Int'l Journal of Computing, Communications & Instrumentation Engg. (IJCCIE) Vol. 2, Issue 2 (2015) ISSN 2349-1469 EISSN 2349-1477

Radar Dwelling Time Design Method Based on Wind Driven Optimization

Zhenkai Zhang, and Sana Salous

***Abstract*—**It is necessary to dynamically control the radar's dwelling time for radar's performance of low probability of intercept (LPI). A novel radar dwelling time control method based on wind driven optimization (WDO) algorithm is presented in this paper, which optimizes the dwelling time of radar during the tracking. Firstly, the predicted covariance matrix is computed. Secondly, the influence of the dwelling time is considered in the tracking performance of the radar. Finally, the dwelling time of the radar is optimized by WDO method. The tracking accuracy and LPI performance are demonstrated in the Monte Carlo simulations. The simulation results show that the proposed method not only has more excellent tracking performance but also saves more dwelling time.

***Keywords*—**Dwelling time, Target tracking, Wind driven optimization, Low Probability of Intercept

I. Introduction

As we know, the less emitted time of the radar, the more excellent performance of the LPI. It is necessary to dynamically control the radar's dwelling time for radar's performance of LPI. The work in [1] develops a generalized framework for the radar task scheduling problem as an optimization model, and all radar task parameters are treated as variables, thereby allowing greater scheduling flexibility and the ability to handle more targets using single radar. The scheduling of track dwells to minimize radar energy and time with an agile beam radar is considered in [2], where the trade between higher energy waveforms and radar time is further investigated. The paper [3] introduces time-windows that specify allowable earliness and lateness of radar tasks, and proposes a chaining process that combines the dwell times and the time-windows of tasks with consecutive priorities. A distributed, consensus-based approach to optimize radar resource management for ballistic missile surveillance and tracking is presented in [4].

Almost all of those works concern the radar's tracking performance instead of the radar's LPI ability. In this paper, a novel scheduling algorithm of radar's dwelling time is proposed. The remainder of this paper is organized as follows. Section II describes the wind driven optimization method. Section III presents the dwelling time scheduling method in details. Simulations of the proposed algorithms and comparison results with other methods are provided in Section IV. The conclusions are presented in section V.

Zhenkai Zhang, College of Electronic Information, JiangSu University of Science and Technology, P. R. China. Email id: zhangzhenkai@126.com

Sana Salous, School of Engineering and Computing Sciences, Durham University, Durham, U.K. Email id: sana.salous@durham.ac.uk

II. Wind Driven Optimization Technique

Building on the successful record of the existing nature-inspired optimization algorithms, the work in [5] introduces and utilizes an entirely new optimization method which is called Wind Driven Optimization (WDO). In the WDO, each air parcel's velocity and position are updated at every iteration as its exploration of search space progresses. Thus, the change in velocity $\Delta\boldsymbol{u}$, can be written as $\Delta\boldsymbol{u}=\boldsymbol{u}_{new}-\boldsymbol{u}_{cur}$, where $\boldsymbol{u}_{cur}$ is the velocity at the current iteration and $\boldsymbol{u}_{new}$ is the velocity in the next iteration. As described in [8], the influence of the Coriolis force is replaced by the velocity influence from anther randomly chosen dimension of the same air parcel, $\boldsymbol{u}_{cur}^{other\ \dim}$, and all other coefficients are combined into a single term c, e.g., $c=-2|\Omega|U_gT_e$. The $\boldsymbol{u}_{new}$ can be written as:

$$\begin{aligned}\boldsymbol{u}_{new} &= (1-\alpha)\boldsymbol{u}_{cur}-g\boldsymbol{x}_{cur}\\ &+\left(U_gT_e\left|\frac{1}{i}-1\right|(\boldsymbol{x}_{opt}\text{-}\boldsymbol{x}_{cur})\right)+\left(\frac{c\boldsymbol{u}_{cur}^{other\ \dim}}{i}\right)\end{aligned} \tag{1}$$

Where Ω represents the rotation of the earth, i represents the ranking among all air parcels, $\boldsymbol{x}_{opt}$ and $\boldsymbol{x}_{cur}$ represent the current location and optimum location respectively, α is the friction coefficient, g is the earth's gravitational field, U_g is the universal gas constant and T_e is the temperature.
Once the new velocity is calculated the position can be updated by utilizing the following equation,

$$\boldsymbol{x}_{new}=\boldsymbol{x}_{cur}+\boldsymbol{u}_{new}\Delta t \tag{2}$$

Where Δt is a time step.

