (4)$$

In Hopfield model, the evolution of the activity of each neuron (its rate of change with time) is described by

$$\frac{dS_i(t)}{dt} = -\frac{\partial E}{\partial X_i}. \quad (5)$$

The time evolution of the energy function is

$$\frac{dE}{dt} = \sum_i \frac{\partial Si(t)}{\partial t}\frac{\partial X_i(t)}{\partial S_i(t)}\frac{\partial E}{\partial X_i(t)} \quad (6)$$

To show that the model in (5) minimize **E**, we substitute (5) into (6) and obtain

$$\frac{dE}{dt} = -\sum_i(\frac{\partial S_i(t)}{\partial t})^2(\frac{dX_i(t)}{dS_i(t)}) \leqq 0 \quad (7)$$

Equation (7) show that **E** is a decreasing function of time *t*. In the case of stable recurrent networks it is possible to verify that the energy function (Lyapunov function) given by

$$E = -\frac{1}{2}\sum_i\sum_j W_{ij}X_iX_j - \sum_i I_iX_i, \quad (8)$$

necessarily admits local minima, corresponding to some vertices of the $m(n+1)$-dimensional hypercube defined by the condition $X_i = 0$ or 1 [8]. For the unipolar activation function, the Hopfield operational equation for the *i*th neuron is

$$\begin{aligned}\frac{dSi}{dt} &= -\frac{S_i}{S_o} - \frac{\partial E}{\partial X_i}, \\ &= -\frac{S_i}{S_o} + \sum_i W_{ij}Xj + I_i.\end{aligned} \quad (9)$$

where S_o is a free parameter to be chosen and W_{ij} is the connection weight from *j*th neuron to *i*th neuron and I_i is the external input data for the *i*th neuron. The solution of (7) shows that the energy **E** converge to a local minimum as *t* progresses. Thus, the set of neural activities $\{X_i\}$ in the final stationary state describes a minimum energy state of the system.

3.2 Modification of Energy Equation

In Hopfield network, when the operation is approaching the steady state, at most one neuron gets into the ON state in each row and column and the other neurons must be in the OFF state.

To guarantee the this state, we add the following constraints additionally for Hopfield network :

$$E_s = \frac{1}{2}\sum_{j=1}^{m}\sum_{t=0}^{n}\sum_{\tau\neq t}^{n} w_{jt}w_{j\tau} + \frac{1}{2}\sum_{t=1}^{n}\sum_{j=1}^{m}\sum_{l\neq j}^{m} w_{jt}w_{lt}. \quad (10)$$

Finally, we get the final energy equation for Hopfield network:

$$\begin{aligned}E_{HDA} = &\frac{A}{2}\sum_{j=1}^{m}\sum_{t=0}^{n}\sum_{\tau\neq t}^{n} w_{jt}w_{j\tau} + \frac{B}{2}\sum_{t=1}^{n}\sum_{j=1}^{m}\sum_{l\neq j}^{m} w_{jt}w_{lt} \\ &\frac{C}{2}\sum_{t=1}^{n}\sum_{j=1}^{m}(w_{jt} - \hat{w}_{jt})^2 + \frac{D}{2}\sum_{t=1}^{n}(\sum_{j=1}^{m} w_{jt} - 1) \\ &\frac{F}{2}\sum_{j=1}^{m}(\sum_{t=0}^{n} w_{jt} - 1)^2 + \frac{G}{2}\sum_{t=1}^{n}\sum_{j=1}^{m} r_{jt}w_{jt}\end{aligned} \quad (11)$$

The first two terms of (11) correspond to row and column inhibition and the third term suppressed the activation of uncorrelated part(*i.e.* if $w_{jt} = 0$, then $w_{jt}=0$). The fourth and fifth terms biased the final solution towards a normalized set of numbers. The last term favors associations which have a nearest neighbor in view of target velocity.

