International Journal of Grid Distribution Computing
Vol. 8, No.5, (2015), pp.233-244
http://dx.doi.org/10.14257/ijgdc.2015.8.5.23

The Optimization Assignment Model of Multi-sensor Resource Management Based on Rough Entropy

Xiang-yang Chen[1] and Sun-yong Wu[2]

School of Mathematics and Computating Science，Guangxi key Laboratory of Crytography and Information Security, Guilin University of Electronic Technology，Guilin,Guangxi, China, 541004
E-mail:xiangyangchenip@163.com
School of Mathematics and Computating Science，Guangxi key Laboratory of Crytography and Information Security, Guilin University of Electronic Technology，Guilin,Guangxi, China, 541004
E-mail:wusunyong121991@163.com

Abstract

The management of Multi-sensors in information fusion system occupies an important role with the development of modern weapon platform. Therefore, scientific and rational management of limited sensors resources is essential or urgent, and improvement the capability of air defense operations is necessary. According to the management optimization problem in Multi-sensor optimal resource, we analyzed the definition of rough entropy and presented the method of Multi-sensor management based on rough entropy and target threat degree. By calculating rough entropy of the sensors to the target, the maximum information gain access for each sensor on each target, which acts as cost function, taking into account the target threat degree, and using a linear programming optimization assignment multi-sensor to multi-target. In this paper, we adopted maximum information gain optimization criterion in target tracking, then discussed optimization assignment problem about multi-sensor to multi-target. In addition, we are validate the optimized allocation algorithm with the experimental simulations, and case analysis shows that the effectiveness of the method.

Keywords: *Multi-sensors management, Rough entropy, Target threat degree*

1. Introduction

Due to sensor management technology started lately, current maturity methods are limited. Sensor management decides how to select sensors, operation mode of sensors and sensor search strategies in order to optimize the overall performance system. Reference [1] proposed sensor search strategy based on the maximum detection probability, which is a higher success rates strategy for searching a single goal, but higher error rates for multi-objective; References [2] and [3] put forward resource allocation method for single sensor and multi-sensor to multi-target based on resolution, but required to a prior probability distribution before define the resolution;

Reference [4] offered a method of sensor management based on efficiency function, although the method is easily and widely used, some reasonable quantification of factors need further study. From the references [5-8] can be seen that, hot research direction is the management of wireless sensor networks, management of multi-sensor fusion detection and tracking, but study of management multi-sensor for air defense combat system in an extremely rare.

In modern warfare, battlefield environment is constantly changing, in order to get the best fighting effect, so the sensor quantity, quality, and synergy between sensors are put

ISSN: 2005-4262 IJGDC

forward higher requirements. Therefore, Multi-sensor data fusion technology is driven by such emergence requirements. Multi-sensor data fusion not only emphasizes synthesis of the multiple information sources, but also requires the coordination and management of the sensor. Sensor management studies how to select a sensor, how to select sensors, operation mode of sensors, so that unit sensor and sensor group might be effectively meet mission even it distributed across different platforms.

Some studies on the issue have been reported [9], such as Leon and Heller describes management and control expert system for sensor network. Slagel and Hamburger studied resource allocation for the weapon on target system, and so on. These theory can be done the management of sensors, but, from the practical point of view, if considered target information (such as distance, threats etc.) can make the management more effective and more consistent with the actual situation in the sensor management. For example, assigning radar to track the target, give priority to track whose the largest threaten goal is more reasonable.

Therefore, according to the management optimization problem in Multi-sensor optimal resource, we analyzed the definition of rough entropy and presented the method of Multi-sensor management based on rough entropy and target threat degree. By calculating rough entropy of the sensors to the target, the maximum information gain access for each sensor on each target, which acts as cost function, taking into account the target threat degree, and using a linear programming optimization assignment multi-sensor to multi-target. At same time, we adopted maximum information gain optimization criterion in target tracking, then discussed optimization assignment problem about multi-sensor to multi-target. In addition, we are validate the optimized allocation algorithm with the experimental simulations, and case analysis shows that the effectiveness of the method.