A population of air parcels starts at random positions in the search space with random velocities. Each air parcel's velocity and position are adjusted at every iteration, as the parcels move toward an optimum pressure location and the optimum solution at the end of the last iteration. In this manner WDO offers a simple and effective way to solve complex optimization problems. The implementation of WDO is illustrated in Figure1. As seen in the flowchart, the algorithm starts with the initialization stage, where all parameters related to the WDO as well as the other parameters related to the optimization problem have to be defined. Also, one must define a pressure function as a fitness function, and establish parameter boundaries. Once the optimization problem is set up, the population of air parcels are randomly distributed over the N-dimensional search space and assigned random velocities. The next step is to evaluate the pressure values of each air parcel at its current position.

Once the pressure values have been evaluated, the population is ranked based on their pressure, and the velocity update according to (1) is applied with the restrictions given in (3).

$$u_{new}^{*} = \begin{cases} u_{\max} & if\ \ u_{new} > u_{\max} \\ -u_{\max} & if\ \ u_{new} < -u_{\max} \end{cases} \tag{3}$$

The positions for the next iteration are updated by utilizing (2), and the boundaries are checked to prevent any air parcel from exiting the search space. Once all the updates are carried out, the parcel pressures at the new locations are evaluated. This procedure continues until the maximum number of iterations is reached. Finally, the best pressure location at the end of the last iteration is recorded as the optimization result and, hence, the best candidate solution to the problem.

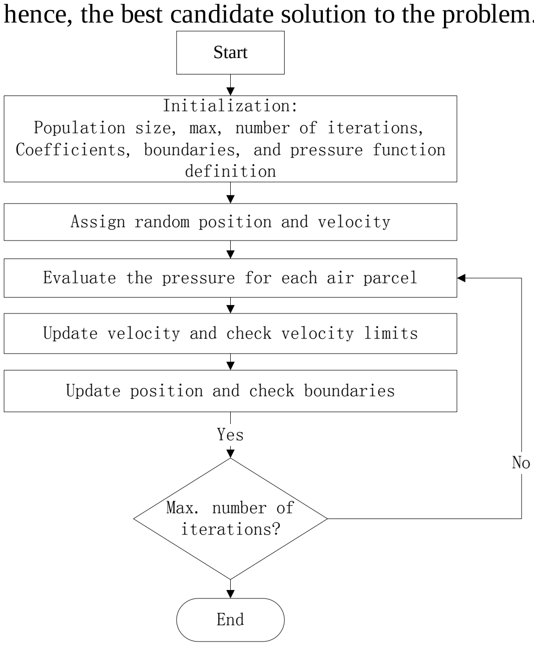


Fig. 1 Implementation of WDO

III. Dwelling Time Scheduling Algorithm Based On WDO

A. Computation of predicted tracking covariance matrix

Let $\boldsymbol{X}(k)$ and $\boldsymbol{Z}(k)$ represent the state vector and the observation vector respectively, the state equation and transfer equation at time k are:

$$\boldsymbol{X}(k+1) = \boldsymbol{\phi}_j(k+1)\boldsymbol{X}(k) + \boldsymbol{w}_j(k) \tag{4}$$

$$\boldsymbol{Z}(k) = \boldsymbol{H}_j\boldsymbol{X}\ \ (k) + \boldsymbol{v}_j(k) \tag{5}$$

Where $\boldsymbol{w}_j(k)$ and $\boldsymbol{v}_j(k)$ are stationary white noise processes with covariance matrices $\boldsymbol{Q}_j(k)$ and $\boldsymbol{W}(k)$ of model j, $\boldsymbol{\phi}_j(k)$ is the transition matrix and $\boldsymbol{H}_j$ is the observation matrix.

The prediction of covariance for model j at time k can be represented as:

$$\boldsymbol{P}_j^{'}(k+1) = \boldsymbol{\phi}_j(k+1)\boldsymbol{P}_{0j}(k)(\boldsymbol{\phi}_j(k+1))^T + \boldsymbol{Q}_j \tag{6}$$

Where, the covariance $\boldsymbol{P}_{0j}(t_{k-1})$ of model j is obtained from all the states and model probabilities of last recurrence.

