Adaptive passive sensor selection for maneuvering target localization and tracking using a multisensor surveillance system

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Abstract: This paper investigates maneuvering-target tracking problem based on a multisensor system and interacting multiple model (IMM). The estimation is performed by a novel particle filter (PF) with a capability to deal with the state-dependent noises and interference of the sensors’ coverage environment. An adaptive sensor selection algorithm, where some sensors are selected in each stage based on the signal-to-interference pulse noise ratio (SINR) and participate in the state estimation, is proposed. To deal with the effect of interference, we focus on designing and implementing the sensor selection algorithm, where a multisensor system with nonuniform arrays is derived by solving a convex optimization problem. On this basis, a nonuniform array of sensors is selected in each time interval aiming at maximizing the SINR of the received information from the undercoverage area. This would allow tracking in practical environments experiences interference. This method also is able to reduce the tracking error rate.

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PUBLIC INTEREST STATEMENT

In modern society, radar plays an increasingly important role, where the target detection and tracking is among the problems that has attracted the researchers’ attention since long ago and is applied in various fields such as military and commercial environments. A multi-sensor system comprises multiple sensors used for target detection and tracking within the intended area. Advantages of a multi-sensor system include wide coverage area, improved tracking quality, increased identification power, improved target resolution, reduced error probability, and improved capability of the system for tracking maneuvering targets.

Taking the linear arrangement of the sensors into consideration plays an important role in many practical tracking applications. In other words, in many real applications, the assumption that the targets are surrounded by the sensors is not operational. This reveals the importance of considering non-uniform linear arrangement of the sensors. In this paper by considering non-uniform linear arrangement for the set of sensors, the maneuvering targets’ position can be detected in the surveillance and monitoring systems.
Subjects: Systems & Control Engineering; Dynamical Control Systems; Technology

Keywords: maneuvering target tracking; particle filter; interacting multiple models; adaptive sensor selection; SINR maximization; interference

1. Introduction

Being nonexpensive and easily accessible, sensors are commonly used in large numbers in problems such as target tracking. Due to their limited lifetime, it is greatly important to make effective use of the sensors during the target tracking operation. Furthermore, the limitation of bandwidth has made it possible to use only a limited number of sensors concurrently. Therefore, it is of special importance to select a subset of sensors to participate in the target localization and tracking operation (Koch & Fkie, 2014; Popoli & Blackman, 1999).

The target localization using the input angle estimation is one of the most commonly used methods. This method is used in various applications including radar, drone equipment, and wireless telecommunications. So far, many studies have been conducted concerning the localization of active and passive targets. The passive target localization problem can be expressed as a nonlinear least square problem, where the maximum likelihood approach is used to estimate the location of the targets (Herath & Pathirana, 2013). In a tracking using a multisensor array problem, the arrangement and selection of the sensors affect the targets’ tracking precision. This is why numerous studies and research projects are focused on this subject area.

One of the common sensor selection approaches is based on posterior Cramer-Rao lower bound (PCRLB). In Hernández et al. (2004), the authors have proposed a PCRLB-based method for the management of the multisensor systems considering the uncertainty in measurements. The reason for using this criterion for the sensor selection is the fact that it results in a reduction in the target’s state estimation error by applying the prediction of the lower bound of the estimation variance. This criterion is indeed the inverse of the Fisher information matrix. Thus, by using the Fisher information matrix, the sensors containing the most information can be selected for tracking purpose. However, the volume of calculations and long term convergence emerging are considered as the major disadvantages of these methods. In Mohammadi and Asif (2015), a distributed posterior Cramer-Rao lower bound (DPCRLB) algorithm has been presented for the adaptive sensor selection that has lower volume of calculations.

Among other methods that are used for sensor selection, the graph-based method and the PF-based method can be mentioned (Meyer et al., 2017). PF is a powerful tool for the state estimation of the nonlinear systems.

