EVALUATION OF DATA FUSION IN RADARS NETWORK AND DETERMINATION OF OPTIMUM ALGORITHM

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ABSTRACT

Functionality of radars network strongly depends on data fusion algorithms. Because of ambiguous in radar backscatter, probability of detection is an important parameter in choosing optimized algorithm. Radar gating and swerling of targets are two fundamental parameters for probability of detection. In this paper, three custom data fusion algorithms, Averaging, Bayesian and Dempster-Shafer are simulated. Results are compared by simulated radar input data, and evaluated by convergence, precious, influence of fluctuations, running time and complexity of implementation. Results of evaluation declare Dempater-Shafer algorithm is optimized for two-cell network. In four-cell network, if radars outputs are mass functions directly, hierarchical topology with Dempater-Shafer algorithm in both layers will be optimize. When radars outputs are probability, because of pignistic transform in radar output and inverse pignistic transform in radar input, hierarchical topology with Average algorithm in first layer and Bayesian algorithm in second layer will be optimize.

KEYWORDS

Radars Network, Data Fusion, Averaging, Bayesian, Dempster-Shafer

1. INTRODUCTION

Today any radar can be find that not linked to a network. Radars network has several purposes and applications for army and civil demands, like air defence, hydrology, and air traffic control. Moreover, radars network covers vast aims from information fusion to refuse unwanted parameters. Correctness of functionality of radars network strongly depends on data fusion of cells of radars. Some data fusion algorithms in radar have explained like PDA (Probability Data Association), MHT (Multiple Hypotheses Tracking) and IMM (Interacting Multiple Model). In radars network, the received data from radars have different precious. Therefore, data must be fuse by suitable weight. Probability of correctness of data is an important parameter of weighting. Many efforts have made to extract data in radars with extreme precious. Nevertheless, some subjects generate ambiguous, like swerling of targets, white noise and clatter, jamming,

DOI:10.5121/iju.2011.2405

quantization and colour noises from communications channels. Classic, Bayesian and Dempster-Shafer or Evidence reasoning are three custom algorithms that usually use for probability fusion. Classic algorithms use statistical methods or Boolean algebra, like majority voting or averaging. Bayesian algorithms use stochastic processing and estimation methods, and fuse data by probability of events. Bayes equation is the base of them. Evidence algorithms fuse data by possibility of events, and Dempster-Shafer theory is the base of them. Of course, some other algorithms have prepared to use in sensors network, like fuzzy logic, neural networks or image processing algorithms [1]. In continue, important concepts of fusion and data extraction in radar have described.

1.1. Data Fusion Principles

The methods of fusion classify to four types, across sensors, attributes, domains, and time. For communications between sensors, three methods of configuration have classified; complementary, it means sensors do several duties in same time and complete one demand; cooperative, it means sensors do one duty in several time and complete one demand; competitive, it means sensors do one duty in same time and complete one demand. In addition, three models of topologies have classified; centralized, decentralized and hierarchical, they are illustrated in figure 1. Selection of topology depends on missions and applications. Some models of data fusion have also developed, like JDL, multiple-sensors integration and waterfall. All models commonly have three levels, signal or pixel, feature and decision. Choosing model depends on processing power and aim of networking [2, 3].

1.2. Data extraction in radar

Data in Radars have ambiguous. Sources of ambiguous are in backscatter signals. Received power depends on transmitted power; if signals send in high power, received signals will have high SNR (Signal to Noise Ratio). Also received signals contain noises. Received noises generally are composition of false alarm probability (p_{fa}) from white noise and constant false alarm ratio (p_{CFAR}) from clatter. is little number. There are methods to minimize it, like integration of received pulses. Also there are technics for removing clatter influences. Other noises generate in network, like signal quantization that is type of color noises and attempts have made to remove them by special Kalman filters. Nevertheless, reported results always have ambiguous. It means there is difference between posterior and measured data. If the measured distance and angle are $R_m$and θ_m ,and the estimated distance and angle are R_p and θ_p , and σ_R^2 and σ_θ^2 are variances of $(R_p – R_m)$ and $(\theta_p – \theta_m)$ respectively, Normalized Gating will be:

$$d^2 = (R_p - R_m)^2/\sigma_R^2 + (\theta_p - \theta_m)^2/\sigma_\theta^2 \tag{1}$$

If Maximum of normalized gating is G, it must be d<G. If coordinates are M dimensions and every components change by Gaussian probability density function, sum of M Gaussian probability density functions will equal to Chi-square by M degrees of freedom (χ_M^2)According [4] probability of observation of targets in ellipsoidal gate, when coordinates have two dimensions, is equal to:

$$p_G = 1 - e^{-G/2} \tag{2}$$

Ambiguous in data also depends on fluctuations of radar cross section (RCS) and angle of aspect of targets. Four models for swerling of targets are introduced that are described in Table 1. In addition, the non-fluctuating model is called swerling 0. Swerling depends on PRF (pulse repetition frequency), SNR, P_{fa} , P_{CFAR} [5, 6, 7].

2. RELATED WORK

Data fusion can occur in every level, signal or pixel, feature and decision. Comparison between fusion methods depends on aim and level of model. In [16], at pixel level and for satellite pictures, fusion methods have compared. In [17], Bayesian and Dempster-Shafer algorithms compared, authors, after comparison of differences and similarities, show results of algorithms for decision level is nearby similar. In [18], authors compare two custom algorithms at feature level and in human activity, and in [19] at decision level and in landmine detection. In [21], at feature and decision levels for remote sensing, three algorithms, Bayesian, Dempster-Shafer and Neural Network have compared and survey their advantages and limits.

