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VFF-PASTd Based Multiple Target Angle Tracking with Angular Innovation

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Abstract

Ryu *et al.* recently proposed a multiple target angle-tracking algorithm without a data association problem. This algorithm, however, shows the degraded performance on evasive maneuvering targets, because the estimated signal subspace is degraded in the algorithm. In this Paper, we proposed a new algorithm, in which VFF-PASTd (Variable Forgetting Factor PASTd) algorithm is applied to Ryu's algorithm to effectively handle the evasive target tracking with better time-varying signal subspace.

Keywords: *Target tracking, Variable forgetting factor, PASTd*

I. Introduction

The angle tracking of moving targets has been studied for several decades in various fields, e.g. radar, sonar and so forth. A conventional algorithm for tracking multiple target angles consists of an angle estimator and a data association filter.

An alternative approach has already been considered by Sword and others, where the tracking algorithms estimate the angles of the targets and associate the data simultaneously[1]. This approach makes the algorithm simple. Recently, Ryu et al. proposed an effective angle-tracking algorithm, which used the angular innovation from the estimated signal subspace[2]. However, as angular variation rate increases, the algorithm shows the degraded performance because it cannot estimate the time-varying signal subspace well. Generally, even under the same target trajectory, the angle variation rate gets different according to the altitude of the target. In addition, evasive maneuvering target has from slow angle variation to fast angle variation in a trajectory. Therefore, changeable angle variation rate is a common case in the target tracking.

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In this paper, we propose a new angle-tracking algorithm, which effectively copes with the changeable angle variation rate with better signal subspace. This algorithm applies the VFF-PASTd method to Ryu's algorithm. We have proposed the VFF-PASTd (Variable Forgetting Factor PASTd), which effectively estimates the time-varying signal subspace without knowledge of subspace variation[3].

II. Problem Formulation

Consider a linear array of M sensors with an inter-sensor distance d receiving uncorrelated signals from N targets. The sensor output vector can be written at the sampling time k as

$$\mathbf{r}(k) = \sum_{n=1}^{N} s_n(k)\mathbf{a}_n(k) + \mathbf{n}(k) \tag{1}$$

where $s_n(k)$ is the nth target signal and the sensor noise vector $\mathbf{n}(k)$ is assumed to be zero mean white with a constant power σ^2, be uncorrelated between sensors and uncorrelated with target signals. The nth target steering vector $\mathbf{a}_n(k)$ is given by

$$\mathbf{a}_n(k) = \left[1, \gamma_n(k), \cdots, \gamma_n^{M-1}(k)\right]^T \tag{2}$$

where $\gamma_n(k) = e^{j\omega(d/c)\sin\theta_n(k)}$, ω and c are the carrier frequency and the signal propagation speed, respectively, $\theta_n(k)$ is the direction angle of the nth target and the superscription T denotes a transpose. The angles of the targets are tracked by using the sensor output in eqn. (1).

III. Multiple Target Angle Tracking with Angular Innovation

The algorithm in[2] considers the dynamics and the measurement of the direction angles for target i modeled as follows.

$$\begin{aligned} x_i(k+1) &= Fx_i(k) + w_i(k) \\ z_i(k+1) &= Hx_i(k) + v_i(k) \end{aligned} \tag{3}$$

where $\hat{x}_i(k) = [\theta_i(k) \ \ \dot{\theta}_i(k)]^T$, $F = \begin{bmatrix} 1 & T \\ 0 & 1 \end{bmatrix}$, $H = [1 \ 0]$. $\theta_i(k)$ is the angle of target i and $\dot{\theta}_i(k)$ is its first derivative. T is an angle tracking time step. $w_i(k)$ and $v_i(k)$ are process noise and measurement noise which are assumed to be normally distributed with zero mean and variances, $Q_i(k)$ and $\sigma_{z_i}^2(k)$, respectively.

If the estimates $\hat{x}_i(k \mid k)$ of the state vector and its covariance matrix $P_i(k \mid k)$ are available at k, Ryu's algorithm consists of the following steps.