3.3 Transformation of Energy Function into Hopfield Network

A Hopfield network with $m(n+1)$ neurons was considered. The neurons were subdivided into $n+1$ target's column of m neurons each. Henceforward we will identify each neuron with a double index, tl(where the index $t=0,1,\cdots,n$ relates to the target, whereas the index $l=1,\cdots,m$ refers to the neurons in each column), its output with X_l^t, the weight for neurons jt and $l\tau$ with $W_{jl}^{t\tau}$, and the external bias current for neuron tl with I_l^t. According to this convention, we can extend the notation of the Lyapunov energy function (8) to two dimensions.

Using the Kronecker delta function

$$\delta_{ij} = \begin{cases} 1 & \text{if } i = j \\ 0 & \text{if } i = j \end{cases} \tag{12}$$

(8) can be written as

$$\begin{aligned} E_{BDA} = {} & \frac{A}{2}\sum_l\sum_j\sum_t\sum_\tau \delta_{lj}(1-\delta_{t\tau})X_l^t X_j^\tau + \frac{B}{2}\sum_l\sum_j\sum_t\sum_\tau \delta_{t\tau}(1-\delta_{lj})(1-\delta_{0t})X_l^t X_j^\tau \\ & + \frac{C}{2}\sum_l\sum_j\sum_t\sum_\tau \delta_{t\tau}\delta_{lj}(1-\delta_{0t})X_l^t X_j^\tau - C\sum_l\sum_t \rho_{lt}(1-\delta_{0t})X_l^t \\ & + \frac{Dn}{2} - D\sum_l\sum_t (1-\delta_{0t})X_l^t + \frac{D}{2}\sum_l\sum_j\sum_t\sum_\tau \delta_{t\tau}(1-\delta_{0t})X_l^t X_j^\tau \\ & + \frac{Fm}{2} - F\sum_l\sum_t X_l^t + \frac{F}{2}\sum_l\sum_j\sum_t\sum_\tau \delta_{lj}X_l^t X_j^\tau + \frac{G}{2}\sum_l\sum_t r_{lt}(1-\delta_{0t})X_l^t \end{aligned} \tag{13}$$

We also can extend the notation of the Lyapunov energy function (8) to two dimensions:

$$E = -\frac{1}{2}\sum_t\sum_j\sum_l\sum_\tau W_{jl}^{t\tau}X_l^t X_j^\tau - \sum_t\sum_l I_l^t \tag{14}$$

By comparing (14) and (13), we get the connection strength matrix and input parameters each :

$$\begin{cases} W_{jl}^{t\tau} = -[A(1-\delta_{t\tau}) + C\delta_{t\tau}(1-\delta_{0t}) + F]\delta_{lj} - [B(1-\delta_{lj}) + D]\delta_{t\tau}(1-\delta_{0t}) \\ I_l^t = (C\rho_{lt} + D - G r_{lt}/2)(1-\delta_{0t}) + F \end{cases} \tag{15}$$

Here we omit the constant terms such as $\dfrac{Dn+Fm}{2}$ + $\dfrac{C}{2}\sum\sum w_{jl}^2(1-\delta_{ot})$. These terms do not affect the neuron's output since they just act as a bias terms during the processing.

Using the (15), the connection strength $W_{jl}^{t\tau}$ from the neuron at location (τ,l) to the neuron at location (t,j) is

$$W_{jl}^{t\tau} = \begin{cases} -[(C+D)(1-\delta_{0t}) + F] & \text{if } t=\tau,\ j=l \text{ (self feedback)} \\ -(A+F) & \text{if } t=\tau,\ j=l \text{ (row connection)} \\ -(B+D)(1-\delta_{0t}) & \text{if } t=\tau,\ j=l \text{ (column connection)} \\ 0 & \text{if } t=\tau,\ j=l \text{ (global connection)} \end{cases} \tag{16}$$

Fig.3.2 sketches the resulting two-dimensional network architecture as a directed graph using the (16). We note that only 39 connections of possible 81 connections are achieved in this 3 × 3 neurons example. This means that modified Hopfield network can be represented as a sparse matrix. In Fig.3.2, we also note that there are no connections between diagonal neurons.