2. The Optimization Linear Assignment Model of Multi-Sensor Resource Management Distribution

Sensor target optimized assignment problem for networked air defense combat system, can be regarded as/multi-sensor multi-target tracking problem, of course, should take into account the regional target detection, recognition, control of bi static or multi static radar transmitting timing, and management of sensor probe mode. Therefore, the core issues of linear programming model for sensor resources optimal allocation, is bases a set of criteria, and establish an easily quantified objective function and some constraints of sensor resource, then obtain efficient allocation of sensor on the target following optimization of the objective function.

2.1. Linear Assignment Model

Setting sensor s was assigned to the target m, earnings is E_{sm}, optimization targets are for all or specified goal, and obtain the maximum sensor efficiency. After a given tracking performance scale of sensor to the target, target sensor can be assigned to the target.

Problems can be described as: the sensors are recorded as $s=1,...,S$, goals are recorded as $m=1,...,M$, each sensor has a fixed testing capacity c_K , meaning sensor can detect the maximum number for each time scanning. So, linear programming model for optimal allocation of sensor resources can be definitions as follows[10]:

$$\text{Maximize} \quad C=\sum_{i=1}^{2^{S-1}}\sum_{j=1}^{T}E_{ij}x_{ij} \tag{1}$$

$$\sum_{i=1}^{2^{S-1}} x_{ij} \le 1 \qquad 1 \le j \le T \qquad (2)$$

$$\sum_{i e V(K)} \sum_{j=1}^{r} x_{ij} \le c_K \qquad 1 \le K \le S \qquad (3)$$

$$x_{ij} \ge 0 \qquad all\ \ i\ \ and\ \ j \qquad (4)$$

Taking into account may be have more than one sensor is assigned to the same objective, virtual sensors can be consisted of a single sensor and allow the virtual sensor as a single sensor is assigned to a target. Thus, the number of "sensor" increased from s to the number of 2^{S-1} and the question became how to optimization assigned all these single and virtual sensors.

2.2. Constraints

In the assignment problem, there are some constraints, and one of the most important constraints is the maximum number of each sensor tracking, that is, for a given specified period of time, a sensor can only scan a certain space and follow up a certain number of goals. During a specific time period, they do not exceed their maximum tracking size. If the maximum number of tracking for every single sensor is known, it must also be taken into account this limitation for assigning virtual sensor. Therefore, the above constraint can be handled as follows: the numbered from 1 to s for single sensors and virtual sensor number is from $S+1$ to 2^S-1 For each single sensor K, setting $V(K)$ is integers set which is consisting of a single sensor k and virtual sensor containing a single k sensor, and each $V(K)$ has 2^{S-1} integer. For example there are 3 single sensor, that is, S=3 and 2^{S-1}. They are *S1, S2, S3, ..., S7*.

S4={ S1，S2}，S5={ S1，S3}，S6={ S2，S3}，S7={ S1，S2，S3}. Integer set $V(K)$ contains $2^{S-1}=4$ integer, in which, *V(1)={1，4，5，7}，V(2)={2，4，6，7}，V(3)={3，5，6，7}*. Maximum number of tracking for single sensor K is c_K . In the Solution of LP, $x_{sm} = 0$ or $x_{sm} = 1$, $x_{sm} = 1$indicates that the sensor s assigned to the target *m*.

The equation (1) calculates total returns of the sensor to target. The equation (2) calculation sensor number which is assigned to the target j , including the virtual sensor. This constraint means that just one sensor (or virtual sensor) is assigned to the target. According set *V(k)* , the equation (3) ensure that the tracking number assigned to a single sensor does not exceed the number maximum tracking of sensors, and virtual sensors will be assigned to a single target. If target numbers are greater than the total track capacity, equation (2) allows certain target does not assign the sensor. In multiple-objective/multiple sensor environments, the plan is coordinate multiple sensors to word. A limited number of targets can only be observed for each sensor at each detection cycle. Through the coordination of various detection platform, as much as possible to avoiding excessive probe are focused on individual goals, and some are not observed.