Prediction Step: The predicted state vector and its covariance matrix for target i can be obtained from the equations.

$$\begin{aligned} \hat{x}_i(k+1|k) &= F\hat{x}_i(k|k) \\ P_i(k+1|k) &= FP_i(k|k)F^T + Q_i(k) \end{aligned} \tag{4}$$

Estimation of Innovation Step: The steering vector $\mathbf{a}_n(k)$ and signal subspace $\mathbf{W}(k)$ have the same column span[2,3]. Therefore, the steering vector $\mathbf{a}_n(k)$ can be represented by a linear combination of the vectors of the signal subspace $\mathbf{W}(k)$, as follows

$$\mathbf{a}_n(k) = c_{n1}(k)\mathbf{w}_1 + c_{n2}(k)\mathbf{w}_2 + \cdots + c_{nN}(k)\mathbf{w}_N, \qquad n = 1, 2\cdots, N \tag{5}$$

where $\mathbf{W}(k) = [\mathbf{w}_1(k), \mathbf{w}_2(k), \cdots, \mathbf{w}_N(k)]$, and $\{c_{ni}(k), n = 1, \cdots, N, i = 1, \cdots, N\}$ are complex coefficients.

The signal subspace $\mathbf{W}(k)$ can be recursively estimated by sensor measurements using PAST or PASTd[2,3]. The estimated angle $\theta_i(k)$ of ith target is represented with predicted angle, $\theta_i(k \mid k-1)$, and innovation angle, $\delta\theta_i(k)$.

$$\theta_i(k) = \hat{\theta}_i(k \mid k-1) + \delta\theta_i(k) \tag{6}$$

Accordingly, the mth element of the steering vector $\mathbf{a}_n(k)$ in eqn. (2) can be represented by

$$\gamma_i^{m-1}(k) = e^{j\omega(d/c)(m-1)\sin\theta_i(k)} = e^{j\omega(d/c)(m-1)\sin(\hat{\theta}_i(k|k-1)+\delta\theta_i(k))} \tag{7}$$

Eqn. (7) can be approximated by a Talyor series with the *0*th and the *1*st term. This gives

$$\gamma_i^{m-1}(k) \cong \hat{\gamma}_i^{m-1}(k \mid k-1) + j\omega(d/c)(m-1) \times \cos\hat{\theta}_i(k \mid k-1)\hat{\gamma}_i^{m-1}(k \mid k-1)\delta\theta_i(k) \tag{8}$$

where $\hat{\gamma}_i^{m-1}(k) = e^{j\omega(d/c)(m-1)\sin\theta_i(k/k-1)}$. Eqn. (8) makes eqn. (2) as follows.

$$\mathbf{a}_i(k) = \mathbf{a}_i(k \mid k-1) + \hat{\mathbf{b}}_i(k \mid k-1)\delta\theta_i(k), i = 1, \cdots, N \tag{9}$$

where, $\hat{\mathbf{b}}_i(k \mid k-1) = j\omega(d/c) \lfloor 0, \cos(\hat{\theta}_i(k \mid k-1)\hat{\gamma}_i(k \mid k-1),$
$\cdots, (M-1)\cos(\hat{\theta}_i(k \mid k-1)\hat{\gamma}_i(k \mid k-1))\hat{\gamma}_i^{M-1}(k \mid k-1) \rfloor$

$\mathbf{a}_i(k|k-1)=\left[1,\hat{\gamma}_i(k|k-1),\ldots,\hat{\gamma}_i^{M-1}(k|k-1)\right]^T$. The equation for angle innovation can be derived from eqn. (9).

$$\tilde{\mathbf{y}}_i(k)=\left(\tilde{\mathbf{B}}_i(k)^T\tilde{\mathbf{B}}_i(k)\right)^{-1}\tilde{\mathbf{B}}_i(k)^T\tilde{\mathbf{a}}_i(k) \tag{10}$$

where $\tilde{\mathbf{y}}_i(k)=\begin{bmatrix}\mathbf{y}_{iR}(k)\\ \overline{\mathbf{y}}_{iI}(k)\end{bmatrix}$,

$\mathbf{a}_i(k|k-1)=\hat{\mathbf{a}}_{iR}(k|k-1)+j\mathbf{a}_{iI}(k|k-1)$,

$\tilde{\mathbf{a}}_i(k)=\begin{bmatrix}\hat{\mathbf{a}}_{iR}(k|k-1)\\ \hat{\mathbf{a}}_{iI}(k|k-1)\end{bmatrix}$, $\tilde{\mathbf{B}}_i(k)=\begin{bmatrix}\mathbf{B}_{iR}(k) & -\overline{\mathbf{B}}_{iI}(k)\\ \mathbf{B}_{iI}(k) & \overline{\mathbf{B}}_{iR}(k)\end{bmatrix}$,