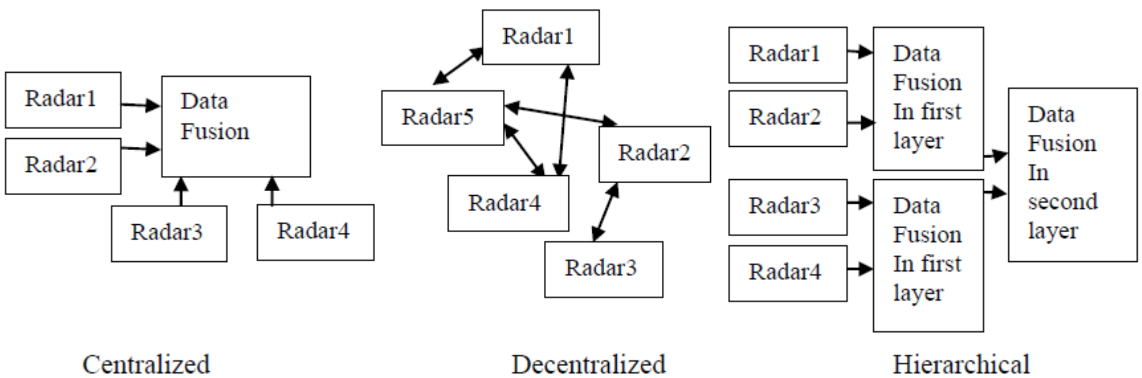

Figure1: Topologies of Data Fusion

Table 1: Swerling Models

	Probability Density Function: $p(\sigma)$	**Average**	**Standard Deviation**	**Fluctuations of RCS**	**Receive Pulse Independence**
Swerling1	$e^{(-\sigma/\sigma_{av})}/\sigma_{av}$	σ_{av}	σ_{av}	High / Slowly	Scan to Scan
Swerling2	$(\pi\sigma/2\sigma_{av}^2)\, e^{(-\pi\sigma^2/4\sigma_{av}^2)}$	σ_{av}	$\sigma_{av}/2$	High / Rapidly	Pulse to Pulse
Swerling3	$(4\sigma/\sigma_{av}^2)\, e^{(-2\sigma/\sigma_{av})}$	σ_{av}	$\sigma_{av}/\sqrt{2}$	Low /Slowly	Scan to Scan
Swerling4	$(\alpha^4\sigma^3/2\sigma_{av}^4)e^{(-\alpha^2\sigma^2/2\sigma_{av}^2)}$	σ_{av}	$0.36\sigma_{av}$	Low / Rapidly	Pulse to Pulse

Comparison in radars network depends on level, too. Bieker in [20], compare fusion algorithms, Bayesian, Dempster-Shafer and voting, at feature level. Another research is in [14], at feature level and in target identification two custom algorithms have compared. In these works, methods have compared but have not proposed method for evaluation. In other hand, comparison is not in signal level. In this paper, data fused in signal level and statistical method has proposed for evaluation algorithms.

3. DATA FUSION ALGORITHMS

Some algorithms are prepared in fuzzy logic, expert systems, neural networks and image processing, for sensors network. Three custom algorithms, Classic, Bayesian and Dempster-Shafer usually use for radars network [1]. These algorithms survey for two-cell and four-cell network with centralized and hierarchical topologies. In this network, fusion type is sensory, configuration is competitive, and data are fused in signal level. Probability of detection of target is named E and $\overline{\mathrm{E}}$ is NOT of it. Reported probability in *n*th step and *i*th radar is $\mathrm{p}_{(n,i)}$ and result of fusion in *n*th step is $\mathrm{p}_{(n,f)}$

3.1. Classic Algorithm

Statistical methods and Boolean algebra have used for data fusion like majority voting or averaging from received data [8]. In this paper, data are fused by averaging. Two-cell fusion is named C and four-cell fusion with centralized topology is named C4. Fusion of N radars in *n*th step is equal to:

$$\mathrm{p}_{(n,f)}(\mathrm{E}) = \frac{\sum_{i=1}^{N} \mathrm{p}_{(n,i)}(\mathrm{E})}{N} \tag{3}$$

3.2. Bayesian algorithm

Two-cell fusion by Bayesian algorithm is named B and four-cell fusion with centralized topology is named B4. Bayes equation is:

$$\mathrm{p}(A|B) = \frac{\mathrm{p}(B|A)\mathrm{p}(A)}{\sum_{i=1}^{n} \mathrm{p}(B|A_i)\mathrm{p}(A_i)} \tag{4}$$

In Bayes equation, if probability of detection of target is A and probability of received data is B, probability of detection in fusion node will be equal to [9]:

$$\mathrm{p}(\text{ detection of target} \mid \text{received data}) = \frac{\mathrm{p}(\text{ received data}|\text{detection of target})\mathrm{p}(\text{detection of target})}{\mathrm{p}(\text{received data}|\text{detection of target})\mathrm{p}(\text{detection of target}) + \mathrm{p}(\text{received data}|\text{none detection})\mathrm{p}(\text{none detection})} \tag{5}$$

Fusion of N radars in *n*th step is equal to:

$$\mathrm{p}_{(n,f)}(\mathrm{E}) = \frac{\mathrm{p}'_{(n,f)}(\mathrm{E})}{\mathrm{p}'_{(n,f)}(\mathrm{E}) + \mathrm{p}'_{(n,f)}(\overline{\mathrm{E}})}$$

Where:

$$p'_{(n,f)}(E) = \frac{\{\prod_{i=1}^{N} p_{(n,i)}(E)\}\ p_{(n-1,f)}(E)}{\prod_{i=1}^{N} p_{(n-1,i)}(E)}$$

$$p'_{(n,f)}(\bar{E}) = \frac{\{\prod_{i=1}^{N} p_{(n,i)}(\bar{E})\}\, p_{(n-1,f)}(\bar{E})}{\prod_{i=1}^{N} p_{(n-1,i)}(\bar{E})} \tag{6}$$

And value in first step is:

$$p_{(0,f)}(E) = \frac{\sum_{i=1}^{N} p_{(0,i)}(E)}{n}$$

$$p_{(0,f)}(\bar{E}) = \frac{\sum_{i=1}^{N} p_{(0,i)}(\bar{E})}{n} \tag{7}$$

3.3. Dempster-Shafer or Evidence algorithm

Two-cell fusion by Evidence algorithm is named D and four-cell fusion with centralized topology is named D4. Some radars and sensors explain their outputs by possibility. For description of Dempster-Shafer or Evidence reasoning [9], A_1, A_2,....A_n are members of θ (frame of discernment). θ has 2^n subsets that a number between (0, 1) is assigned to them and it is called mass function; m ({A_i,...,A_j}), where:

$$\sum_{A\subseteq\theta} m(A) = 1 \ ,\forall\ m(A) > 0 \ ,\ m(\emptyset)=0 \tag{8}$$

If two witnesses describe an event,$m_1(A)$ from first person and $m_2(A)$ from second person are fused by Shafer equation:

$$m_1 \oplus m_2\ (A) = \frac{\sum_{B\cap C=A} m_1(B)m_2(C)}{1-\sum_{B\cap C=\emptyset} m_1(B)m_2(C)} \tag{9}$$