3. Optimization Model of Multi-Sensor Management Based On Rough Entropy in Information Gain

From the concept of the indiscernibility relation in rough set theory, we know that for information system $IS=(U,A)$, $P\subseteq A$ is a subset of the attributes sets, indiscernibility relation $ind(P)$ reveal the grainy structure of domain knowledge and indiscernibility relation is an equivalence relation. Through this equivalence relation, we can obtained a division about decision-making system, represented by $U/ind(P)$ or U/P, and this division is known as a knowledge base about U, represented as (U,P). Assuming $K_p=(U,P)$ and $K_q=(U,Q)$ are knowledge base, if $U/ind(P)\subseteq U/ind(Q)$, that is, for any $A\in U/ind(P)$, there is $B\in U/ind(Q)$ to let $B\in U/ind(Q)$, so the roughness of knowledge P smaller than the knowledge Q, denoted by $P<Q$;Conversely, if $U/ind(P)\supset U/ind(Q)$,that is $P>Q$;if $U/ind(P)=U/ind(Q)$, that is knowledge P and knowledge Q is said to be equal to each other.

Assuming division of P on U is X, $X=\{X_1,X_2,...,X_n\}$, the subsets of P on U consist σ, which the algebra probability distribution is defined as follows:

$$\begin{bmatrix} x \\ p \end{bmatrix}=\begin{bmatrix} X_1 & X_2 & ... & X_n \\ p(X_1) & p(X_2) & ... & p(X_n) \end{bmatrix} \tag{5}$$

Here, the probability definition of variables is $p(X_i)=card(X_i)/card(U), i=1,2,...,n$, the symbol $card(U)$ indicates the cardinality of the set U.

From the perspective of information, information entropy $H(P)$ of knowledge P is defined as:

$$H(P)=-\sum_{i=1}^{n}P(X_i)\log P(X_i) \tag{6}$$

The conditional entropy $H(Q|P)$ of knowledge Q relative to knowledge P as follows:

$$\begin{aligned} H(Q|P)&=-\sum_{i=1}^{n}P(X_i)\sum_{j=1}^{m}P(Y_j|X_i)\log_2 P(Y_j|X_i) \\ &=-\sum_{i=1}^{n}\sum_{j=1}^{m}P(X_iY_j)\log_2 P(Y_j|X_i) \end{aligned} \tag{7}$$

Conditional entropy $H(Q|P)$ represents the average uncertainty of knowledge Q still exists in the situation of knowledge P is known. From the definition of roughness can be known that, the roughness of knowledge P is lower, then provided more average amount of information, and its uncertainty and randomness are smaller, which means its entropy should be smaller.

For knowledge, the rough entropy $E(P)$ is defined as follows:

$$E(P) = -\sum_{i=1}^{n} P(X_i) lb_2 \omega_i \tag{8}$$

In the formula: ω_i is the reciprocal of the number of elements X_i , that is $\omega_i = 1/card(X_i)$

3.1. Rough Entropy in Information Gain

Considering an air defense combat system has M sensors to recognize m targets, the targets type have N , are recorded as O_j , $j = 1, 2, ..., N$ respectively, and assuming observation of the same sensor at different times and different sensors are independent of each other.

Rough entropy method applied to sensor management, setting the current time involved in the h management cycle, Z_{ik} is observations vector of predicting sensor (s) k to the target i . So, when predicting sensor (s) k assigned to the target i under the assumption, the classification rough entropy is $E(P)_i^{(h+1)}$ for the next observation period end to target i , which passed and quantification of uncertainty.

The predicting rough entropy in information gain is recorded as $I_{ik}^{(h,h+1)}$, then:

$$I_{ik}^{(h,h+1)} = E(P)_i^{(h)} - E(P)_i^{(h+1)} \tag{9}$$

3.2. Integrated Efficiency Function

Setting threat degree is TD_j for targets j , integrated performance function can be expressed as E_{ij} :

$$E_{ij} = \begin{cases} 0 & SR_{ij} = 0 \\ TD_j I_{ij} & SR_{ij} \neq 0 \end{cases} \tag{10}$$

Here, SR_{ij} indicates whether the objectives to meet detection conditions of the sensor (combined) i , $SR_{ij} = 0$ is not satisfied.