Then the variance matrix $\boldsymbol{S}_j(k+1)$ and filtering gain $\boldsymbol{K}_j(k+1)$ can be written respectively:

$$\boldsymbol{S}_j(k+1) = \boldsymbol{H}_j\boldsymbol{P}_j^{'}(k+1)(\boldsymbol{H}_j)^T + \boldsymbol{W}_j(k+1) \tag{7}$$

$$\boldsymbol{K}_j(k+1) = \boldsymbol{P}_j^{'}(k+1)(\boldsymbol{H}_j)^T(\boldsymbol{S}_j(k+1))^{-1} \tag{8}$$

The covariance estimation for every model can be represented as:

$$\boldsymbol{P}_j^{pre}(k+1) = (\boldsymbol{I} - \boldsymbol{K}_j(k+1)\boldsymbol{H}_j)\ \boldsymbol{P}_j^{'}(k+1) \tag{9}$$

At last, the predicted covariance matrix is given as:

$$\boldsymbol{P}^{pre}(k+1) = \sum_{j=1}^{r}\boldsymbol{\mu}_j(k)(\boldsymbol{P}_j^{pre}(k)) \tag{10}$$

Where $\boldsymbol{\mu}_j(k)$ is model probability at time k.

B. Design for covariance matrix W_k of measurement noise

The covariance matrix W_k of measurement noise is controlled by the emitted energy. As we know, radar equation at time k is as follows:

$$R_k^4 = t_B^k\frac{P_{av}^kG_TG_R\lambda^2\sigma_k}{(4\pi)^3KT_RS_{NR}^kL} \tag{11}$$

Where t_B^k is the single dwelling time of the beam from the normal direction at time k, P_{av}^k is the average radiated power, G_R is the receiver gain, σ_k is the radar cross section(RCS) of the target, K is Boltzmann constant, T_R and L are respectively effective noise temperature and radar system loss, R_k is the detection range, G_T is the transmit gain, S_{NR}^k represents the signal to noise ratio of the system at time k. Suppose when the target whose range is R_0, the radar has to emit the power P_{av0}, and the radar equation become

$$R_0^4 = t_{B0}\frac{P_{av0}G_TG_R\lambda^2\sigma_0}{(4\pi)^3KT_RS_{NR0}L} \tag{12}$$

Combined (11) with (12), the emitted signal to noise ratio at time k can be written as

$$S_{NR}^k = \frac{t_B^kP_{av}^kS_{NR0}}{t_{B0}P_{av0}}\frac{R_0^4}{R_k^4} \tag{13}$$

Where, the emitted power is supposed to be a constant parameter in this paper.

Range and range-rate measurements are obtained using the type of linear frequency modulated (LFM) Gaussian pulses [6]. The measurement noise covariance is given by:

$$\boldsymbol{W}_k = \begin{bmatrix} \dfrac{c^2p^2}{2S_{NR}^k} & -\dfrac{c^2bp^2}{w_0S_{NR}^k} \\ -\dfrac{c^2bp^2}{w_0S_{NR}^k} & \dfrac{c^2bp^2}{w_0S_{NR}^k}\left(\dfrac{1}{2p^2} + 2b^2p^2\right) \end{bmatrix} \tag{14}$$

Here c denotes the wave speed (m/s), and w_0 denotes the carrier frequency (Hz), $p > 0$ denotes the pulse length (s) and b denotes the sweep rate (Hz/s). b can be positive (LFM upsweep), negative (LFM downsweep) or zero. All the waveform parameters are constant except the signal to noise ratio S_{NR}^k.

We can see that different t_B^k can lead to different $\boldsymbol{W}$. However, during the tracking process, R_k is unknown before radar detection. So R_k in (14) is replaced by R_k^{pre} which is predicted by R_{k-1} and v_{k-1}. R_k^{pre} is presented as

$$R_k^{pre} = R_{k-1} + v_{k-1}T \qquad (15)$$

R_{k-1} and v_{k-1} are the target's range and velocity which are estimated by the IMM tracking algorithm at time k-1, T is the tracking interval.

C. Parcel pressure model for optimization

The desired tracking covariance matrix $\boldsymbol{P}^{des}$ should be set for the *radar* firstly. Then the parcel pressure model is presented as:

$$t_B^{k+1*} = \arg\min_{t_B^{k+1}} \left(trace(\boldsymbol{P}^{pre}(k+1) - trace(\boldsymbol{P}^{des}(k+1))\right) \qquad (16)$$

The WDO method is used to select dwelling time t_B^{k+1} for the tracking at time k+1.