N mass functions are fused by Yager equation:

$$m_1 \oplus \cdots \oplus m_n\ (A) = \frac{\sum_{\cap_{i=1}^{n} A_i=A}\left(\prod_{j=1}^{n} m_j(A_j)\right)}{1-\sum_{\cap_{i=1}^{n} A_i=\emptyset}\left(\prod_{j=1}^{n} m_j(A_j)\right)} \tag{10}$$

For comparison between Bayesian and Dempster-Shafer results, transformation is needed. Mass function transfers to probability domain by pignistic transform [10]:

$$p(x_j) = \sum_{x_j\in A_i} \frac{m(A_i)}{|A_i|} \tag{11}$$

That | A_i| is number of A_i members. Many methods have proposed for probability to mass function transformation. The custom method is inverse pignistic transform that is described by below algorithm [11]. For θ = { A_1,A_2,...,A_n}, possibility density function is defined:

$$\pi(A_k) = \sum_{l=1}^{n} \min(p_k, p_l)$$

Where these functions must be monotonic:

$$1 \geq \pi(A_1) \geq \pi(A_2) \geq \cdots \geq \pi(A_n)$$

Mass functions are equal to:

$$m(\{A_1\}) = |\pi(A_1) - \pi(A_2)| \ \ldots$$

$$m(\{A_1, \ldots, A_i\}) = |\pi(A_i) - \pi(A_{i+1})| \ \ldots$$

$$m(\theta) = \pi(A_n) \tag{12}$$

3.4. Algorithms for hierarchical topology

Another type of topology in radars network is hierarchical. Composite algorithms are named by algorithms are used in layers. If classic algorithm is used in both layers, it will be named CC. According to [15] results of CC algorithm are equal to C4. If data is fused in both layers by Bayesian algorithm, it will be named BB and by Dempster-Shafer algorithm, it will be named DD. According to [15], if values of BB and B4 in their first steps are equal, results of algorithms will equal, and if mass functions in all radars are simple mass functions, results of algorithms will equal (if θ has only one member, mass functions are called simple). Difference between CC and C4, BB and B4, DD and D4 is in running time and complexity of implementation. If first and second layers fusion are classic and Bayesian algorithm respectively, it will name CB. Others will name similarly; for Bayesian-classic algorithm BC, for classic-evidence algorithm CD, for evidence-classic algorithm DC, for Bayesian-evidence algorithm BD and for evidence-Bayesian algorithm DB.

4. SIMULATION AND COMPARISON DATA FUSION ALGORITHMS FOR RADARS NETWORK

According to radar gating and swerling of targets, probability of detection of radars is simulated by MATLAB and is compared by radar simulator results in [12]. Data fusion also is simulated. Simulated scenario is surveillance radars signals in L band that contains target backscatter data. Range of target is 150km, velocity is 200 m/s, and height is 1000m. RCS and SNR are about 10 m2 and 7 dB, respectively. False alarm with clatter is 10-6. Radars arrangement is serial that means target move with consistent distance from radars in simulation time. Radars have 2 dimensions and G=10. Duration of simulation is 2 minutes and 25 scans. Every scan is integration of 16 pulses. First for two-cell network, (R1, R2), target is assumed by swerling 0 and radars detect trajectory of it. Then scenario is repeated by swerling 1 to 4, respectively. It must be attend swerling 0, 1 and 3 are simulated for 25 scans that every scan is integration of 16 pulses and are illustrated in figures 2, 3 and 4. Swerling 2 and 4 also are simulated for 400 pulses and are illustrated in figures 5 and 6. For better view, initial forty samples are illustrated. Simulation is repeated for swerling 1 to 4 for five times and averages and standard deviations of results of simulations are summarized in table 2. Then scenario is repeated for four-cell network (R1, R2, R3, R4). Results of fusion are illustrated in figures 7 to 11. Simulation is run for swerling 1 to 4 for five times and averages and standard deviations of results of simulations are summarized in table 3. It must be attend, in algorithms with Dempster-Shafer equations, mass functions are derived from inverse pignistic transform and then data are fused, results of fusion are transferred to probability domain by pignistic transform and are illustrated for comparison.