$\mathbf{B}_i(k)=\left[-\hat{\mathbf{b}}_i(k|k-1),\mathbf{w}_1(k),\cdots,\mathbf{w}_N(k)\right]=\mathbf{B}_{iR}+j\mathbf{B}_{iI}$ and $\mathbf{y}_i(k)=\left[\delta\theta_i,c_{i1}(k),\cdots,c_{iN}(k)\right]^T=\mathbf{y}_{iR}(k)+j\mathbf{y}_{iI}(k)$. $\overline{\mathbf{B}}_{iR}(k)$ and $\overline{\mathbf{B}}_{iI}(k)$ are submatrices of $\mathbf{B}_{iR}(k)$ and $\mathbf{B}_{iI}(k)$, the first columns of which are deleted. $\overline{\mathbf{y}}_{iI}(k)$ is the subvector of $\mathbf{y}_{iI}(k)$, the first element of which is deleted.

We can estimate the angle innovation for ith target, $\delta\theta_i(k)$, by solving eqn. (10) and the value is as follows.

$$\delta\theta_i(k)=\tilde{\mathbf{y}}_i(k)_{1,1} \tag{11}$$

The other innovations are also calculated in the same way.

Update Step: With the estimated innovations $\{\delta\hat{\theta}_i(k+1),\ i=1,\cdots,N\}$, we can obtain the state estimate and its convariance matrix by

$$\begin{aligned}\hat{x}_i(k+1|k+1)&=\hat{x}_i(k+1|k)+G_i(k+1)\delta\hat{\theta}_i(k+1)\\ P_i(k+1|k+1)&=\left[I-G_i(k+1)H\right]P_i(k+1|k)\end{aligned} \tag{12}$$

where $G_i(k+1)$ is the Kalman gain matrix $G_i(k+1)=P_i(k+1|k)H^T\left[HP_i(k+1|k)H^T+\sigma^2_{z_i}\right]^{-1}$. Table 1 summarizes the algorithm.

Table 1. Multiple target tracking with angle innovation[2].

Restimation ecursive of the subspace vector $\mathbf{w}_1,\cdots,\mathbf{w}_N$ by PAST.

If k is the renewal time T,
For Target i=1,·,N Do [2]
$\hat{x}_i(k+1\|k)=F\hat{x}_i(k\|k)$,
$P_i(k+1\|k)=FP_i(k\|k)F^T+Q_i(k)$,
where $\hat{x}_i(k)=\left[\theta_i(k)\quad \dot{\theta}_i(k)\right]^T$, $F=\begin{bmatrix}1 & T\\ 0 & 1\end{bmatrix}$.
$\hat{\mathbf{a}}_i(k\|k-1)=\left[1,\quad \hat{\gamma}_i(k\|k-1),\quad \cdots\quad \hat{\gamma}_i^{M-1}(k\|k-1)\right]^T$
$\hat{\mathbf{b}}_i(k\|k-1)=j\omega(d/c)\left[0\quad \cos(\theta_i(k\|k-1))\hat{\gamma}_i(k\|k-1)\quad \cdots\quad (M-1)\cos(\theta_i(k\|k-1))\hat{\gamma}_i^{M-1}(k\|k-1)\right]^T$
$\mathbf{B}_i(k)=\left[-\hat{\mathbf{b}}_i(k\|k-1),\mathbf{w}_1(k),\cdots,\mathbf{w}_N(k)\right]$
$\tilde{\mathbf{a}}_i(k)=\begin{bmatrix}\hat{\mathbf{a}}_{iR}(k\|k-1)\\ \hat{\mathbf{a}}_{iI}(k\|k-1)\end{bmatrix}$, $\tilde{\mathbf{B}}_i(k)=\begin{bmatrix}\mathbf{B}_{iR}(k) & -\overline{\mathbf{B}}_{iI}(k)\\ \mathbf{B}_{iI}(k) & \overline{\mathbf{B}}_{iR}(k)\end{bmatrix}$
$\tilde{\mathbf{y}}_i(k)=\left(\tilde{\mathbf{B}}_i(k)^T\tilde{\mathbf{B}}_i(k)\right)^{-1}\tilde{\mathbf{B}}_i(k)^T\tilde{\mathbf{a}}_i(k)$,
$\delta\theta_i(k)=\tilde{\mathbf{y}}_i(k)_{1,1}$
$g_i(k)=P_i(k\|k-1)H^T\left[HP_i(k\|k-1)H^T+\sigma^2_{z_i}\right]^{-1}$,
where $H=\left[1\quad 0\right]$.
$\hat{\theta}_i(k\|k)=\hat{\theta}_i(k\|k-1)+g_i(k)\delta\hat{\theta}_i(k)$
else
go to signal subspace estimation
endif