Above shows that detect conditions of sensors i are met, when information gain is the same for the sensor i to different goals, assign the sensor to high threat degree obtained more benefit.

4. Experimental Results

4. 1. Scenarios of 2 Sensors

In several phased array radar networks, phased-array radar l and phased array radar 2 take as sensor l and sensor 2, achieving the tracks of 5 goals. So, $s = 2, 2^s - 1 = 3$, sensor l can keeping track 2 targets, and sensor 2 can track 3 goals. S_1 and S_2 are two basic sensors, $S_3 = \{S_1, S_2\}$ is virtual sensor groups. $J(1) = \{1, 3\}, J(2) = \{2, 3\}$. Using the above model following 5 targets, sampling cycle $T = 1s$, tracking time $100s$. Target State model matrix for

$$A=\begin{bmatrix}1 & T & 0 & 0\\ 0 & 1 & 0 & 0\\ 0 & 0 & 1 & T\\ 0 & 0 & 0 & 1\end{bmatrix} \qquad G=\begin{bmatrix}0.5T & 0\\ T & 0\\ 0 & 0.5T\\ 0 & T\end{bmatrix} \qquad H=\begin{bmatrix}1 & 0 & 0 & 0\\ 0 & 0 & 1 & 0\end{bmatrix}$$

(10)

Tracked target 1,2,4,5 are doing uniform linear motion, model noise respectively are

$$\text{Target1}=\begin{bmatrix}1.96 & 0\\ 0 & 1.96\end{bmatrix} \qquad \text{Target2}=\begin{bmatrix}1.96 & 0\\ 0 & 1.96\end{bmatrix}$$

$$\text{Target4}=\begin{bmatrix}1.69 & 0\\ 0 & 1.69\end{bmatrix} \qquad \text{Target5}=\begin{bmatrix}2.25 & 0\\ 0 & 2.25\end{bmatrix}$$

Target 3 keep doing uniform linear motion before the first 10 s, then $\omega = 0.03 rad / s$ for uniform circular motion, and its noise model is

$$\text{Target3}=\begin{bmatrix}2.56 & 0\\ 0 & 2.56\end{bmatrix}$$

The model of 5 tracking targets is shown in Figure 1. Measuring noise of this two sensors respectively are

$$\mathrm{R}_1=\begin{bmatrix}1.44 & 0\\ 0 & 1.44\end{bmatrix} \qquad \mathrm{R}_2=\begin{bmatrix}1.96 & 0\\ 0 & 1.96\end{bmatrix}$$

Pared with the sequence search method, sensor 1 search and track the target sequence is (1, 4), (2. 5) (3, 6) and the search order of sensor 2 are (2, 5), (3, 6), (4. 7), and so on.

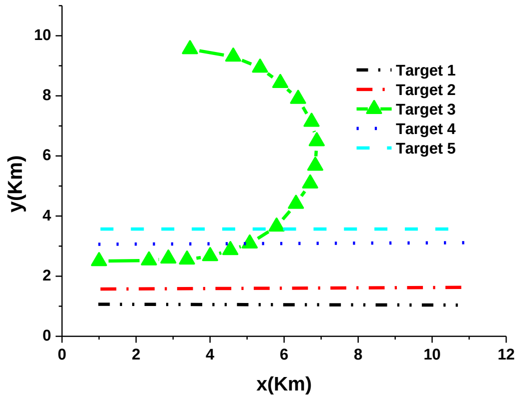

Figure 1. The Model of Target Motion

Figure 2 to Figure 6 shows the tracking effective of the target 1-5, in which, long dash represents relative entropy tracking, the solid line for sequential search and track.