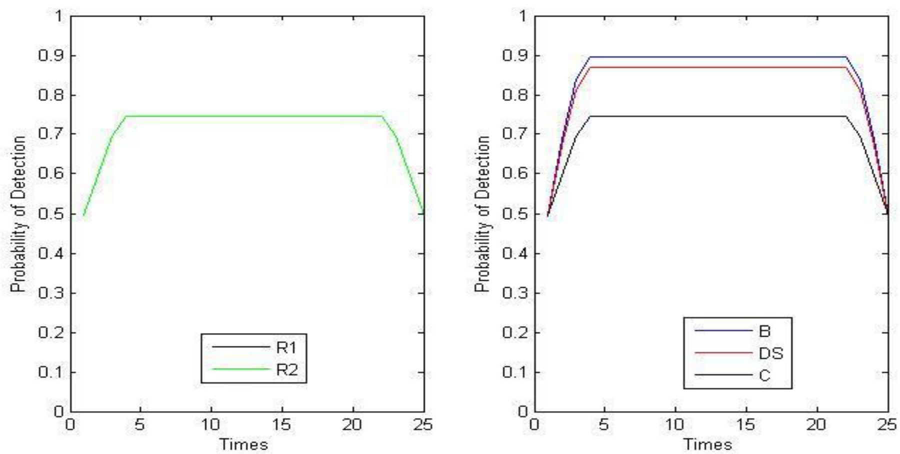

Figure 2*: 2 radars data Fusion for target with swerling model 0

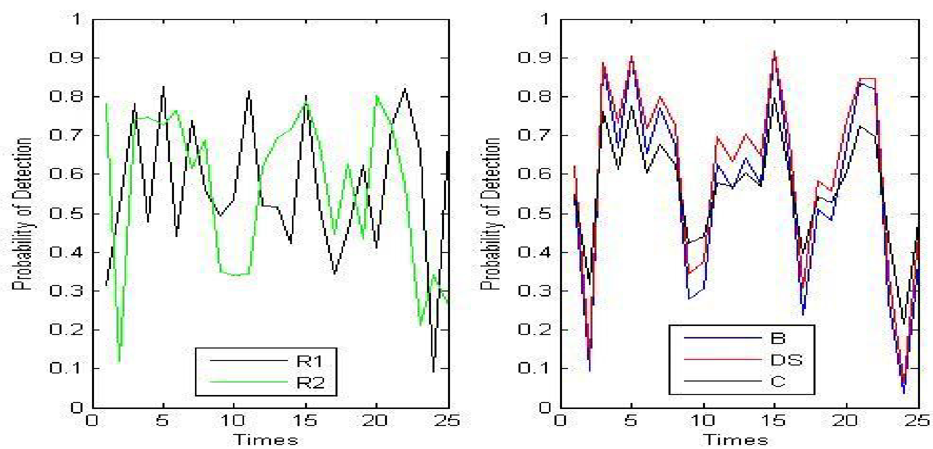

Figure 3*: 2 radars data Fusion for target with swerling model 1

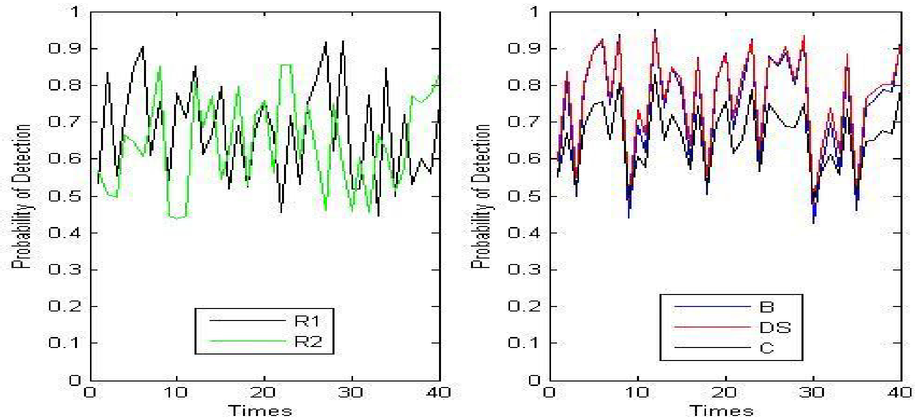

Figure 4: 2 radars data Fusion for target with swerling model 2

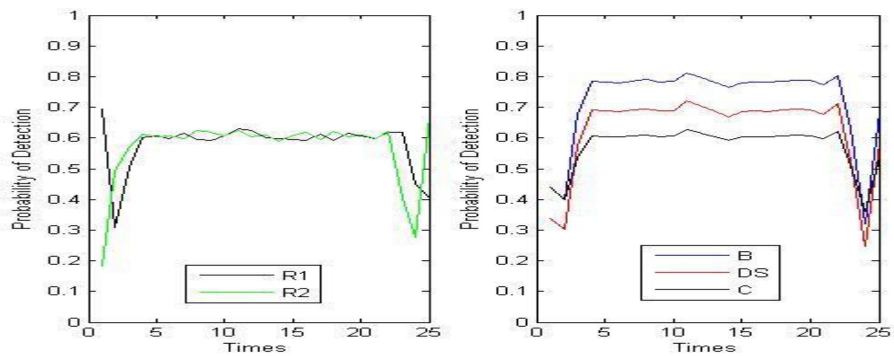

Figure 5: 2 radars data Fusion for target with swerling model 3

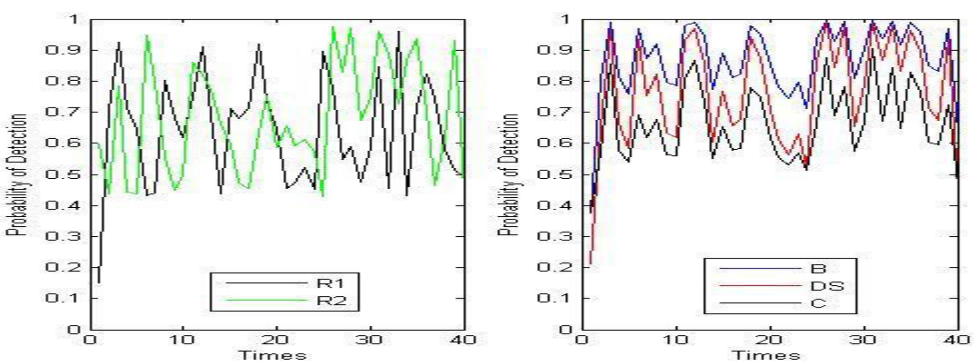

Figure 6: 2 radars data Fusion for target with swerling model 4

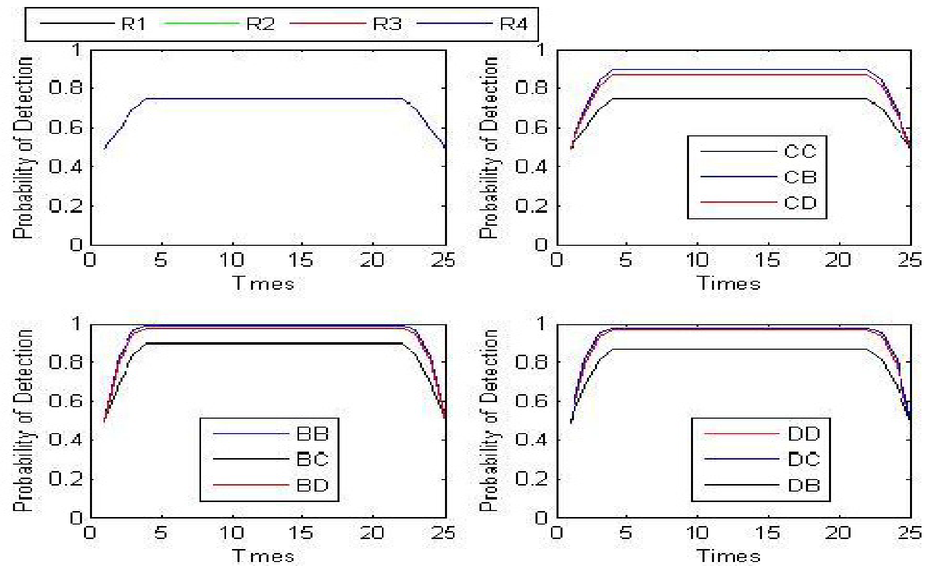

Figure 7**: 4 radars data Fusion for target with swerling model 0

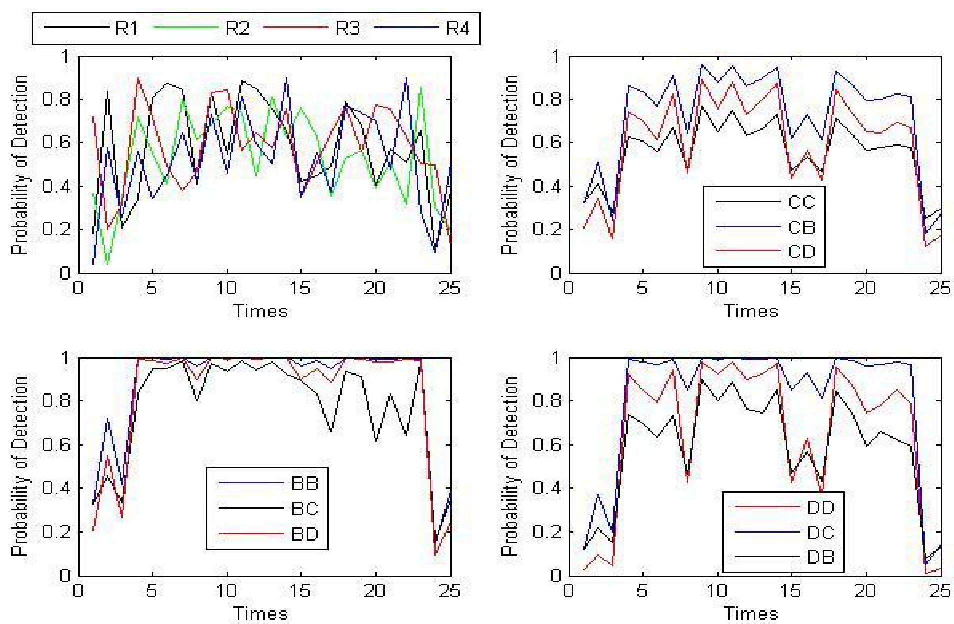

Figure 8**: 4 radars data Fusion for target with swerling model 1

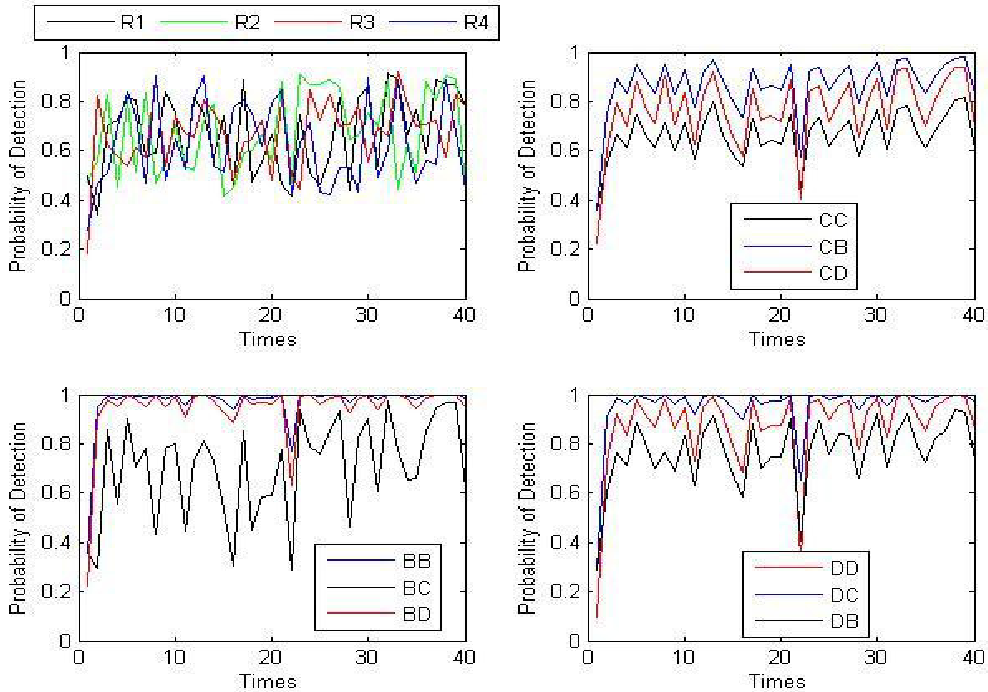

Figure 9**: 4 radars data Fusion for target with swerling model 2

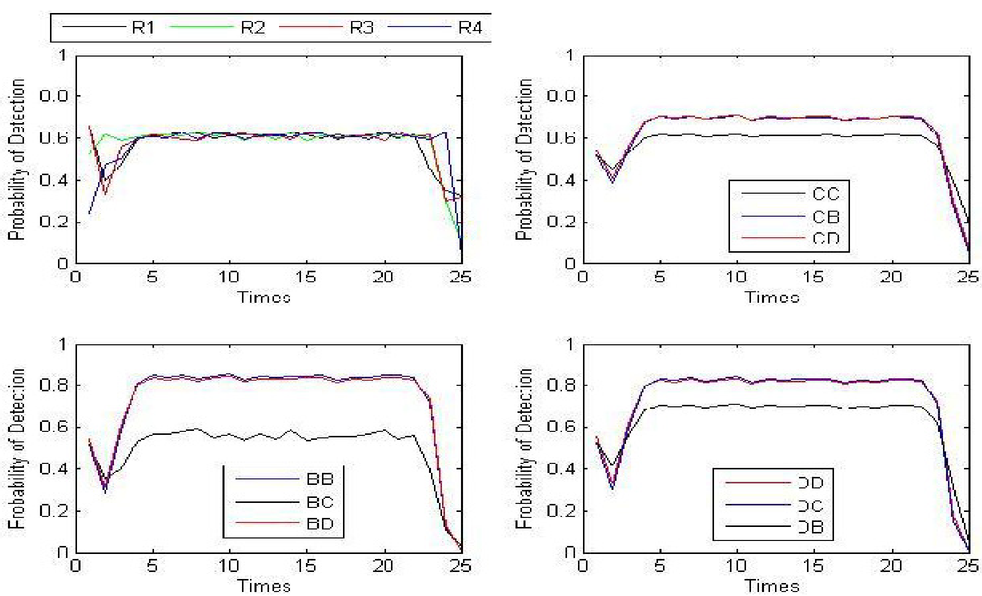

Figure 10**: 4 radars data Fusion for target with swerling model 3

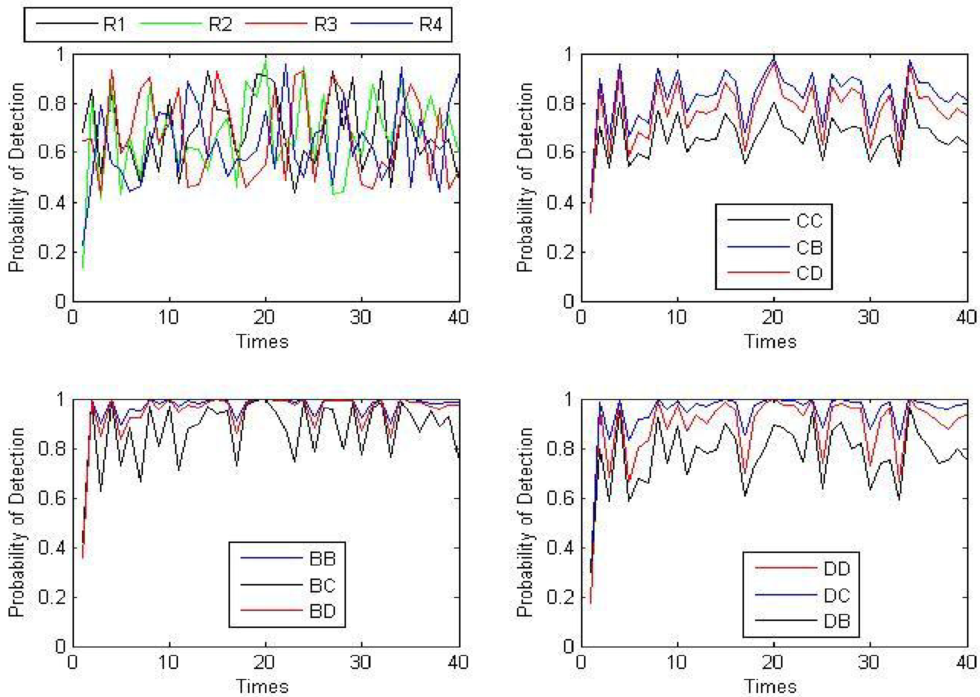

Figure 11**: 4 radars data Fusion for target with swerling model 4

*: Left Up- Radars Probability of detection, Left Down – Fusion of Probabilities of detection by 2 algorithms, Right Up – Radars Decision, Right Dow – Fusion of Decisions by 2 algorithms

**: Left Up- Radars Probability of detection, Left Down – Fusion of Probabilities of detection by BB-BC-BD, Right Up – Fusion of Probabilities of detection by CC-CB-CD, Right Dow – Fusion of Probabilities of detection by DD-DC-DB

Table 2: Results for five times tests of Data Fusion of 2 radars