IV. Proposed Algorithm

4.1. Variable Forgetting Factor PASTd Algorithm

The signal subspace for the *Estimation of Innovation Step* in section 3 can be derived by PAST or PASTd[2,4].

The PAST is one of the subspace tracking families with the low complexity[4]. It is based on the minimum property of the unconstrained cost function

$$J(\mathbf{W}(k))=\sum_{i=1}^{k}\beta^{k-i}\left\|\mathbf{r}(i)-\mathbf{W}(k)\mathbf{W}^H(k)\mathbf{r}(i)\right\|^2, \tag{13}$$

where $\mathbf{r}(i)$ is $M\times 1$ input vector, $\mathbf{W}(k)$ is $M\times N$ matrix and N is the rank of signal subspace. The PASTd is the sequential estimation variant of the PAST by deflation. The PASTd algorithm, however, can not effectively handles the nonstationarity with a forgetting factor, β. To cope with the nonstationary, author et al. introduced the variable forgetting factor to the PASTd algorithm[3,5]. This paper applies the algorithm to the angle tracking problem. The variable forgetting factor properly adjusts

Table 2. VFF-PASTd.

$\tilde{x}_1(k) = \mathbf{r}(k)$, Ns is the number of targets.
For $i = 1,\cdots,N_s$ Do
$y_i(k) = \mathbf{w}_i^H(k-1)\tilde{x}_i(k)$
$\lambda_i(k) = \beta(k,k-1)\lambda_i(k-1) + \lvert y_i(k)\rvert^2$
$\varepsilon_i(k) = \tilde{x}_i(k) - \mathbf{w}_i(k-1)y_i(k)$
$\varepsilon_i'(k) = -\Psi_i(k-1)\mathbf{w}_i^H(k-1)\tilde{x}_i(k) - \mathbf{w}_i(k-1)\Psi_i^H(k-1)\tilde{x}_i(k)$
$\tilde{J}_i(k) = \beta_i(k,k-1)\tilde{J}_i(k-1) + \varepsilon_i^H(k)\varepsilon_i'(k)$
$\beta_i(k) = \beta_i(k,k-1) - \alpha\,\mathrm{Re}[\tilde{J}_i(k)]$
$y_i'(k) = \Psi_i^H(k-1)\tilde{x}_i(k)$
$S_i(k) = d_i(k-1) - \beta_i(k)S_i(k-1) + 2\mathrm{Re}[\Psi_i^H(k-1)\tilde{x}_i(k)\tilde{x}_i^H(k)\mathbf{w}_i(k-1)]$
$\Psi_i(k) = \Psi_i(k-1) + \varepsilon_i'(k)[y_i^*(k)/d_i(k)] + \varepsilon_i(k)[y_i'^*(k)d_i(k) - y_i^*(k)S_i(k)]/d_i^2(k)$
$\mathbf{w}_i(k) = \mathbf{w}_i(k-1) + \underline{\varepsilon}_i(k)\dfrac{y_i^*(k)}{\lambda_i(k)}$
$\tilde{x}_{i+1}(k) = \tilde{x}_i(k) - \mathbf{w}_i(k)y_i(k)$
END
where $y_i'(k) = \dfrac{\partial y_i(k)}{\partial \beta_i}$ $\Psi_i(k-1) = \dfrac{\partial \mathbf{w}_i(k-1)}{\partial \beta_i}$,
and $S_i(k) = \dfrac{\partial \lambda_i(k)}{\partial \beta_i}$

itself to the nonstationarity of subspace.

