A NEW HIGH RELIABILITY AND DUAL MEASURE METHOD FOR MULTI-SYSTEM/SENSOR REMOTE-SENSING DECISION FUSION

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ABSTRACT:

In this paper we will introduce a new high reliability multi-system/sensor decision fusion scheme based on dual measure calculations and formulations. The data are collected from remote sensing of the ground targets in different spectral bands including visible, near infrared (NIR), IR, thermal, and microwave by multi-system/sensor systems. At first, we will review the decision fusion methods such as voting methods, rank based algorithm, Bayesian inference, and Dempster-Shafer combination scheme. We show that the essential and common weaknesses of these formal methods are ignoring the class correlation of local classification results and classification error distributions for all classes at different pixels. Then by establishing the commission and omission errors distribution vectors and matrixes, we will formulate and introduce a new dual measure decision fusion (DMDF) algorithm. Formulation the similarity and correlation of local classification results and errors for different classes and need to hard decisions, can be considered as the main features of DMDF. The assumption of uncorrelated errors is not necessary for DMDF, because an optimal class selector always selects the most appropriate class for each pixel. Finally, we deploy these methods for fusion of local classification results, obtained from remote sensing in 12 different spectral bands. In commission and omission errors viewpoints, we will obviously show that the DMDF method is more accurate and reliable than other methods.

1. INTRODUCTION

The recent developments of new sensor technologies (Trankler H. R. and Kanoun O., 2001) and applying the multiple sensor systems have necessitated new needs for advanced data processing techniques that are able to fuse received data from different variety of sensors and systems. Multi-sensor data fusion is a technology concerned with the problem of how to combine data and information from multiple sources/sensors in order to achieve improved accuracies and better inference about the observed target than could be achieved by the use of a single source/sensor alone. In recent years, the multi-sensor data fusion has been significantly considered for military and non-military applications, such as target and pattern recognition (Bhanu, 1986, Mirjalily *et al.*, 2003), automatic landing guidance (Sweet and Tiana, 1996), remote-sensing (Benediktsson and Kanellopoulos,1999, Jimenez and Creus, 1999, Rashidi *et al.*, 2002, Rashidi and Ghassemian, 2003), manufacturing processes monitoring (Chen and Jen, 2000), robotics (Bond *et al*., 2002), and medical applications (Hernandez *et al.* ,1996, Djafari, 2002). Data fusion considering the phase of processing, in which the fusion is carried out, is performed in three levels including the image/signal, feature, and decision fusion. In decision level fusion (Jimenez and Creus, 1999, Rashidi *et al.*, 2002, Mirjalily *et al.*, 2003, Rashidi and Ghassemian, 2003), the received results from different local classifiers will be combined for determination of final decision. The input decisions are some symbols (labels) with different degrees of confidence. This level of fusion has a great use in distributed and parallel processing systems. Figure 1 illustrates, the concept of multi-sensor decision fusion in distributed target sensing network. The useful decision fusion methods, which have been applied in different applications, are voting, rank based, Bayesian inference and Dempster-Shafer methods.

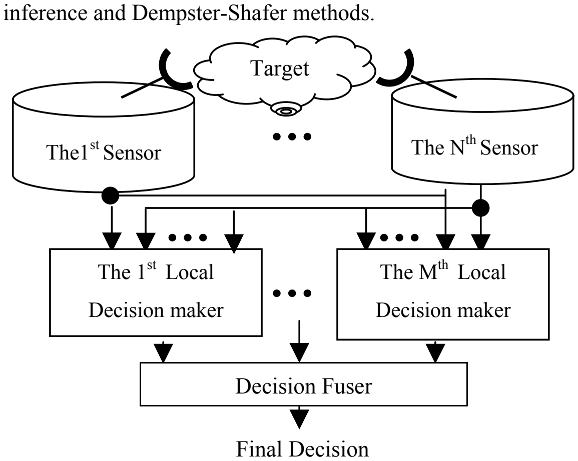

Figure 1. Multi-sensor decision fusion framework.