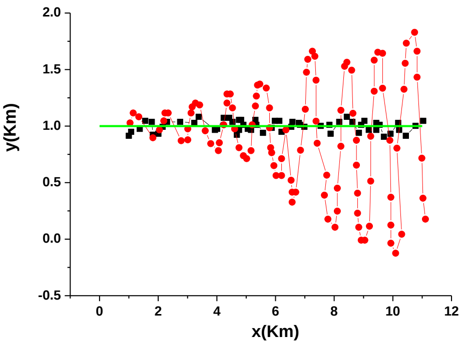

Figure 2. The Position Tracking Of the Target 1

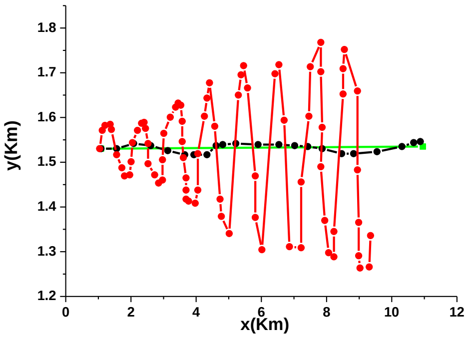

Figure 3. The Position Tracking Of the Target 2

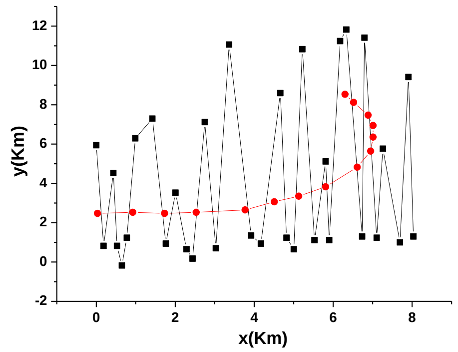

Figure 4. The Position Tracking Of the Target 3

The simulation results show that, for the target 3, the motion is shift from uniform linear motion to uniform circular motion, and its entropy has much more uncertainty. So this method can be timely allocated to sensor, whose tracking effective is better than a sequential search.

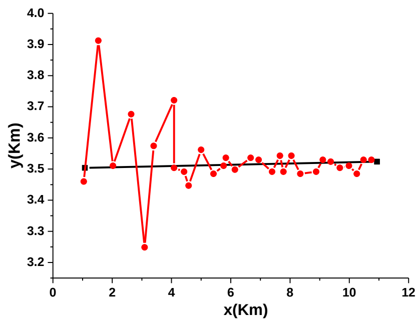

Figure 5. The Position Tracking Of the Target 4

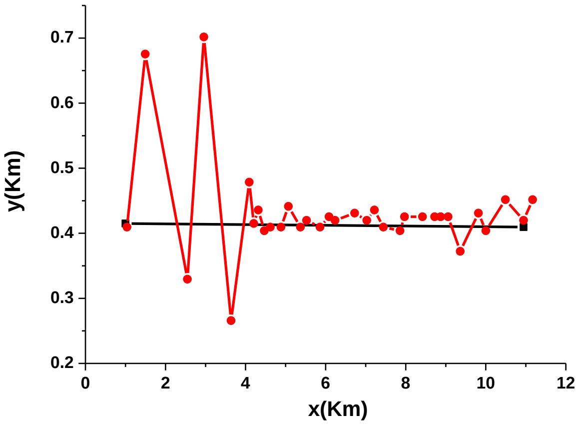

Figure 6. The Position Tracking Of the Target 5

Simulation results also indicate that the 5 the target can be timely allocated to sensor, making the tracking results significantly improved.

4. 2. Scenarios of 3 Sensors

There are 3 sensors, the combinations number of virtual sensors is $2^3-1=7$, represented by S_1, S_2, ..., S_7 .Here, $S_4=\{S_1,S_2\}$, $S_5=\{S_1,S_3\}$, $S_6=\{S_3,S_2\}$, $S_7=\{S_1,S_3,S_2\}$. Setting track volume is $c_K=[1,3,2]$, and the target threat degree respectively are $TD_j=[0.55,0.75,0.31,0.9,0.18]$, table 1 shows comprehensive efficiency and information gain of each sensor to different targets before comprehensive.