The variable forgetting factor is determined as the minimizing arguments of cost function,

$$J_i = \sum_{j=1}^{k}\overline{F}_i(k,j)(\varepsilon_i(j)\varepsilon_i^H(j)) \tag{14}$$

where $\overline{F}_i(k,j) = \prod_{t=j+1}^{k}\beta_i(t)$, $0 \le \beta_i(t) \le 1$ $\beta_i(t) = 1$ and $\varepsilon_i(j) = \tilde{x}_i(j) - \underline{w}_i(j-1)\tilde{y}_i(j) \cdot \underline{w}_i(j)$ is the *ith* column of $W(j)$, $\tilde{x}_1(j) = \mathbf{r}(j)$, $\tilde{y}_i(j) = \underline{w}_i\tilde{x}_i(j)$, and $\tilde{x}_{i+1}(j) = \tilde{x}_i(j) - \underline{w}_i(j)\,y_i(j)$. The steepest descent method can be applied to minimize eqn.9 and the variable forgetting factor migrates as follows.

$$\beta_i(k+1) = \beta_i(k) - \frac{1}{2}\alpha\frac{\partial E_i}{\partial \lambda} \tag{15}$$

where $E_i = \varepsilon_i^H(k)\ \varepsilon_i(k)$, $\varepsilon'_i(k) = \dfrac{\partial \varepsilon_i(k)}{\partial \beta_i}$ and α is a control factor.

Table 2 Summary of VFF-PASTd

4.2. VFF PASTd Based Multiple Target Angle Tracking Algorithm

Ryu's algorithm in[2] derives the angular innovation equation from the fact that the steering vector $\mathbf{a}_n(k)$ can be represented by a linear combination of the vectors of the signal subspace $\mathbf{W}(k)$, as eqn. 3. In the Ryu's algorithm, tracking performance is dependent on the subspace quality from the PAST or the PASTd. However, the PAST or the PASTd does not effectively estimate the subspace under the fast time-varying environments[3]. VFF-PASTd in section 4.1 can effectively estimate the time-varying subspace with the variable forgetting factor. Therefore, the tracking performance in the fast time-varying environments can be improved by applying the VFF-PASTd to the Ryu's algorithm. The proposed algorithm summarized in Table 3.

Table 3. Proposed Algorithm.

Recursive estimation of the subspace. vector $\mathbf{w}_1, \cdots, \mathbf{w}_N$ by VFF-PASTd

$\tilde{\varsigma}_1(k) = \mathbf{r}(k)$, input array snapshot as Table 2.

If k is the renewal time T,

For Target i=1,·,N Do [2]

$$\hat{x}_i(k+1|k) = F\hat{x}_i(k|k),$$

$$P_i(k+1|k) = FP_i(k|k)F^T + Q_i(k),$$

where $\hat{x}_i(k) = \left[\theta_i(k) \quad \dot{\theta}_i(k)\right]^T$, $F = \begin{bmatrix} 1 & T \\ 0 & 1 \end{bmatrix}$.

$$\hat{\mathbf{a}}_i(k|k-1) = \left[1, \quad \hat{\gamma}_i(k|k-1), \quad \cdots \quad \hat{\gamma}_i^{M-1}(k|k-1)\right]^T$$

$$\hat{\mathbf{b}}_i(k|k-1) = j\omega(d/c)\big[0 \quad \cos(\theta_i(k|k-1))\hat{\gamma}_i(k|k-1) \quad \cdots \quad (M-1)\cos(\theta_i(k|k-1))\hat{\gamma}_i^{M-1}(k|k-1)\big]$$

$$\mathbf{B}_i(k) = \left[-\hat{\mathbf{b}}_i(k|k-1), \mathbf{w}_1(k), \cdots, \mathbf{w}_N(k)\right]$$

$$\tilde{\mathbf{a}}_i(k) = \begin{bmatrix} \hat{\mathbf{a}}_{iR}(k|k-1) \\ \hat{\mathbf{a}}_{iI}(k|k-1) \end{bmatrix}, \quad \tilde{\mathbf{B}}_i(k) = \begin{bmatrix} \mathbf{B}_{iR}(k) & -\overline{\mathbf{B}}_{iI}(k) \\ \mathbf{B}_{iI}(k) & \overline{\mathbf{B}}_{iR}(k) \end{bmatrix}$$

$$\tilde{\mathbf{y}}_i(k) = \left(\tilde{\mathbf{B}}_i(k)^T \tilde{\mathbf{B}}_i(k)\right)^{-1} \tilde{\mathbf{B}}_i(k)^T \tilde{\mathbf{a}}_i(k),$$

$$\delta\theta_i(k) = \tilde{\mathbf{y}}_i(k)_{1,1}$$

$$g_i(k) = P_i(k|k-1)H^T\left[HP_i(k|k-1)H^T + \sigma_{z_i}^2\right]^{-1},$$

where $H = \left[1 \quad 0\right]$.