In a multisensor tracking system, effects of the environment on the sensors’ performance should be taken into account. The presence of interference in the environment and the sensors’ bias are two major challenges in a multitarget tracking system. Thus, considering these two effects, measurements of the sensors will not be valid and credible. In Guo et al. (2016), Taghavi et al. (2016), an algorithm has been presented to estimate the bias and compensate it in order to reduce the tracking error rate. In Lee and Song (2016), the task sensor selection for target tracking has been performed on the basis of sensors’ bias variations in the multisensor circumstances. This method necessitates, initially, detection the sensors’ bias variations and, then, selection the valid sensors (those with constant bias) to integrate information. In fact, the strategy of selecting valid sensors is based on the results of the detection of the bias variations.
An efficient approach to confront the effect of interference is to use adaptive beamforming algorithms. The nonuniform array design methods can be considered from this point of view. The building block of nonuniform array selection methods is based on the selection of the sensors that cause the isolation of the subspace of the sources and interference or maximization of the signal power-to-interference ratio. Currently, the application of sparse sensor arrays is highly regarded in many of the sensor systems (Amin et al., 2016; Wang et al., 2017). A fundamental point in designing the optimal sparse arrays is the selection of an appropriate criterion in order to achieve certain objectives such as finding the target’s direction, optimal beam pattern synthesis, and target detection (Jiang et al., 2016; Yang & Niu, 2018).

To date, several studies have been conducted concerning performance improvement of the tracking methods. In He et al. (2018), the authors have presented an algorithm to track the targets with highly-variant maneuvering. In this method, relying on modifications applied to design of the IMM estimator and introduction of a new motion model named white noise turn-rate (WNTR), the rapid variations of the maneuvering targets are detectable. The data allocation methods in multitarget tracking applications are applied by using multiple sensors. In Guo et al. (2017), Wang (2014), the data aggregated from multiple sensors are integrated via data allocation processing methods in order to estimate the target’s location and path more properly.

The current work is aimed to present a new algorithm with the capability to select the optimal array in the presence of multiple interference sources. Having such a feature, the proposed algorithm will be applicable in the multitarget tracking problems. The adaptive selection of the sensors that must contribute to the tracking operation at any time will be performed by the proposed algorithm. Through this algorithm, two objectives including the maximization of the signal power-to-interference ratio and orthogonalization of the vector subspace of the sources and interference are accomplished. Considering the adaptive selection of sensors, some modifications are applied to the tracking algorithm. Therefore, the new algorithm is modified in the particle weighting calculation stage. When the interference is close to the source, a larger weight is assigned to the particles with measurement errors compared to the case that the interference is far from the source. Thus, the standard PF’s weighting stage is modified according to interference distance.

The rest of the paper is organized as follows. In Section 2, the model and equations of the multisensor surveillance system are presented. Section 3 introduces the adaptive sensor selection algorithm based on the SINR maximization. The proposed PF algorithm for reducing the adverse effects of interference is presented in Section 4. In Section 5, the simulation results are provided to demonstrate the proposed algorithm’s performance. Finally, conclusions are provided in Section 6.

2. Multisensor surveillance system
A multisensor system comprises multiple sensors used for target detection and tracking within the intended area. Advantages of a multisensor system include wide coverage area, improved tracking quality, increased identification power, improved target resolution, reduced data allocation ambiguity, reduced error probability, and improved capability of the system for tracking maneuvering targets.

Taking the linear arrangement of the sensors into consideration plays an important role in many practical tracking applications. In other words, in many real applications, the assumption that the targets are surrounded by the sensors is not operational. This reveals the importance of considering nonuniform linear arrangement of the sensors. As shown in Figure 1, by considering nonuniform linear arrangement for the set of sensors, the maneuvering targets' position can be detected in the surveillance and monitoring systems.
According to Figure 1, the given network consists of $N$ sensor nodes, which are deployed in a two-dimensional (2D) space with different distances. Each node is equipped with an angle sensor. All information of the sensors is aggregated in a data fusion center that is located at the center of this environment. The intended targets are able to move in the 2D space and under nearly constant velocity (NCV) and nearly coordination turn (NCT) models. Dynamics of the target are described by the following state vector

$$X(k) = [x(k) \quad v_x(k) \quad y(k) \quad v_y(k) \quad \omega(k)]^T$$

where the entries represent the position and velocity along x-axes, position and velocity along y-axes, and turn rate of the targets, respectively.

The target’s dynamic equation is expressed as follows:

$$X(k + 1) = F_k(X(k), W(k))$$

where $X(k)$ is the system’s state variable at $k^{th}$ sample time and $W(k)$ is the system’s noise vector. Also, in the general case $F_k$ is defined as a nonlinear function on the state variable. The model of the $i^{th}$ sensor’s observations at each $k^{th}$ sample time is represented as follows:

$$z_i(k) = h_i(X(k))(1 + \alpha_i(k)) + v_i(k)$$

where $z_i(k)$ represents observations of the $i^{th}$ sensor, $h_i(\cdot)$ is a nonlinear observation function represents relative angle between target and $i^{th}$ sensor, $\alpha_i(k)N(0, R_i(\cdot))$ is zero-mean white state dependent noise $i^{th}$ sensor with Gaussian probability distribution and covariance matrix of $R_i(\cdot)$, and $v_i(k)N(0, C_i(\cdot))$ is zero-mean white interference and additive noise $i^{th}$ sensor with Gaussian probability distribution and covariance matrix of $C_i(\cdot)$.