Model of Target	P_D *(Probability of Detection)*	R1	R2	C	B	DS
Swerling 0	Average (μ_{s0})	0.73	0.73	0.73	0.88	0.85
Swerling 1 (25 scans)	Average (μ_{s1})	0.57	0.57	0.57	0.70	0.62
	Standard Deviation (%) (σ_{s1})	4.3	3.1	1.72	15.2	2.8
Swerling 2 (400 pulses)	Average (μ_{s2})	0.66	0.66	0.66	0.76	0.77
	Standard Deviation (%) (σ_{s2})	0.6	0.5	0.4	10.9	0.4
Swerling 3 (25 scans)	Average (μ_{s3})	0.57	0.56	0.56	0.76	0.62
	Standard Deviation (%) (σ_{s3})	1.2	1.5	1.0	18.4	1.6
Swerling 4 (400 pulses)	Average (μ_{s4})	0.67	0.68	0.67	0.81	0.78
	Standard Deviation (%) (σ_{s4})	0.6	0.5	0.5	8.2	0.6

5. Evaluation of Data Fusion Algorithms for radars network

Five criterions are assumed; convergence, precious, fluctuations, running time and complexity of implementation. These criterions can compare performance of algorithms.

Convergence means that results of data fusion are near to acceptable value. Convergence of algorithms is calculated by:

$$C^{Al} = \frac{1}{5m}\sum_{j=1}^{m}\sum_{i=1}^{5} C_{s_i}^{R_j\,Al}$$

Where:

Table 3: Results for five time tsests of Data Fusion of 4 radars

Model of Target	P_D	R1	R2	R3	R4	CC	CB	CD
Swerling 0	Average (μ_{s0})	0.73	0.73	0.73	0.73	0.73	0.88	0.85
Swerling 1 (25 scans)	Average (μ_{s1})	0.58	0.56	0.58	0.60	0.58	0.70	0.64
	Standard Deviation (%) (σ_{s1})	1.33	1.47	4.03	2.33	1.47	8.7	2.7
Swerling 2 (400 pulses)	Average (μ_{s2})	0.66	0.67	0.67	0.67	0.66	0.80	0.77
	Standard Deviation (%) (σ_{s2})	0.49	0.89	0.4	0.80	0.49	5.19	0.63