Table 1. Comprehensive Efficiency

Analysis of the data in table 1 are as follows:

Sensor	Target1 $TD_1=0.55$	Target2 $TD_2=0.75$	Target3 $TD_3=0.31$	Target4 $TD_4=0.9$	Target5 $TD_5=0.18$	c_K
S_1	1.07 (2.54)	1.33 (1.96)	0.65 (1.8)	2.10 (2.11)	0.44 (2.43)	**1**
S_2	1.36 (2.55)	1.35 (1.86)	0.64 (2.01)	2.56 (2.88)	0.542 (3.1254)	**3**
S_3	1.632 (1.135)	0.4824 (0.6352)	0.2548 (0.6483)	1.1054 (1.2454)	0.2542 (1.2713)	**2**
S_4	1.9214 (3.241)	2.085 (2.745)	0.9471 (3.325)	3.541 (3.9625)	0.752 (4.251)	
S_5	1.685 (3.2004)	1.8254 (2.351)	0.8524 (2.62541)	3.1541 (3.545)	0.651 (3.816)	
S_6	1.6254 (2.952)	1.6235 (2.1235)	0.7215 (2.3554)	3.255 (3.3622)	0.6125 (3.654)	
S_7	2.181 (3.952)	2.5412 (3.1002)	1.0521 (3.9251)	4.1022 (4.025)	0.8413 (4.74)	

Analysis of the data in table 1 is as follows:

1) When no consideration of targets threat degree, the optimizing allocation results are as follows $S_2 \to T_1$, T_3 and T_4, , $S_3 \to T_2$, virtual sensor $S_5(S_1 \textit{ and } S_3) \to T_5$。 At

present, the important target T_4 only tracked by the sensor S_2, and sensor S_2 are tracking T_1 and T_3 at same time.

2) When considering the target threat degree and the constraints condition $\sum_{i=1}^{2S-1} x_{ij} \le 1$, the optimized allocations result is: $S_2 \to T_1$, virtual sensor $S_6(S_2\ and\ S_3) \to T_2$, virtual sensor $S_7(S_2, S_2\ and\ S_3) \to T_4$. An important target T_4 tracked by the sensor S_2, $S_2\ and\ S_3$ simultaneously, more important target T_2 tracked by the sensor $S_2\ and\ S_3$ simultaneously. But relatively smaller important targets T_3 and T_5, in which constraints are not sensors tracked.

3) When considering the target threat degree and the constraints condition $\sum_{i=1}^{2S-1} x_{ij} = 1$, the optimized allocations result is: $S_2 \to T_1$, T_2 and T_3, $S_3 \to T_5$, virtual sensor $S_5(S_1\ and\ S_3) \to T_4$。An important target T_4 tracked by the sensor $S_1\ and\ S_3$, and all targets be tracked by the sensors under the constraint.

In the above analysis, taking into account the relative threat degree, therefore important target T_4 have 2 or more sensors are tracking, shows that the model have the sensitivity to important targets.

Rough entropy method, sequence search method, and our method of error rate are respectively shown in Figure 7.You can see from Figure 7, the error rate of our method much lower than the order method and entropy of mixing method in average per-unit sampling times. Because if target number far less than detection unit number, order method of most sampling is not contained detection target unit, and mixed entropy method only through using different of sensor to predict different detection unit. While our method can guarantee the sampling unit is the most likely to contain targets detection unit, and can be maximum ensure tracked focus, making a more rational management of resources.

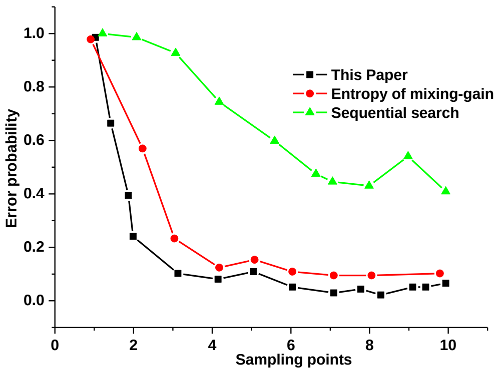

Figure 7. The Error Probabilities Versus With Sampling Points under Different Methods