$$\hat{\theta}_i(k|k) = \hat{\theta}_i(k|k-1) + g_i(k)\delta\hat{\theta}_i(k)$$

else

go to signal subspace estimation

endif

V. Simulation Results

We illustrate our approach with a simulation of two targets tracked with a linear array of 12 sensors spaced by a half-wavelength. Fig. 1 is a sketch illustrating the simulated target trajectory. The target velocities are 1,500 ft/s.

The angle sampling period is T=1sec and the number of snapshots during the sampling interval varies from 20 to 60 to demonstrate the performance of the proposed algorithm. For the non-evasive maneuvering target scenario, we assume the track1 and track 2 in Fig. 1. For the evasive maneuvering target scenario, we also assume the track1 and track 3. Table 4 summarizes the tracking performance for non-evasive and evasive targets in SNR = 10 dB after Monte Carlo simulations of 100 runs. Fig. 2 and Fig. 3 show the tracking trajectories in the case of 20 snapshots and 60 snapshots, respectively.

In Table 4, the proposed algorithm is compared with the

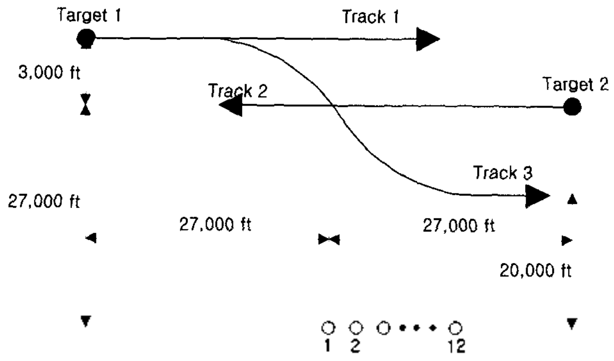
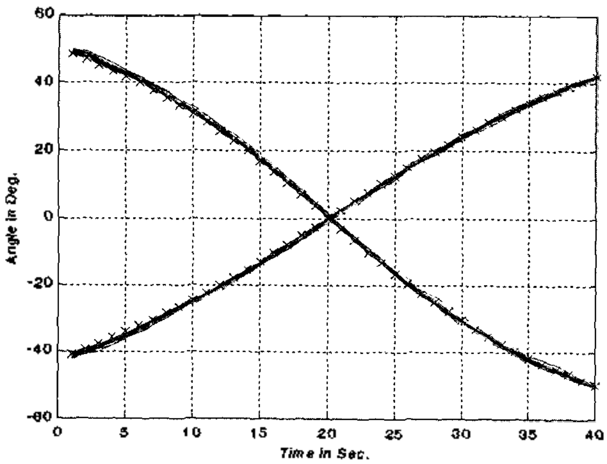
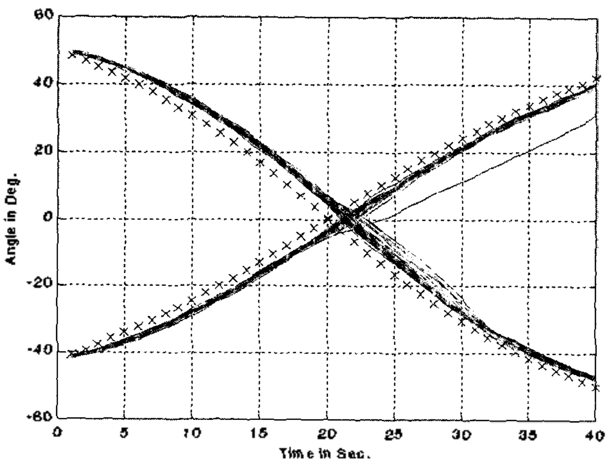


Figure 1. Target simulation geometry in simulation.