Swerling 3 (25 scans)	Average (μ_{s3})	0.58	0.57	0.56	0.57	0.57	0.66	0.63
	Standard Deviation (%) (σ_{s3})	0.4	1.17	1.36	1.41	0.4	9.00	0.49
Swerling 4 (400 pulses)	Average (μ_{s4})	0.67	0.67	0.68	0.68	0.67	0.82	0.78
	Standard Deviation (%) (σ_{s4})	0.49	0.63	1.02	0.75	0.4	5.82	0.4
			BB	BC	BD	DD	DB	DC
Swerling 0	Average (μ_{s0})		0.97	0.88	0.96	0.95	0.96	0.85
Swerling 1 (25 scans)	Average (μ_{s1})		0.80	0.74	0.78	0.74	0.78	0.64
	Standard Deviation (%) (σ_{s1})		12.0	17.6	8.7	1.2	8.8	2.0
Swerling 2 (400 pulses)	Average (μ_{s2})		0.91	0.78	0.90	0.88	0.90	0.77
	Standard Deviation (%) (σ_{s2})		8.07	11.97	5.02	0.63	5.51	0.63
Swerling 3 (25 scans)	Average (μ_{s3})		0.74	0.58	0.74	0.71	0.74	0.63
	Standard Deviation (%) (σ_{s3})		14.53	13.91	8.77	0.8	11.06	0.8
Swerling 4 (400 pulses)	Average (μ_{s4})		0.91	0.77	0.90	0.88	0.91	0.78
	Standard Deviation (%) (σ_{s4})		5.48	5.2	3.93	0.49	4.31	0.63

$$C_{s_i}^{R_j\,Al} = \begin{cases} 0 & \text{for} \quad \mu_{s_i}^{Al} \le \mu_{s_i}^{R_j} \\ \dfrac{\mu_{s_i}^{Al} - \mu_{s_i}^{R_j}}{\mu_{max} - \mu_{s_i}^{R_j}} & \text{for} \quad \mu_{s_i}^{R_j} < \mu_{s_i}^{Al} \le \mu_{max} \\ 1 & \text{for} \quad \mu_{max} < \mu_{s_i}^{Al} \end{cases} \qquad (13)$$

That m is the number of radars, $\mu_{s_i}^{R_j}$ is average of *j*th radar in *i*th swerling, $\mu_{s_i}^{Al}$ is average of data in *i*th swerling and is maximum acceptable average in radars that means if value is over it, target will detect certainly. is assumed 0.8.