The main problem in voting methods is that they suffice to local classification results for local winner class in its defined pixel, which causes an intensive decrease in accuracies of decision fusion results for the obtained class-correlated data. Comparing with voting schemes, the rank based method has more attention on data. It uses the results of local classification for a defined pixel, but in all classes. In this method, the results of local classification should include the rank or classification measure values of all classes, which cause intensive increasing in data volume of local classifiers outputs, communication systems between local classifier and fusion centre, and the input of decision fusion centre. The Bayesian method does not consider uncertainty and may have error and complexity in the posterior probabilities measurements. When the number of unknown propositions is large compared to the number of known propositions, the probabilities found by Bayesian method can become unstable. Dempster-Shafer method is an extension of the Bayesian inference, which overcomes some of the drawbacks. This method can be used without prior probability distributions and is able to deal with uncertainty. The main and common problem in suggested fusion methods is the ignorance of nature of local data classifiers and similarity of classes. Also, these methods use only the local classification results in one point (pixel), without attention on result distribution for all classes and other different pixels. These problems demand searching for new methods and tools for accessing desirable results. In this article, after a short review of the above-mentioned methods, by using the mathematical features and distributions of multi-sensors local classification results, we introduce two new measures. These new measures are commission and omission errors functions. Then we derive and explain the commission and omission errors distribution vectors and appropriate matrixes that we can use as new tools for Dempster-Shafer method. Finally, we use these two measures jointly for presentation of a new powerful decision fusion method, which we called as Dual Measures Decision Fusion (DMDF) method. Deployment of these methods for fusion of local classification results, for data obtained from remote sensing in 12 different spectral bands show that the performances of DMDF is higher than another methods. In commission and omission errors viewpoints, we will show that DMDF method that uses special properties of multi-sensors local classification results has better accuracies and reliability than other methods.

2. DECISION FUSION METHODS

In this section, we explain the decision fusion methods, which applied for different application such as pattern recognition, automatic word recognition, target acquisition and remote sensing. These methods include voting, rank based, Bayesian inference, and Dempster-Shafer schemes. Now, we briefly explain about some criterions, which have been used in this article. For local classification, we have applied the maximum probability method that we will accordingly have:

$$X \in \omega_i \quad if \quad g_i(X) > g_j(X) \qquad \forall j \neq i \tag{1}$$

In which, the $g_i(X)$ is classifier discrimination function and ω_i is the selected data class. In addition, the output of each classifier can be generally defined as follow (Parker, 1998):

$$R^i = \{(n_1^i, s_1^i), (n_2^i, s_2^i), \ldots, (n_N^i, s_N^i)\} \tag{2}$$

In which, the N is the number of ranked classes by i^{th} classifier, $n_j^i (j = 1,2,\ldots,N)$ is the name of class, j is the class rank and s_j^i is the value of classification measure for j^{th} rank. Also, the rank of n^{th} class in i^{th} classifier is shown as r_n^i.

2.1. Majority voting fusion method (MVF)

This method just uses the first rank of classifiers (hard decision) and is simple for applying. In MVF method, we have allocated X pixel to ω_j according to the following criterion (Jimenez& Creus, 1999):

$$X \in \omega_j \quad if \quad V(j) = \max_{k=1}^{M}[V(k)] \tag{3}$$

where:

$$V(k) = \sum_{i=1}^{N} \Delta_{ki}, \Delta_{ki} = \begin{cases} 1 & if \quad g_k^i(x_i) = \max_{j=1}^{N}\left[g_j^i(x_i)\right] \\ 0 & else \end{cases} \tag{4}$$

The $g_j^i(x_i)$ is the classifier discrimination function.

2.2. Rank based method

The classification measures and criterions in different classifiers can be different with each other, so it is not possible to compare them directly. For avoiding the disadvantages related to exchanging these criterions, the rank based method can be applied. A simple way for this method is calculation the summation of ranks for each class in the combination set. The class with minimum rank summation is the choice of decision fusion system.

$$r_{\Sigma(n)} = \sum_{i=1}^{m} r_n^i \tag{5}$$

$$X \in \omega_k \quad if \quad r_{\Sigma(k)} = \min_n (r_{\Sigma(n)}) \tag{6}$$

In which, m is the number of classifiers, and $r_{\Sigma(n)}$ is total ranks of n^{th} class [Acherman& Bunde, 1996], [Parker, 1998], [Rashidi& Ghassemian, 2003].