IV. Simulation Results

In this section, Monte Carlo simulations are performed to analyze the performance of the proposed dwelling time scheduling algorithm based the wind driven optimization (WDO). The IMM filter [7] here is comprised of Constant Velocity model (CV) F_{CV} and Coordinated Turn rate model (CT) F_{CT}.

$$F_{CV} = \begin{bmatrix} 1 & T & 0 & 0 \\ 0 & 1 & 0 & 0 \\ 0 & 0 & 1 & T \\ 0 & 0 & 0 & 1 \end{bmatrix} \qquad (17)$$

$$F_{CT} = \begin{bmatrix} 1 & \frac{\sin \omega T}{\omega} & 0 & \frac{1-\cos \omega T}{\omega} \\ 0 & \cos \omega T & 0 & \frac{\sin \omega T}{\omega} \\ 0 & \frac{1-\cos \omega T}{\omega} & 1 & \frac{\sin \omega T}{\omega} \\ 0 & \sin(\omega T) & 0 & \cos \omega T \end{bmatrix} \qquad (18)$$

Where T is the sampling interval, ω is the turn factor, T=2s, $\omega = 0.1$.

A. Trajectory design

Fig. 2 shows the target trajectory in 100s.

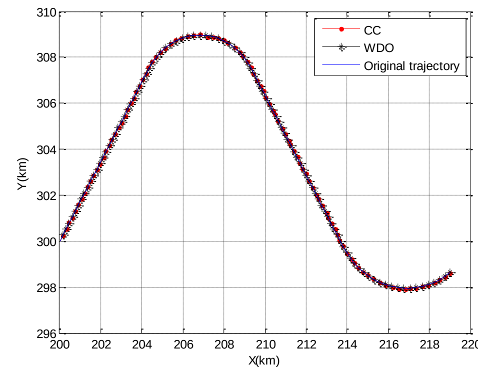


Fig. 2 Trajectory of the target

B. Comparison of tracking performance

The proposed dwelling time design method (WDO), is realized in the simulation, which is also compared with the performance covariance control (CC) in the paper[4]. The Root-mean-square error (RMSE) of time k can be formulated as:

$$\boldsymbol{RMSE}(k) = \sqrt{\frac{1}{M_c}\sum_{m=1}^{M_c}(x_k - \hat{x}_k^m)^2} \qquad (19)$$

Where M_c is the number of the Monte-Carlo simulation, x_k is the true state of the system, $\hat{x}_k^m$ is the estimated vector at the m^{th} simulation, M_c=100.

Fig.3 shows the range RMSE of the proposed method during the tracking.

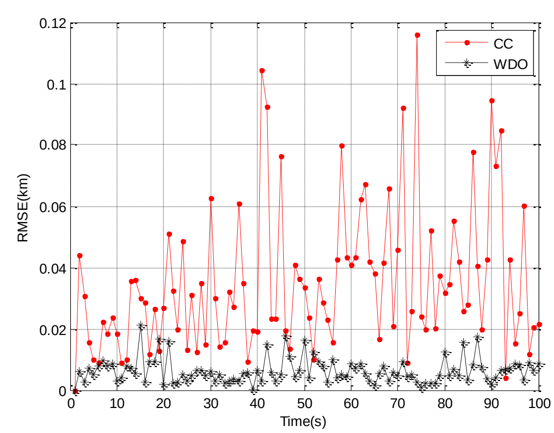
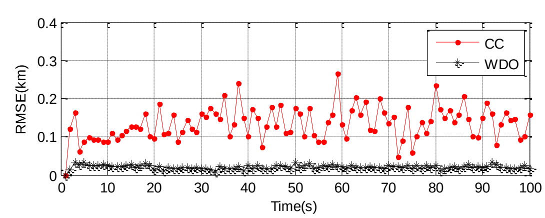
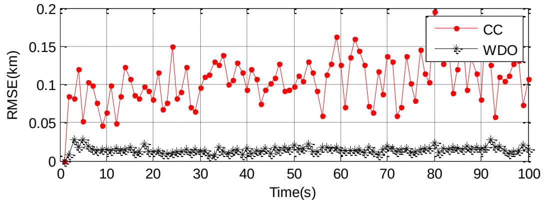


Fig.3 Comparison of tracking performance

Fig. 4(a) and Fig.4(b) show the RMSE of the proposed method in X and Y direction respectively. We can see that the proposed method of WDO presents much more excellent tracking accuracy.