Furthermore, the nonlinear function of measured angle is expressed as follows:
\[ h_i(X(k)) = \tan^{-1}\left(\frac{x(k) - x_i}{y(k) - y_i}\right) \quad (4) \]

where \(x_i\) and \(y_i\) indicates the location of the \(i^{th}\) sensor in 2D space.

In these conditions, it can be observed that the angle sensor's measurement noise depends on the distance between sensor and target and the existing interference in undercoverage area. Also, it is assumed that \(a_j\) and \(v_i\) are uncorrelated. As can be seen, equation of the observations consists of two nonlinear terms. Due to nonlinearity of the observations' model, the modified PF is used for tracking the targets.

\(F_{SV}\) in (2) in general is a nonlinear function. Regarding this definition, various dynamic models could be considered for the target. For example, the constant-velocity (CV) dynamic model and the coordination turn (CT) dynamic model are two examples of models for mobile targets.

In a 2D CV mode the state vector of target's dynamics is described by

\[ X_{CV}(k) = \begin{bmatrix} x(k) \\ y(k) \\ v_x(k) \\ v_y(k) \end{bmatrix}^T \quad (5) \]

where the entries represent the position and velocity of the target along \(x\)- and \(y\)-axes. Also, the dynamic model of the target is described by

\[ X_{CV}(k + 1) = F_{CV}X_{CV}(k) + G_{CV}W_{CV}(k) \quad (6) \]

where \(W_{CV}\) is the process noise and \(F_{CV}\) and \(G_{CV}\) are defined as (Li & Jilkov, 2005)

\[ F_{CV} = \begin{bmatrix} 1 & 0 & T & 0 \\ 0 & 1 & 0 & T \\ 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 1 \end{bmatrix} \quad \text{and} \quad G_{CV} = \begin{bmatrix} 0.5T^2 & 0 \\ 0 & 0.5T^2 \\ T & 0 \\ 0 & T \end{bmatrix} \quad (7) \]

\(T\) represents the sampling period and shows the time interval between every two received samples.

To describe the target's turning motions, the CT dynamic mode is considered. In this case, the target's state vector is described by

\[ X_{CT}(k) = \begin{bmatrix} x(k) \\ y(k) \\ v_x(k) \\ v_y(k) \\ \omega(k) \end{bmatrix}^T \quad (8) \]

where \(\omega\) is the target's turn rate. The first four entries of \(X_{CT}\) are the same as those in \(X_{CV}\). The dynamic model of the target is described in 2D coordinates by

\[ X_{CT}(k + 1) = F_{CT}(k)X_{CT}(k) + G_{CT}W_{CT}(k) \quad (9) \]

where \(W_{CT}\) is the process noise and \(F_{CT}\) and \(G_{CT}\) are defined as (Li & Jilkov, 2005)

\[ F_{CT} = \begin{bmatrix} 1 & 0 & \sin(\omega(k)T)/\omega(k) & \cos(\omega(k)T)/\omega(k) \\ 0 & 1 & -\cos(\omega(k)T)/\omega(k) & \sin(\omega(k)T)/\omega(k) \\ 0 & 0 & \cos(\omega(k)T) & -\sin(\omega(k)T) \\ 0 & 0 & \sin(\omega(k)T) & \cos(\omega(k)T) \end{bmatrix} \quad \text{and} \quad G_{CT} = \begin{bmatrix} 0.5T^2 & 0 \\ 0 & 0.5T^2 \\ T & 0 \\ 0 & T \end{bmatrix} \quad (10) \]
As can be clearly seen, due to the presence of target’s turn rate \( \omega \) in components of \( F_{CT} \), the NCT dynamic model would be nonlinear.