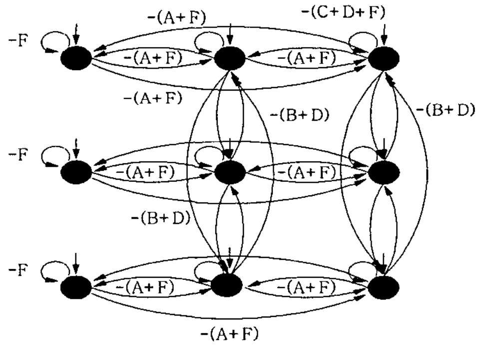

Fig. 3.2 Example of Hopfield network for two targets and three plots

With the specific values from (15), the equation of motion for the MTT becomes

$$\begin{aligned} \frac{dS_l^t}{dt} = {} & -\frac{S_l^t}{R_0} - \sum_\tau\sum_j[\{A(1-\delta_{t\tau}) + C\delta_{t\tau}(1-\delta_{0t}) + F\}\delta_{lj} - \{B(1-\delta_{lj}) \\ & + D\}\delta_{t\tau}(1-\delta_{0t})]X_j^\tau + (C\rho_{lt} + D - \frac{r_{lt}}{2}G)(1-\delta_{0t}) + F \end{aligned} \tag{17}$$

The final equation of data association is

$$\frac{dS_l^t}{d\tau} = -\frac{S_l^t}{S_o} - A\sum_{\tau=1,\tau\neq t}^{n} X_l^\tau - B(1-\delta_{lt})\sum_{j=1,j\neq l}^{n} X_j^t$$
$$- D(1-\delta_{lt})\left(\sum_{j=1}^{m} X_j^t - 1\right) - F\left(\sum_{\tau=1}^{m} X_l^\tau - 1\right) - C(1-\delta_{lt})(1-\omega_{jt})$$
$$- \frac{\omega_{jt}}{2}(1-\delta_{lt})G \tag{18}$$

The parameters A,B,C,D,F and G can be adjusted to control the emphasis on different constraints and properties. A larger emphasis on A,B, and F will produce the only one neuron's activation both column and row. A large value of C will produce X_l^t close to w_{jt} except the duplicated activation of neurons in the same row and column. A larger emphasis on G will make the neuron activate depending on the value of target's course weighted value. Finally, a balanced combination of all six parameters will lead to the most desirable association. In this case, a large number of targets and measurements will only require a larger array of interconnected neurons instead of an increased load on any sequential software to compute the association probabilities.

IV. Simulation Results

4.1 Data Association Experiments

To exactly test the data association capability of the MHDA method, predefined targets and measurements value are used to exclude any effects due to miss detection that are moderately occurring in real environment. An example of three targets and seven measurements is depicted in Fig.4.1 In Fig. 4.1 large circles represent track gates and symbol * means plots of measurements and small circles on the some measurement's plots represent the plots of measurements which are associated with tracks by MHDA.

During the iteration, Fig.4.2 and 4.3 show how the distance and matching energy change respectively. In this example, the association pairs are track 1 and measurement 4, track 2 measurement 2 ,and track 3 and measurement 6. Note that the results of data association is correct with respect to nearest neighbor. In the simulation, the constants appeared to be suitable for this scenario. S_o was selected to be 1 s.