(a) Tracking performance of X direction



(b) Tracking performance of Y direction

Fig.4 Comparison of tracking performance

C. Comparison of dwelling time

Dwelling time of WDO and CC method are shown in Fig. 5, the mean dwelling time of the two methods are 1.9915ms and 2.8334ms. We can see that the proposed method not only present excellent tracking accuracy, but also reduce more radiated time. As it is shown in [5], the position and velocity updates rules in WDO are similar to those in Particle swarm optimization (PSO), however, the gravitational pull within the velocity update equation in WDO can provide advantages over PSO, where particles occasionally attempt to fly out of and sometimes get stuck at the boundaries, preventing their positions from changing for many iterations.

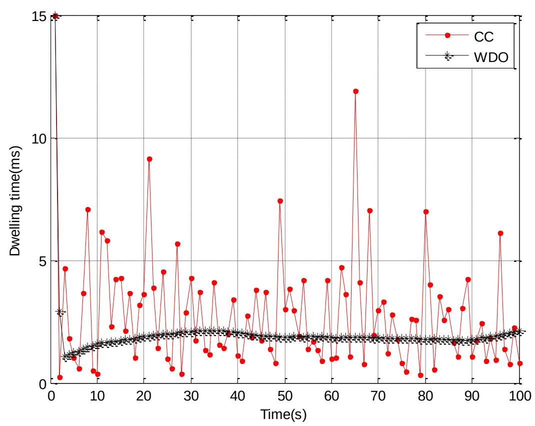


Fig.5 Comparison of dwelling time

V. Conclusions

In this paper, we have presented a new strategy of dwelling time allocation based the WDO method and predicted covariance theory. The dwelling time is obtained after the WDO at every time in order to meet the requirement of the tracking accuracy. The simulation results show that the proposed method can save much more dwelling time with more excellent tracking accuracy.

Acknowledgement

This work was supported by the National Natural Science Funds Fund (61401179), Colleges of Jiangsu Province Natural Science Fund (14KJB510009), the Science and Technology on Electronic Information Control Laboratory Project, Scientific Research Start-up Funding from Jiangsu University of Science and Technology, Fundamental Research Funds for the Central Universities (NJ20140010), and a Project Funded by the Priority Academic Program Development of Jiangsu Higher Education Institutions.

References

[1] H.S. Mir, A. Guitouni. "Variable Dwell Time Task Scheduling for Multifunction Radar," *IEEE Transactions on Automation Science and Engineering*, vol. 11, pp.463-472, April 2014.

[2] J.D. Glass, W.D.Blair, Y.Bar-Shalom. "Optimizing radar signal to noise ratio for tracking maneuvering targets," in *Proc. 17th International Conference on Information Fusion (FUSION)*, Salamanca, 2014, pp.1-7.

[3] Dae-Sung Jang, Han-Lim Choi, Ji-Eun Roh. "A time-window-based task scheduling approach for multi-function phased array radars," in *Proc. 11th International Conference on Control, Automation and Systems (ICCAS)*, Gyeonggi-do, 2011, pp.1250 -1255.

[4] T.A. Severson, D.A. Paley. "Distributed Multitarget Search and Track Assignment With Consensus-Based Coordination," *IEEE Sensors Journal*, vol.15, pp.864-875, February, 2015.

[5] Zikri Bayraktar, Muge Komurcu, Jeremy A. Bossard, Douglas H. Werner. "The Wind Driven Optimization Technique and its Application in Electromagnetics," *IEEE transactions on antennas and propagation*,vol.61, pp. 2745-2757, May 2013.

[6] J.B.D. Cabrera. "Tracker-based adaptive schemes for optimal waveform selection". in *Proc. IEEE Radar Conference*, Cincinnati, OH, 2014, pp.298-302.

[7] Zhenkai Zhang, Jianjiang Zhou, Fei Wang, Weiqiang Liu and Hongbing Yang. "Multiple-target tracking with adaptive sampling intervals for phased-array radar," *Journal of Systems Engineering and Electronics*, vol.22, pp.760-766, October, 2011.