If an algorithm has less standard deviation, then it is more precious. For comparison, precious is calculated by:

$$P^{Al} = \frac{1}{4m}\sum_{j=1}^{m}\sum_{i=1}^{4} P_{s_i}^{R_j\,Al}$$

Where:

$$P_{s_i}^{R_j Al} = \begin{cases} \frac{10\sigma_{s_i}^{R_j} - 2\sigma_{s_i}^{Al}}{10\sigma_{s_i}^{R_j}} & \text{for} \quad \sigma_{s_i}^{Al} \le \sigma_{s_i}^{R_j} \\ 0.8\frac{P_{max} - \sigma_{s_i}^{Al}}{P_{max} - \sigma_{s_i}^{R_j}} & \text{for} \quad \sigma_{s_i}^{R_j} < \sigma_{s_i}^{Al} \le P_{max} \\ 0 & \text{for} \quad P_{max} < \sigma_{s_i}^{Al} \end{cases} \tag{14}$$

That $\sigma_{s_i}^{R_j}$ is standard deviation of *j*th radar in *i*th swerling, $\sigma_{s_i}^{Al}$ is standard deviation of data in *i*th swerling and P_{max} is maximum acceptable standard deviation. P_{max} is assumed 20%.

Table 4: Running time of algorithms for two-cell network (mili second)

C	**B**	**DS**	**DDS**
200	310	910	420

Table 5: Running time of algorithms for four-cell network (mili second)

C4	**CC**	**CB**	**CD**	**B4**	**BB**	**BC**
460	790	890	1550	1020	720	860

BD	**D4**	**DD**	**DB**	**DC**	**DDD**	**DD4**
1680	1910	3110	2310	2440	1260	580

Table 6: Complexity of data fusion algorithms for two-cell network

	multiplication	**division**	**addition**	**subtraction**	**sets**	**conditions**
C	0	25	25	0	0	0
B	144	73	145	125	0	0
DDS	~75	~0	~25	~75	~50	~25
DS	~125	~50	~75	~150	~50	~125

Table 7: Complexity of data fusion algorithms for four-cell network

	multiplication	division	addition	subtraction	sets	conditions
C4	0	28	75	0	0	0
CC	0	75	75	0	0	0
CB	144	27	27	120	0	0
CD	~125	~100	~75	~150	~50	~100
B4	350	73	28	225	0	0
BB	432	219	75	375	0	0
BC	288	171	51	250	0	0
BD	~413	~170	~75	~365	~50	~100
D4	~700	~125	~100	~700	~150	~415
DD	~375	~150	~225	~450	~150	~375
DB	~400	~150	~150	~400	~100	~200
DC	~250	~100	~150	~250	~50	~100
DD4	~550	~100	~75	~550	~150	~350
DDD	~250	~30	~75	~225	~150	~150

Influence of fluctuations means that results of algorithms change because of unwanted fluctuations. Influence of fluctuations is evaluated by coefficient of variation that is defined as standard deviation divided by average. Suitable algorithm must have high average and low standard deviation. Influence of fluctuations is calculated by:

$$F^{Al} = \frac{1}{4m} \sum_{j=1}^{m} \sum_{i=1}^{4} F_{s_i}^{R_j\,Al}$$

Where:

$$F_{s_i}^{R_j\,Al} = \begin{cases} 0 & \text{for} \quad \mu_{s_i}^{Al} \le \mu_{s_i}^{R_j} \\ 1 - \sigma_{s_i}^{Al} \Big/ \frac{\mu_{s_i}^{Al} - \mu_{s_i}^{R_j}}{\mu_{max} - \mu_{s_i}^{R_j}} & \text{for} \quad \mu_{s_i}^{R_j} < \mu_{s_i}^{Al} \le \mu_{max} \\ 1 & \text{for} \quad \mu_{max} < \mu_{s_i}^{Al} \end{cases} \quad (15)$$

Table 8: Evaluation of data fusion algorithms for two-cell network

%	DS	DDS	B	C
convergence	61.53	61.53	82.17	0
precious	82.13	82.13	28.86	85.61
fluctuations	94.75	94.75	83.82	0
time	77.25	89.50	92.25	95
complexity	47.30	75	51.30	95
Average	72.59	80.58	67.68	55.13

Table 9: Evaluation of data fusion algorithms for four-cell network

%	BB	B4	CD	CB	CC	C4	BC
convergence	94.95	94.95	63.20	78.82	1.14	1.14	67.69
precious	42.26	42.26	84.45	54.49	87.47	87.47	32.80
fluctuations	95.14	95.14	96.74	88.91	32.53	32.53	63.56
time	82.00	74.50	61.25	77.75	80.25	88.50	78.50
complexity	44.95	66.2	70	84.1	92.5	95	62
Average	71.86	74.61	75.13	76.81	85.78	60.93	60.91
	DD4	**DDD**	**DC**	**DB**	**DD**	**D4**	**BD**
convergence	84.33	84.33	62.15	92.97	84.33	84.33	92.97
precious	82.32	82.32	83.68	53.23	82.32	82.32	56.08
fluctuations	98.03	98.03	96.75	93.79	98.03	98.03	94.35
time	85.5	68.5	39.00	42.25	22.25	52.25	58.00
complexity	11.25	56	55	30	13.75	0	41.35
Average	72.29	77.48	67.32	62.45	60.14	63.39	68.55

Time of operation is assigned to some process, like network implementation or data transmission. Suitable time for detection process in simulated scenario is 2 to 4 seconds [13]. In same condition of processing for all algorithms, scenario run for swerling 0 and time is measured. For evidence algorithm, time of pignistic and inverse pignistic transform is calculated too. If radars outputs can be mass functions directly, because of evidence algorithm, time will be decrease. This condition for two-cell network is named Direct Dempster-Shafer or DDS. For four-cell network is named DD4 and DDD.