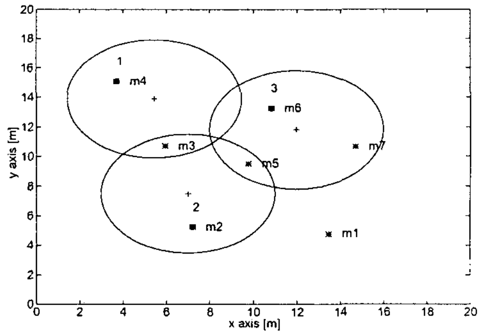

Fig. 4.1 : Diagram of Hopfield network for three targets and senec plots

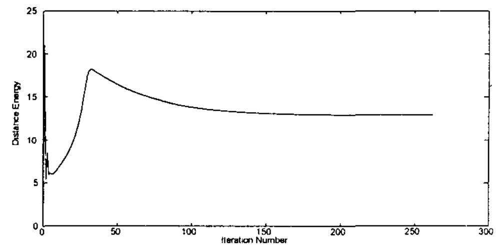

Fig. 4.2 : Distance energy convergence for three targets and seven plots

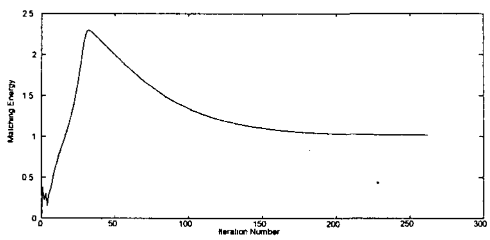

Fig. 4.3 : Matching energy of Hopfield network for three targets and seven plots

4.2 Sequential Tracking Experiments

In Fig.4.4 and 4.5, track estimation errors between MHDA and HNPDA for the crossing targets are shown with respect to rms error in position and velocity in clutter density, $C = 0.2$. Both MHDA and HNPDA maintain tracks and have a good performance even if a large error occurred in the vicinity of crossing point.

In Fig. 4.4 and 4.5, the rms estimation errors for the maneuvering targets are shown. HNPDA can not track the dog leg maneuvering targets but the constant acceleration target. Table 4.1 summarizes the rms position and velocity errors for each target. The rms errors of the HNPDA about maneuvering targets have not been included since it loses track of one of targets. The performance of the MHDA is superior to that of HNPDA in terms of tracking accuracy about 8.8 % and in terms of track maintenance about 3.3 %.

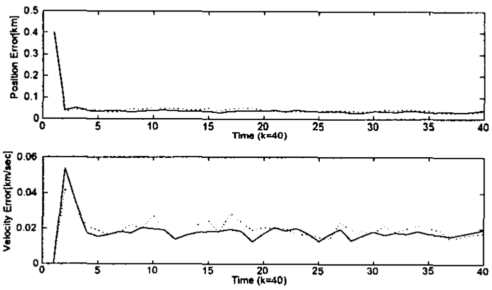

Fig. 4.4 : RMS errors in X axis for target 8 :- MHDA....HNPDA

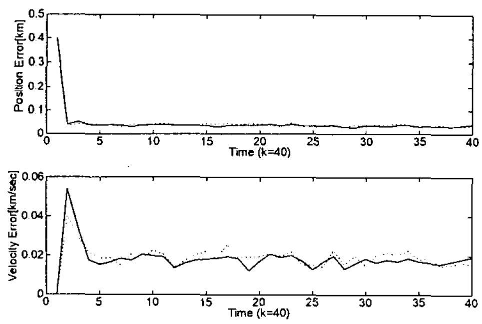

Fig. 4.5 : RMS erros in X axis for target 9 : - MHDA ... HNPDA

V. Conclusions

In this paper, we have developed the MHDA scheme for data association. This scheme is important in providing a computationally feasible alternative to complete enumeration of JPDA which is intractable. We have proved that given an artificial measurement and track's configuration, MHDA scheme converges to a proper plot in a finite number of iterations.

Table 4.1 : RMS Errors in case of ten targets

Target i	Position error (km)		Velocity error (km/s)		Track maintenance(%)	
	HNPDA	MHDA	HNPDA	MHDA	HNPDA	MHDA
1	0.048	0.044	0.024	0.021	95	98
2	0.051	0.048	0.028	0.018	95	98
3	0.065	0.044	0.021	0.018	85	98
4	0.049	0.041	0.020	0.018	93	98
5	0.041	0.044	0.018	0.018	100	100
6	0.042	0.043	0.021	0.018	100	100
7	0.040	0.040	0.018	0.018	100	100
8	-	0.295	-	0.118	0	53
9	0.058	0.047	0.027	0.022	100	100
10	0.037	0.039	0.011	0.012	100	100

Also, a proper plot which is not the global solution can be corrected by re-initializing one or more times. In this light, even if the performance is enhanced by using the MHDA, we also note that the difficulty in tuning the parameters of the MHDA is critical aspect of this scheme. The difficulty can, however, be overcome by developing suitable automatic instruments that will iteratively verify convergence as the network parameters vary.

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저자 소개

Yang Weon Lee(이양원)

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 1998, 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 DefenseDevelopment 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 associate professor. His current research interests include radar signal processing, target estimation and tracking filter design, communication signal processing, distance education using satellite and its Internet application.