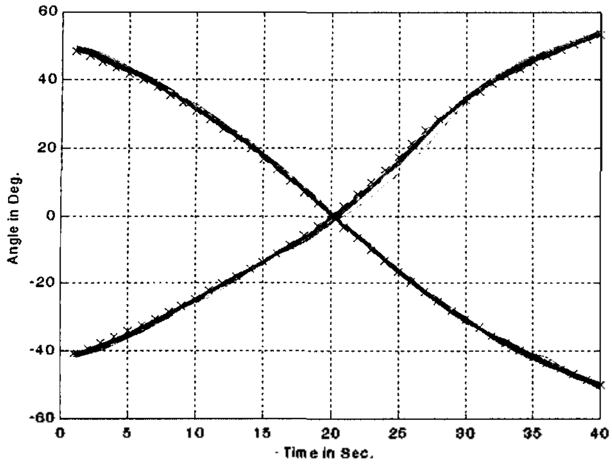


(a) Proposed method in the non-evasive target

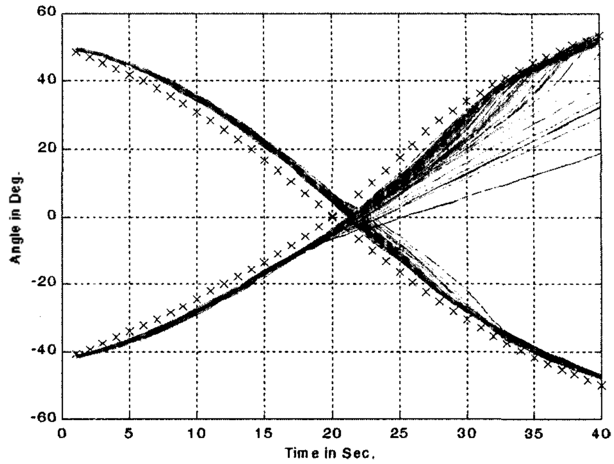


(b) The method in [2] in the non-evasive target

Figure 2. Target Tracking simulation results in 20 snapshots case (x: exact track, solid: estimated track).