2.3. Bayesian inference method

The Bayesian theory is applied for inference of joint probability of input classifiers. Supposing $\Omega = \{\omega_1, \omega_2, \ldots, \omega_N\}$ is the data class set. In this case, X allocated to ω_k class if:

$$X \in \omega_k \quad if \quad P(\omega_k / X) > P(\omega_j / X) \quad \forall j \neq k \tag{7}$$

where $P(\omega_k / X)$ is the posterior conditional probability. In this method, the complexity of the posterior probabilities calculation is a serious problem [Hall, 1992], [Acherman& Bunde, 1996].

2.4. Dempster-Shafer method (DS)

Dempster-Shafer evidence theory, also known as theory of belief functions, is regarded as a generalization of the Bayesian theory (Dempster, 1968, Hall, 1992, Foucher *et al.*, 2002, Hongwei *et al.*, 2002). Suppose that $\theta = \{A_1, \ldots, A_N\}$, which is called as a frame of discernment, is a finite set of N mutually exclusive and exhaustive sets of propositions about a subject area. Therefore the power set of θ (denoted as 2^θ), composed all subsets of θ, is as follow:

$$2^\theta = \{A_1, \ldots, A_N, A_1 \cup A_2, \ldots, A_1 \cup A_N, \ldots\} \tag{8}$$

where $\cup$ is the sets union operator. The DS method, instead of assigning probability to hypotheses (Bayesian method), assigns probability masses $m(A_i)$ to both single and combined propositions. The probability mass function is defined as follow:

$$m : 2^\theta \longrightarrow [0,1], \quad \sum_{B_i \subset 2^\theta} m(B_i) = 1, \quad m(\phi) = 0 \tag{9}$$

In which, ϕ is the empty set and $\subset$ is the subset operator. The DS rule of combination for two independent sources can be written as follow:

$$m(u_l) = \sum_{A_i \cap B_j = u_l} m_1(A_i) m_2(B_j) / \sum_{A_i \cap B_j \neq \phi} m_1(A_i) m_2(B_j) \tag{10}$$

where $\cap$ represents sets intersection and m_i is the probability mass function of i^{th} source (classifier). In addition u_l is a proposition that defined as a combination of the elemental hypotheses, A_i and B_j .

3. DUAL MEASURE DECISION FUSION (DMDF) METHOD

In this section, we introduce new tools including commission and omission errors functions, distribution vectors, and matrixes based on local classification results. Then, we use commission and omission errors measures jointly, and present the algorithm of DMDF decision fusion method.

3.1. Extraction and offering DMDF tools

We consider the $conf_i$ as the confusion matrix obtained from the local classification results. In addition, we suppose that the N_{C_i} is the total number of pixels related to the C_i class and we denote the n_{ij} as confusion matrix general element. The n_{ij} is the number of pixels which related to the C_i class that the local classifier is assigned them to the C_j class.

$$conf_i \triangleq [n_{ij}] = \begin{bmatrix} n_{11} & n_{12} & \cdots & n_{1(M-1)} & n_{1M} \\ n_{21} & n_{22} & \cdots & n_{2(M-1)} & n_{2M} \\ \cdots & \cdots & \cdots & \cdots & \cdots \\ n_{(M-1)1} & n_{(M-1)2} & \cdots & n_{(M-1)(M-1)} & n_{(M-1)M} \\ n_{M1} & n_{M2} & \cdots & n_{M(M-1)} & n_{MM} \end{bmatrix} \quad (11)$$

$$N_{C_i} = \sum_j n_{ij} \quad (12)$$

$$N^*_{C_j} = \sum_i n_{ij} \quad (13)$$

In which, the $N^*_{C_j}$ is the total number of assigned pixels to the C_j class. Now, we define the $mc_{C_iC_j}$ and $mo_{C_iC_j}$ measures as the commission and omission errors functions of the i^{th} classifier results:

$$mc_{C_iC_j} = n_{ij} \Big/ \sum_i n_{ij} = n_{ij} \Big/ N^*_{C_j} \; , j \neq i \quad (14)$$

$$mo_{C_iC_j} = n_{ij} \Big/ \sum_j n_{ij} = n_{ij} \Big/ N_{C_j} \; , j \neq i \quad (15)$$