Equation (3) can be aggregated in the following form to represent a model of the unit observations

\[
Z(k) = h(X(k)) + V(k)
\]

where \( Z(k) = \text{col} \{ h_1(X(k)) \} \), \( 1 \leq i \leq N_s(k) \) is the observations vector and \( V(k) = \text{col} \{ n_1(k) + h_i(X(k)) \alpha_i(k) + V_i(k) \} \), \( 1 \leq i \leq N_v(k) \), \( 1 \leq l \leq N_l(k) \) is the state-dependent noise and interference vector. Here, \( \text{col} \{ \cdot \} \) represents a column vector of the elements inside the brackets, \( N_i \) indicates the number of interferences existing within the undercoverage area, and \( N_s \) represents the number of sensors selected for the tracking operation.

### 3. Adaptive selection of sensors for SIR maximization

It is assumed that the target’s source direction vector and the interference source direction vector are demonstrated as \( [\varphi_1 \ldots \varphi_p] \) and \( [\vartheta_1 \ldots \vartheta_q] \), respectively. In such a case, the steering vectors are defined as

\[
s_w = [e^{j\varphi_1 \lambda} \cos \theta, \ldots, e^{j\varphi_p \lambda} \cos \theta]^T \quad N = 1, \ldots, p
\]

\[
v_l = [e^{j\vartheta_1 \lambda} \cos \theta, \ldots, e^{j\vartheta_q \lambda} \cos \theta]^T \quad l = 1, \ldots, q
\]

where \( x = 2\pi / \lambda \) (\( \lambda \) indicates the wavelength) and \( d \) indicates the distance between two sensors. Then, the signal received by the array of sensors is defined as

\[
x(k) = S u_s(k) + V u_l(k) + n(k)
\]

where \( S = [s_1 \ldots s_p] \in \mathbb{C}^{K \times p} \) and \( V = [v_1 \ldots v_q] \in \mathbb{C}^{K \times q} \) represent the array matrices of source and interference signals, respectively. Also, \( u_s(k) \) and \( u_l(k) \) represent the model vectors of the signal and interference at sample time \( k \), and \( n(k) \) is assumed as the Gaussian white noise vector. Finally, the beamforming output resulting from the nonuniform \( N \)-sensor array is defined as follows:

\[
y(k) = w^H x(k)
\]

where \( w \) indicates the vector of the beamforming weighting coefficients. The results obtained in Wang et al. (2017) show that the optimal beamforming coefficients can be determined by solving the following optimization problem

\[
\min w^H R_n w
\]

\[
s.t. w^H R_n w = 1
\]

where \( R_n \) and \( R_s \) are defined below.

\[
R_s = S C_s S^H
\]

\[
R_n = V C_s V^H + \sigma_n^2 I
\]
In these equations, \( C_s = E\{u_s(k)u_s(k)^H\} \) and \( C_v = E\{u_v(k)u_v(k)^H\} \) represent the correlation matrices of the source and interference signals, respectively, and \( \sigma_n^2 \) indicates value of the noise power level. Using the Lagrangian method, the optimal solution for the aforementioned optimization problem can be obtained from the following relation (Wang et al., 2017):

\[
w_{opt} = P\{R_{n}^{-1}R_s\} \tag{19}
\]

This solution is known as the minimum variance distortionless response solution for beamforming of the sensor array. \( P(\cdot) \) represents the principal eigenvector of a matrix. Furthermore, the maximized SINR value is obtained using the following relation:

\[
\text{SINR}_{\text{opt}} = \frac{w_{opt}^H R_s w_{opt}}{w_{opt}^H R_n W_{opt}} = \lambda_{\text{max}} \{R_{n}^{-1}R_s\} \tag{20}
\]

where \( \lambda_{\text{max}}(\cdot) \) defines principal eigenvalue of a matrix, which is the biggest eigenvalue of the matrix. Algorithm 1 summarizes the sensor selection approach.

Algorithm 1: Sensor selection algorithm.