Results for two-cell and four-cell network with 10% error are summarized in table 4 and 5. If i^{Al} is running time, I_{min} is minimum and I_{max} is maximum of acceptable time, expression of suitable time in percentage is:

$$I^{Al} = \begin{cases} \frac{2I_{min} - i^{Al}}{2I_{min}} & \text{for} \quad i^{Al} \leq I_{min} \\ 0.5\,\frac{I_{max} - i^{Al}}{I_{max} - I_{min}} & \text{for} \quad I_{min} < i^{Al} \leq I_{max} \\ 0 & \text{for} \quad I_{max} < i^{Al} \end{cases} \tag{16}$$

I_{min} and I_{max} are assumed 2 and 4sec, respectively.

According [14] complexity of implementation is expressed and compared by sum of addition/subtraction, multiplication/division, conditions and relations of sets. Results are summarized in tables 6 and 7. Because of conditions and relations of sets, calculations of mathematical operations for evidence algorithms are approximated. For two-cell network, sum of row of table 5 are calculated and results are mapped from (0, 1000) to (0, 100%) and for four-cell network results are mapped from (0, 2000) to (0, 100%).

It must be attend running time is not similar with complexity of implementation, because of relations of sets for evidence algorithms.

Evaluation of algorithms is summarized in table 8 for two-cell network and table 9 for four-cell network. Linear optimization is considered by same weight for five parameters and is calculated average. For two-cell network, direct Dempster-Shafer is optimized. For four-cell network, if radars outputs are probability, CB algorithm will optimized, and if radars outputs are mass function directly, DDD algorithm will optimized.

Networks with more cells and complicated conditions must survey independently.

6. CONCLUSION

In this paper, custom data fusion algorithms, Averaging, Bayesian and Dempster-Shafer are simulated and evaluated. First probability of detection of targets have generated according to radar gating and swerling of targets. Then the generated data have fused by described algorithms and evaluated by five criterions, convergence, precious, influence of fluctuations, running time and complexity of implementation. Results of evaluation declare Dempater-Shafer algorithm is optimized for two-cell network. For four-cell network, if radars outputs are mass functions directly, hierarchical topology with Dempater-Shafer algorithm in both layers will be optimized, and when radars outputs are only probability, pignistic transform is needed for radars outputs and inverse pignistic transform for radars inputs, then hierarchical topology with Average and Bayesian algorithms in first and second layers, respectively, will optimized.

REFERENCE

[1] P. V l n, É. Bossé, A. Jou n, "A rborn ppl t on of nform t on fus on l or thms to l ss f t on", Defence R&D Canada - DRDC Valcartier TR 2004-282, 2006.

[2] H.Mitchell, "Multi-Sensor Data Fusion, An Introduction", Part I ,Chapter 3, Springer, 2007.

[3] A.Klausner, A.Tengg, B.Rinner, "D str but Mult l v l D t Fus on for Networked Embedded Syst ms", IEEE Journ l of S l t Top s n S n l Pro ss n , 2008.

[4] S.Blackman, "Mult -Target Tracking with Ra r Appl t ons", Art h Hous , 1986.

[5] M.Skoln k, "Intro u t on to R r Syst ms", M Gr w-Hill, 1981.

[6] S.Bo qu t, "C l ul t on of R r Prob b l ty of D t t on n K-Distributed Sea Clutter and No s ", DSTO Austr l , 2011.

[7] M.R h r s, "G n r t n Sw rl n R n om S qu n s", 2008.

[8] T.Bieker, "St t st l Ev lu t on of D s on-Level Fusion Methods for Non-Cooperative Target I by R r S n tur s", IEEE 11th Int rn t on l Conference on Information Fusion, 2008.

[9] D.Koks, S.Challa, "An Intro u t on to B y s n n D mpst r Sh f r D t Fus on", DSTO Australia, 2005.

[10] P.Smets, R.Kennes, "Th tr nsf r b l f mo l", In Symbol n Qu nt t t v Appro h s to Uncertainty ,Springer, 1991.

[11] A.Aregui, T.Denoeux, "Constru t n Conson nt B l f Fun t ons from S mpl D t us n Confi n S ts of P n st Prob b l t s", Centrede Recherche de Royallieu, 2008.

[12] H.V rsm ss n, “Stu y of th P rform n D r t on of th B l n S-band Air Surveillance Radars due to th Int rf r n of Up om n 4G T hnolo s, T st R port”, IE-RPT-00357-008 Test Report Study BIPT - Public.odt, Edition Date: 24 Jun 2011.

[13] J.Roux,J,Vuur n, “R l-t m Thr t Ev lu t on n Groun B s A r D f ns Env ronm nt”, ORION Volume24(1), pp.75-101, 2008.

[14] D.Bu , P.G r r , “A T r t I nt f t on Comp r son of B y s n n D mpst r–Shafer Multi-S nsor Fus on”, IEEE Tr ns t ons on Syst ms, Man and Cybernetics, 1997.

[15] O.Azmoon, “Survey of Radars Networking Algorithms and Propose Optimum Algorithm”, Thesis for the Degree of M.S.. Department of Information and Communications Technology, Imam Hossein University, 2011.

[16] K.Khoshelhama, S.Nedkova, C.Nardinocchi, “A Comparison of Bayesian and Evidence-Based Fusion Methods for Automated Building Detection in Aerial Data”, The International Archives of the Photogrammetry, Remote Sensing and Spatial Information Sciences. Vol. XXXVII. Part B7. Beijing, 2008.

[17] B.Cobb, P.Shenoy, “A Comparison of Bayesian and Belief Function Reasoning”, Information Systems Frontiers, Vol. 5, No. 4, pp. 345–358. Dec. 2003.

[18] A.Tolstikovi, et al. “Comparison of fusion methods based on DST and DBN in human activity recognition”, J Control Theory Appl 2011 9(1) 18–27, 2011.

[19] F.Cremer, et al. “A Comparison of Decision Level Sensor Fusion Methods for Anti-personnel Landmine Detection”, Elsevier, Information Fusion 2, 187-208, 2001.

[20] T.Bieker, “Comparison of Fusion Methods for Successive Declarations of Radar Range”, IEEE International Conference on Information Fusion, 2005.

[21] Y.Zeng, J.Zhang, J.Genderen, “Comparison and Analysis of Remote Sensing Data Fusion Techniques at Feature and Decision Levels”, International Journal of Remote Sensing,2004.

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