5. Conclusion

Scientific and rational allocations of sensor resources are important to improved air defense detection of early warning network efficiency access to information under informationized conditions. In practice requires, the improvement of adaptability and robustness not only have good performance model and algorithm, but also need more flexible management structure. Many sensors tracking ability are very strong, and search radar can handle hundreds of tracks, in this time, so the algorithms in real time are very important; In addition, optimized assignment also includes target detection and classification process for sensor to target, so you can get the optimal allocation of the final result. Therefore, in this paper, according to the management optimization problem in Multi-sensor optimal resource, we analyzed the definition of rough entropy and presented the method of Multi-sensor management based on rough entropy and target threat degree. By calculating rough entropy of the sensors to the target, the maximum information gain access for each sensor on each target, which acts as cost function, taking into account the target threat degree, and using a linear programming optimization assignment multi-sensor to multi-target. In addition, we adopted maximum information gain optimization criterion in target tracking, then discussed optimization assignment problem about multi-sensor to multi-target. In addition, we are validate the optimized allocation algorithm with the experimental simulations, and case analysis shows that the effectiveness of the method. Our next study is extending the method to target detection or recognition domains and discussing implementation of the parallel, making it more practical.

Acknowledgements

This work was supported by the National Natural Science Foundation of China(Grant NO.61261033,41201479,61062003 and 61162007), Guangxi science research and technology development plan (14124004-4-10) and Guangxi Natural science Foundation (Grant No. 2013GXNSFBA019270).

Reference

[1] L. Vickers, R Stolkin and J. Nickerson, "Computational environmental models aid sensor placement optimization", Proceedings of IEEE Military Communications Conference MILCOM, **(2007)** October 29-3, pp. 11-6, Orlando, Florida.
[2] K. M. Krishna and H. Hexmoor, "A framework for measuring tracking performance of a sensor network", Integrated Computer Aided Engineering Journal **(2005)**.
[3] K. M. Krishna and H. Hexmoor, "A T-step Ahead Constrained Optimal Target Detection Algorithm for a Multi Sensor Surveillance System", Proceedings of IEEE/RSJ International Conference on Intelligent Robots and Systems, 2005, (IROS 2005), **(2005)** October, pp. 1840-1845, Edmonton, Canada.
[4] R. Raj, M. Ramesh and S. Kumar, "Fault Tolerant Clustering Approaches in Wireless Sensor Network for Landslide Area Monitoring", Proceedings of the International Conference on Wireless Networks (ICWN'08) 107–113, **(2008)** September 14-19, San Francisco, California, USA .
[5] R. K. Ahuja, T. L. Magnanti and J. B. Orlin, "Network Flows-Theory, Algorithms, and Applications, Prentice Hall, Tappan, NJ, USA **(1993)**.
[6] D. Zili, M. Lin and G. Yuan, "Multi sensor Optimal Information Fusion Steady-state Kalman Filter", Science Technology and Engineer, vol. 4, no. 9, **(2004),** pp. 743-747.
[7] H. Cao, R. Zhou and J. Hao, "An introduction of multi sensor optimal information fusion based on kalman filter method", Proceedings of 2011 International Conference on Electronic and Mechanical Engineering and Information Technology (EMEIT)3272-3276, **(2011)**August 12-14, Harbin, China.
[8] W. Q. M. Truccolo, "Efficient decoding with steady-state kalman filter in neural interface systems", NeIEEE Transactions on rural Systems and Rehabilitation Engineering, vol. 19, no. 5, **(2011)**, pp. 25-34.
[9] M. S. Dawood, J. Suganya, R. K. Devi and G. Athisha, "A Review on Wireless Sensor Network Protocol for Disaster Management", International Journal of Computer Applications Technology and Research, vol. 2, no. 2, **(2013)**, pp. 141-146.

Authors

Xiang-yang Chen, **he** received his B.S. and M.S. degrees from Teachers University of Guangxi, Guilin in 1995 and 1998 respectively, all in science. From 1998 he works as a lecturer in Guilin University of Electronic Technology, and PH.D student in University of Electronics

Science and Technology of China. His current research interests include signal processing, information/data fusion, and sensor management.

Sun-yong Wu, he received his B.S. Degree in applied mathematics from China University of geosciences (Wuhan) in 2003, and the Ph.D. degree in Signal and information processing from Xidian University in 2011. His current research interests include signal processing, information/data fusion, and sensor management.