1. Assume the initial value \( z_0 = 0 \), and initializing vectors \( [\varphi_1 \cdots \varphi_p] \) and \( [\psi_1 \cdots \psi_q] \) as the input direction of the sources and interference.
2. Calculate the steering vectors using the following equations for each sensor:
   \[
s_r = [e^{jkd\cos\varphi_1}, \ldots, e^{jkd\cos\varphi_p}]^T, r = 1, \ldots, p.
   \]
   \[
v_l = [e^{jkd\cos\psi_1}, \ldots, e^{jkd\cos\psi_q}]^T, l = 1, \ldots, q.
   \]
3. Calculate the correlation matrices of the sources and interference \( C_s \) and \( C_v \).
4. Generate a random vector \( z^{(i)} \in \mathbb{R}^n \) with a uniform probability distribution within \( (0, 1) \).
5. Find the optimal value of \( z^{(m)}_o \) by solving the following convex optimization problem:
   \[
   \max \ f(z^{(m)}) + \frac{1}{2} \left( z - z^{(i)} \right)^T \left( z - z^{(i)} \right) - \|W\|_2^2
   \]
   \[
   \text{s.t.} \quad \begin{bmatrix} V^{H}\text{diag}(z)V & V^{H}\text{diag}(z)S_2 \intertext{and building on uniform structure of the linear array.}
   \end{bmatrix} \begin{bmatrix} S_2^{H}\text{diag}(z)V & W \end{bmatrix} \leq 0.
   \]
6. Calculate the SINR value for the non uniform array from the following equation:
   \[
   \text{SINR} = \lambda_{\text{max}} \{R_{n}^{-1}R_s\}.
   \]
   Return to Step 2.
   \[
   i \rightarrow i + 1.
   \]
7. Compare the calculated SINR values for different \( z^{(i)} \) arrays and selecting the optimal array based on the maximum SINR value.

To find the binary solution for the selection vector \( z \), a random method is used, which is presented in Algorithm 2. The optimal value of \( z \) represented by \( z_{opt} \) is a binary vector with entries 1 for location of the selected sensors.
Algorithm 2: The random method of finding the selection vector $z$.

1. Assume the initial value $i = 0$ and the maximum frequency of $i_m$.
2. Generate a random vector $z^{(i)} \in \mathbb{R}^n$ with a uniform probability distribution within the range of $(0, 1)$.
3. A logical comparison between $w$ and $z_{out}$ obtained from the optimization problem and forming the binary vector $t$, $t := (w < z_{out})$
4. If the number of nonzero entries is 1, then calculate the SINR value.
   \[ \text{SINR} = \lambda_{\text{max}} \{ R_i^{-1} R_j \} \]
5. If $\text{SINR} > \text{SINR}_m$
   \[ \text{SINR} = t, \text{SINR}_m = \text{SINR}. \]
6. If $i < i_m$
   $i \leftarrow i + 1$. Return to Step 1.

\section{State estimation in the presence of state-dependent noise and interference}

Aiming to reduce the effect of state-dependent noise and interference on the multisensor systems, a new algorithm is presented, which is based on a new PF which differs from the classical methods in the resampling stage. The main idea underlying the resampling is the elimination of the particles with lower weight and putting focus on the higher-weight particles. Execution of this algorithm includes the following stages.

\subsection{Interaction}

In this stage, first, the probabilities of combination at the $k^{th}$ time step are calculated as follows:

\[ \mu_{ij}(k|k) = \frac{1}{c_j} \Phi_{ij} \mu_i(k) \]  
\[ c_j = \sum_{j=1}^{m} \Phi_{ij} \mu_i(k) \]

where $i$ and $j$ represent modes. Combination probability $\mu_{ij}(k|k)$ is indeed the probability that the target moves at time $k - 1$ under mode $i$ and at time $k$ under mode $j$. Moreover, $\Phi_{ij}$ is the probability of the transmission of the motion from mode $i$ to mode $j$. $\mu_i(k)$ is the probability of mode $i$ at time $k$ and $c_j$ is the normalized constant that is defined as follows:

\[ \hat{X}_0(k) = \sum_{i=1}^{m} X_i(k|k) \mu_{ij}(k|k) \]
\[ \hat{P}_0(k) = \sum_{i=1}^{m} \mu_{ij}(k|k) \{ P_i(k|k) + [ \hat{X}_i(k|k) - \hat{X}_0(k|k)] [ \hat{X}_i(k|k) - \hat{X}_0(k|k)]^T \} \]
\[ \hat{X}_i(k|k) \] and $P_i(k|k)$ are the state estimation vector and the related covariance matrix, which is calculated by the PF for each mode at each sample time.

\subsection{Prediction}

In this stage, by applying the new observations and $\hat{X}_0(k|k)$ obtained from the previous stage, the PF prediction is performed for each mode. To do so, the stages of initialization, sampling, and calculation of weights for each mode are performed and then the predicted particles, $\{ X^n_i(k+1) | k \}_{n=1}^{N_i}$, and their corresponding weights, $\{ w^n_i(k+1) | k \}_{n=1}^{N_i}$, are calculated. In the
sampling stage, state transmission function is used. In the particle weighting stage, effects of the state-dependent noise and interference are considered to obtain the likelihood function.