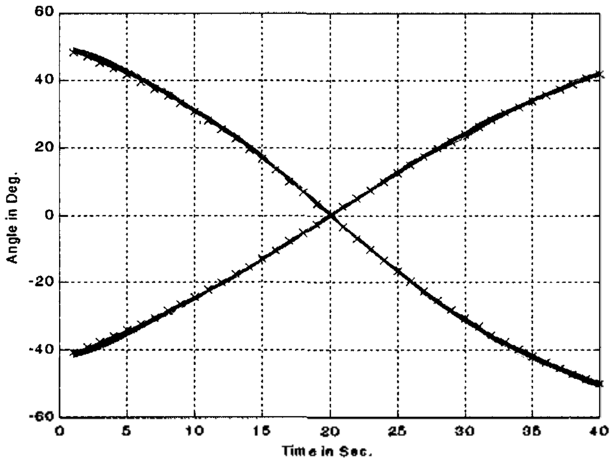


(c) Proposed method in the evasive target

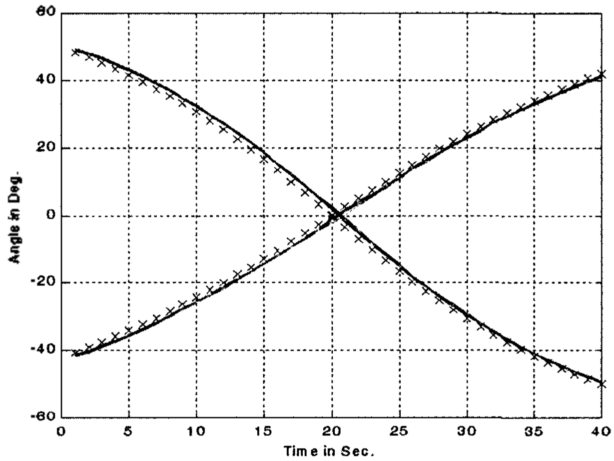


(d) The method in [2] in the evasive target

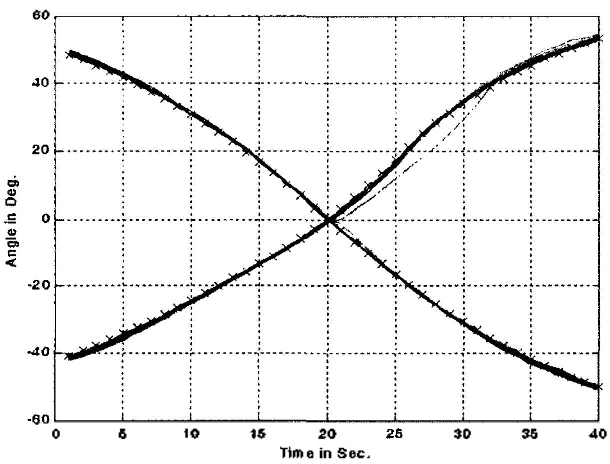
Figure 2. Target Tracking simulation results in 20 snapshots case (x: exact track, solid: estimated track). (Continue)



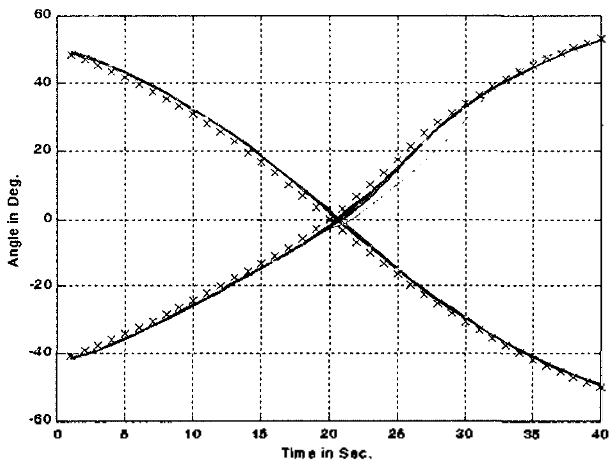
(a) Proposed method in the non-evasive target.



(b) The method in [2] in the non-evasive target



(c) Proposed method in the evasive target



(d) The method in [2] in the evasive target)

Figure 3. Target Tracking simulation results in 60 snapshots case (x: exact track, solid: estimated track).

Table 4. Performance comparison.

Snapshot numbers	Steady Trajectory		Evasive Trajectory	
	Proposed	Ryu's	Proposed	Ryu's
	MSE (deg^2)	MSE (deg^2)	MSE (deg^2)	MSE (deg^2)
20	0.3076	3.7221	0.4588	NA
30	0.2899	1.9161	0.355	NA
40	0.2456	1.1052	0.3131	5.2569
50	0.2371	0.7579	0.2854	2.9227
60	0.2191	0.5784	0.3308	1.8617

NA: fail of tracking

algorithm in[2]. Table 4 shows that the VFF-PASTd application makes tracking algorithm much less sensitive to the number of snapshots than the algorithm in[2]. It also says that the proposed method outperforms in evasive case.

VI. Conclusion

We have presented an improved angle tracking algorithm. The proposed method keeps good tracking even in evasive maneuvering targets. In addition, it shows good performance in low numbers of snapshots as well as in high numbers of snapshots.

References

1. C. K. Sword, M. Samaan and E. W. Kamen, "Multiple target angle tracking using sensor array outputs," *IEEE Trans. Aerosp. Electron. System*, 26 (2), 367-373, 1990.
2. C. S. Ryu, S.-H Lee and K.-K. Lee, "Multiple target angle tracking algorithm using predicted angles," *Electon. Lett.*, 35 (18), 1520-1522, 1999.
3. J.-S. Lim, S.-W. Song and K.-M. Sung, "Variable forgetting factor PASTd algorithm for time-varying subspace estimation," *Electron. Lett.*, 36 (16), 1434-1435, 2000.
4. B. Yang, "Projection approximation subspace tracking," *IEEE Trans. Signal Proc.*, 43 (1), 95-107, 1995.
5. J.-S. Lim, J.-I. Song, Y.-K. Pyeon and K.-M. Sung, "Time-varying subspace tracking algorithm for nonstationary DOA estimation in passive sensor array," *The Journal of The Acoustical Society of Korea*, 20 (1E), 7-13, 2001.

[Profile]

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Jun-Seok Lim was born in Seoul Korea. He received the B. S., M. S. and Ph. D degrees of elecronics engineering in 1988, 1990 and 1999 respectively, from Seoul National University.
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• **Sug-Joon Yoon**

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