In addition we define the $\mu c^i_{C_j}$ and $\mu o^i_{C_j}$ vectors as the commission and omission errors distribution vectors of i^{th} classifier results. Therefore, we have:

$$\mu c^i_{C_j} \triangleq [mc_{C_1C_j}, \ldots, mc_{C_{j-1}C_j}, \frac{n_{jj}}{N_{C_j}}, mc_{C_{j+1}C_j}, \ldots, mc_{C_MC_j}]^T \quad (16)$$

$$\mu o^i_{C_j} \triangleq [mo_{C_1C_j}, \ldots, mo_{C_{j-1}C_j}, \frac{n_{jj}}{N^*_{C_j}}, mo_{C_{j+1}C_j}, \ldots, mo_{C_MC_j}]^T \quad (17)$$

In which, T is the symbol of matrix transposition.

Now, we define the commission and omission errors distribution matrixes of i^{th} classifier results, Mc^i and Mo^i, as follows:

$$Mc^i = [\mu c^i_{c_j}] = [\mu c^i_{c_1} \mid \mu c^i_{c_2} \mid \ldots \mid \mu c^i_{c_M}]_{M \times M} \quad (18)$$

$$Mo^i = [\mu o^i_{c_j}] = [\mu o^i_{c_1} \mid \mu o^i_{c_2} \mid \ldots \mid \mu o^i_{c_M}]_{M \times M} \quad (19)$$

The Mc^i and Mo^i columns are respectively the commission and omission errors distribution vectors ($\mu c^i_{C_j}$ and $\mu o^i_{C_j}$) of local classifiers. As much as we have lower commission or omission errors in classifying results, the Mc^i / Mo^i matrix will be more diagonal. Therefore, in order to be aware of commission or omission errors of a classifier results, it is just sufficient to calculate the Mc^i / Mo^i matrix and consider the diagonal level in different classes. The $mc_{C_iC_j}$, $mo_{C_iC_j}$, $\mu c^i_{C_j}$, $\mu o^i_{C_j}$, Mc^i and Mo^i are DMDF toolbox elements which we will use them in the next section.

Example: For explanation the properties of the DMDF toolbox elements (functions, distribution vectors, and matrixes), we have used the multispectral scanner data obtained from remote sensing related to an agricultural area in Indiana (United State). This data was collected by a 12-channel airborne multi-spectral scanner system during the 1971. In each local classification, the data of 4 bands have been used. (See table 1)

Table 1. Spectral information for data used in example 1

Spectral Bands No.	Wavelength (μm)	Spectral Bands No.	Wavelength (μm)
1	0.46-0.49	7	0.61-0.70
2	0.48-0.51	8	0.72-0.90
3	0.50-0.54	9	1.00-1.40
4	0.52-0.57	10	1.50-1.80
5	0.54-0.60	11	2.00-2.60
6	0.58-0.65	12	9.30-11.70

By using the confusion matrix of the first local classifier we calculate the commission and omission errors matrixes (Mc^i, Mo^i), for this local classifier. The fourth columns of the Mc^i and Mo^i respectively are the commission and omission errors distribution vectors (μc^1_4 and μo^1_4) of the fourth class. (See Figure 2 and Eqs. (20), (21)).