By applying a method described in (Keshavarz-Mohammadiyan & Khaloozadeh, 2017a), the likelihood function of the given problem is determined as

\[ p(Z(k + 1) | X(k + 1)) = p_{V(k + 1)}(Z(k + 1) - h(X(k + 1)) \]  

where \( p_{V(k + 1)}(\cdot) \) is the probability density function of the state-dependent noise vector of sensor and interference in (21). This density function has a multivariate Gaussian distribution. Therefore, the likelihood function is obtained as follows:

\[ p(Z(k + 1) | X(k + 1)) = \frac{1}{\sqrt{(2\pi)^{N_v} \det(R(k + 1))}} \exp \left( -\frac{1}{2} (Z(k + 1) - h(X(k + 1)))^T R^{-1} (Z(k + 1) - h(X(k + 1))) \right) \]  

where \( \psi_j \) (the innovation vector) and \( R(k + 1) \) are defined below

\[ \psi_j = Z(k + 1) - h(X(k + 1)) \]  

\[ R(k + 1) = h_i(X(k)) \delta_{j} + \delta_{j} + V \Sigma V^T \]  

Finally, the non-normalized weights of the particles for each mode are calculated through

\[ \tilde{w}_{j}(k + 1) = p(Z(k + 1) | X(k + 1)) \]  

To calculate the normalized weights, the weights must be divided by the sum of all weights (total weight) (Keshavarz-Mohammadiyan & Khaloozadeh, 2017a).

4.3. Updating the probability of mode changes

In this stage, the probability of modes at time \( k + 1 \) is updated using the residuals vector in the filters. The residual vector of the \( t^{th} \) mode can be calculated as follows:

\[ e_j^{(n)}(k + 1) = Z(k + 1) - Z_j^{(n)}(k + 1|k) \]  

where \( n \) is the number of the intended particle, \( Z(k + 1) \) is the vector of observations at time \( k + 1 \), and \( Z_j^{(n)}(k + 1|k) = \text{cal} \{ h(X_j^{(n)}(k + 1|k)) \} \) is the predicted observations vector of the \( t^{th} \) mode. The covariance matrix of residual of each mode can be determined as follows:

\[ S_j(k + 1) = \frac{1}{N_p} \sum_{t=1}^{N_p} \{ (Z_j^{(n)}(k + 1|k) - \bar{Z}_j(k + 1|k))(Z_j^{(n)}(k + 1|k) - \bar{Z}_j(k + 1|k))^T \} \]  

where \( \bar{Z}_j(k + 1|k) = \frac{1}{N_p} \sum_{t=1}^{N_p} Z_j^{(n)}(k + 1|k) \) is average of the predicted observations vectors. Assuming the Gaussian distribution, the likelihood function for updating the probability of the modes is expressed as

\[ \Lambda_j(k + 1) = \frac{1}{N_p} \sum_{t=1}^{N_p} \Lambda_j^{(t)}(k + 1) \]  

Then, the probability of each mode is updated as
\[ \mu_j(k + 1) = \frac{1}{c} \Delta_j(k + 1) \]  \hspace{1cm} (33)

where \( c \) is obtained from dividing the sum of the likelihood functions by the total number of modes.

4.4. Resampling and state estimation
In this stage, by executing the resampling and state estimation for each filter, the estimated vector for each mode \( \hat{X}_j(k+1|k+1) \) and its covariance matrix \( P_j(k+1|k+1) \) are obtained.

4.5. Combination
Finally, the outputs of the filters of different modes are combined to obtain the final estimation.

\[ \hat{X}(k+1|k+1) = \sum_{j=1}^{m} \hat{X}_j(k+1|k+1) \mu_j(k+1) \]  \hspace{1cm} (34)

\[ P(k+1|k+1) = \sum_{j=1}^{m} \mu_j(k+1)(P_j(k+1|k+1) + \\
\left( \hat{X}_j(k+1|k+1) - \hat{X}(k+1|k+1) \right) \left( \hat{X}_j(k+1|k+1) - \hat{X}(k+1|k+1) \right)^T) \] \hspace{1cm} (35)

As it is observed, the proposed algorithm differs from the standard PF in the weight calculation stage. The first term on the right side of (26) has no effect on the proposed filter’s performance because the effect of this term is eliminated in the weights normalization stage. In the second terms of this equation, which is the exponential part, \( R(k+1) \), in contrast to standard PF, is not constant and depends on the distance between the sensors and target (SINR) and the interference of the environment that is under the sensors coverage. Therefore, whenever the SINR value and interferences of sensors’ undercoverage environment are high, the entries of \( R(k+1) \) are large and thereby, it will have a wider Gaussian-distribution likelihood function in comparison to the cases that the SINR has lower values and there is no interference within the undercoverage environment. This means that when distances between the target and sensor are long, the presence of state-dependent noise of observation and interference would result in higher measurement error rates. The particles with bigger measurement errors are assigned with higher weights compared to the cases with a shorter distance between the target and sensor and less interference. Therefore, in the resampling stage, those particles with bigger measurement errors are replicated with higher probability and eliminated with lower probability. On the other hand, when there is a short distance between the sensor and target and the measurements are performed with higher precision and accuracy, the search space will become smaller and also there will be a higher probability for the elimination of the particles with bigger measurement errors. According to these explanations, in the case of using the proposed algorithm, the adverse effect of the state-dependent noise and interference can be reduced compared to the standard PF.

5. Simulation results
First, the general block diagram of the system is examined. The proposed system in this work is aimed at sensor selection and multtarget tracking in the presence of multiple sources of interference and state-dependent noise. By adding the navigation block, the given problem can be converted into a simultaneous navigation and tracking problem and the sensor selection block can be considered as a part of the navigator block. The block diagram of the proposed system is illustrated in Figure 2.

As can be seen in Figure 2, the existing signals in the undercoverage area are considered by the sensors of linear uniform array as the input of navigator section. In this section, the number and direction of active sources as well as the direction of the interference signals are estimated, and then the obtained information is sent to the sensor selection section. This section, regarding the
obtained information about the sources and their direction, selects the nonuniform linear array structure. In such a case, only the sensors existing in nonuniform array are considered as active sensors, and only these sensors send the information related to the direction of the input signal of different targets to the target tracking section.

In this case, we are going to carry out the sensor selection using the proposed algorithm and based on the input angles of the sources and interference. To do so, a linear uniform array consisting of 100 sensors is considered. The aim of sensor selection is to choose 20 passive sensors and design a linear nonuniform array. To do this, three maneuvering targets, with a combination of the CV and CT models, are considered. These targets are moving within the time interval [0, 200]. Features of the maneuvering of three selected targets are provided in Table 1.

The variance of cumulative and state-dependent noises of the observations for all three targets has been considered as $\sigma^2_0 = 0.6$ and $\sigma^2_n = 0.006$. Besides, it is assumed that the undercoverage area has been disturbed by five interference signals. The interference angles were assumed as follows:

$$\vartheta = \{20^\circ, 70^\circ, 100^\circ, 120^\circ, 140^\circ\}$$

Moreover, the number of particles in the PF has been assumed equal to 1500. Also, the new resampling method is used to reduce the effect of interference and state-dependent noise. Figure 3 illustrates the beamforming pattern at one of the given times of the first interval, where the closeness of the angles of the sources and interference can be clearly observed.

Regarding the block diagram in Figure 2, it can be said that the tracking section receives the information on the target's input angles from the DOA section. In other words, the computational load includes determination of the number of active sources in each time interval and recognition of the sources' input angle on the DOA section, which can be accomplished by applying the algorithms such as the multiple signal classification (MUSIC). The sensors' undercoverage area

| Table 1. Dynamic model of the targets’ motion |
|-----------------------------------------------|
|                               | [0, 40] | [40, 90] | [90, 110] | [110, 160] | [160, 200] | Starting point | Sampling range |
| Target-1                        | CV      | CT      | CV       | CT        | CV        | [5, 5]        | 0.1           |
| Target-2                        | CV      | CV      | CT       | CT        | CV        | [20, 5]       | 0.1           |
| Target-3                        | CV      | CV      | CV       | CT        | CV        | [50, 5]       | 0.1           |

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https://doi.org/10.1080/23311916.2020.1798580
and targets tracking performance are represented in Figure 4. In this figure, the black-colored path is the actual path of the target, and the green-colored curve represents the estimated path. The target tracking error is shown in Figure 5.

The RMSE error criterion obeys the following relation

\[
RMSE = \sqrt{\frac{1}{n_T N_f} \sum_{k=1}^{N_T} (x_{\text{estimate}}(k) - x_{\text{true}}(k))^2}
\]  

(37)
where $N_T = 200$ is the length of the time interval and $n_s$ is the length of the state vector. Also, $x_{\text{estimate}}(k)$ indicates the estimated state vector at the $k^{\text{th}}$ sample time. These results indicate that the highest error rate occurs when the targets pass over the linear array of sensors. In other words, the reduction in the value of targets’ input angle and its inclination toward zero will disturb the performance of the PF. The reason for such an effect is the presence of an inverse tangential nonlinear function as the observations function. Moreover, the error rate is increased also in the case that the dynamic model of the target varies. However, considering the obtained results, the RMSE value under the conditions of this simulation is quite acceptable. Now, the value of observations noise variance is increased and then the simulation is repeated again. In this case, the noise variance is assumed as $\sigma_n^2 = 0.06$.

As it is observed, even in the case that the noise variance is increased tenfold, the tracking operation is still performed. Of course, the increase in tracking error rate compared to the previous case is inevitable. The undercoverage area and the error diagram for this case are demonstrated in Figures 6 and 7. On the basis of these figures, it can be concluded that the highest error rate is related to time of the dynamic model changes and during the target’s motion in the CT motion mode. Also, when Target-1 is passing the linear array’s boundaries, the error rate is increased, which is due to the reduction in target’s input angle and its inclination toward zero.

As can be seen in Table 2, the standard PF method is associated with the highest mean position error because this filter does not take into account the interference and state-dependent noises in its relations. The proposed algorithm provides the lowest mean position error.

The computational load and tracking accuracy of the proposed adaptive particle filter have been compared to those of the UPF and standard particle filter by performing a total of 100 Monte Carlo simulations. The same state space representation as (2) and (3) are used for the UPF and the standard particle filter. The results obtained from these simulations are presented in Table 3. The total execution time of the mentioned estimators has been calculated using the tic/toc commands of MATLAB software run in a PC with 3.1 GHz Intel Core-i7 processor and 1.5 GB RAM. As it is observed, the RMSE value of the proposed estimator is considerably lower than that of the standard particle filter and UPF. Moreover, the total time required for executing the proposed adaptive particle filter is so much less than the UPF estimator. Consequently, in the case of considering both “execution time” and “execution
Figure 6. The undercoverage area and estimated path of targets.

Figure 7. The RSME error rate in the various target tracking conditions.

Table 2. Tracking precision for a target (100 Monte Carlo simulations)

| Noise variance value | Number of interferences | Estimators          | Mean RSME of position (m) | Mean RSME of velocity (m/s) |
|----------------------|-------------------------|---------------------|---------------------------|-----------------------------|
| $\sigma_a^2 = 0.06$  | 5                       | Standard PF         | 1.1348                    | 0.2832                      |
|                      |                         | Proposed algorithm  | 0.5629                    | 0.2002                      |
| $\sigma_a^2 = 0.06$  | 5                       | Standard PF         | 31522                     | 0.3661                      |
|                      |                         | Proposed algorithm  | 1.8321                    | 0.2511                      |
accuracy" criteria, the proposed particle filter is an appropriate choice for solving the state estimation problems with state-dependent noise and intervention.

6. Conclusion

Target tracking is among the problems that has attracted the researchers' attention since long ago and is applied in various fields such as military and commercial environments. Among the methods, tracking the target by multisensor systems is especially important, owing to its advantages including low cost as well as flexibility and tolerance against errors.

The use of passive sensors is unavoidable in many practical applications. Such a limitation brings about many challenges in the presence of noise and interference signals. Therefore, it is highly important to provide methods that can reduce the effect of noise and interference through sensor selection. In the present work, using the proposed algorithm, at each time interval, a nonuniform array of the sensors of a multisensor system, which yields a maximized SINR, is selected in order for receiving information from the undercoverage area. In addition, regarding the given challenges, a new PF is presented, which differs from the standard PF in the weighting stage. Such a modification in the PF reduces the adverse effects in the tracking stage and also reduces the tracking error rate in the environments associated with state-dependent noise and interference.

### Funding

The authors received no direct funding for this research.

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### Citation information

Cite this article as: Adaptive passive sensor selection for maneuvering target localization and tracking using a multisensor surveillance system, S. N. Hosseini, M. Haeri & H. Khalozaedeh, Cogent Engineering (2020), 7: 1798580.

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