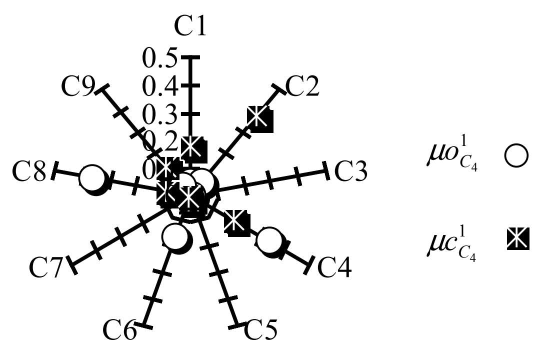

Figure 2. The commission and omission errors ($\mu c^1_4, \mu o^1_4$) vector functions.

$$\mu c^1_4 = \quad (20)$$
$$[0.18 \;\; 0.38 \;\; 0.00 \;\; 0.18 \;\; 0.01 \;\; 0.02 \;\; 0.01 \;\; 0.09 \;\; 0.14]^T$$

$$\mu o^1_4 = \quad (21)$$
$$[0.05 \;\; 0.06 \;\; 0.00 \;\; 0.33 \;\; 0.01 \;\; 0.16 \;\; 0.01 \;\; 0.36 \;\; 0.04]^T$$

As it shown in Figure 2, the commission error distribution of the first classifier in assigning the pixels to the fourth class

(C_4) is not desirable. For example, in this classification, the chance of assigning the pixels of other classes to the C_4 class is higher than the chance of assigning the C_4 pixels to the C_4 class (bad classification). So, in an exact expression, we can write:

$$\underset{c_j \neq c_4}{mc_{c_j c_4}} = 1 - mc_{c_4 c_4} = 1 - 0.18 = 0.82 \tag{22}$$

Also, Figure 2 shows that the omission error distribution of the first classifier in assigning the C_4 pixels is not desirable.

$$\underset{c_j \neq c_4}{mo_{c_4 c_j}} = 1 - mo_{c_4 c_4} = 1 - 0.33 = 0.67 \tag{23}$$

Eq. (24), shows that only %33 of the C_4 pixels allocated to the C_4. In other words, after classification, the most pixels of the fourth class (%67) allocated to the other classes (bad classification). In next section, we will present the DMDF method for decision fusion, by applying the relevant tools and measures, which we have extracted in this section.

3.2. The formulation of DMDF method

We can apply each of the $mc_{C_i C_j}$ and $mo_{C_i C_j}$ measures as the probability mass function that indicated in Eq. (9). Therefore, for fusing the results of the two local classifiers, considering the commission or omission errors matrix of each classifier, we can deploy the new form of Eq. (10) as follow:

$$\mu_{c_l}^{a\oplus b} = \mu_{c_i}^{a} \oplus \mu_{c_j}^{b} = \alpha_{a,b} \left[\underset{i,j}{\overset{m(1),m^*(1)}{\kappa}} \quad \underset{i,j}{\overset{m(2),m^*(2)}{\kappa}} \quad \ldots\ldots \quad \underset{i,j}{\overset{m(M),m^*(M)}{\kappa}} \right]^T \tag{24}$$

In which, $\oplus$ is symbol of classifiers fusion, $\mu_{c_l}^{a\oplus b}$ is commission or omission errors distribution vector obtained from fusion. Also, m and m^* are respectively commission or omission errors distribution functions of ***a*** and ***b*** classifiers and $\alpha_{a,b}$ coefficient is equal to:

$$\alpha_{a,b} = \left(\left[\underset{i,j}{\overset{m(1),m^*(1)}{\kappa}} + \underset{i,j}{\overset{m(2),m^*(2)}{\kappa}} + \ldots + \underset{i,j}{\overset{m(M),m^*(M)}{\kappa}} \right] \right)^{-1} \tag{25}$$

where:

$$\underset{i,j}{\overset{m(l),m^*(s)}{\kappa}} \triangleq m_{c_l c_i} m^*_{c_s c_j} \tag{26}$$

The selected class as the result of fusion is a class, which includes the maximum value of $\mu_{c_l}^{a\oplus b}$ (fusion output). In other words, we have:

$$X \in C_k \text{ if } \max_{c_l} \{\mu_{c_l}^{a\oplus b}(c_l)\} = \max_{l} \{\alpha_{a,b} \underset{i,j}{\overset{m(l),m^*(l)}{\kappa}}\} = \alpha_{a,b} \underset{i,j}{\overset{m(k),m^*(k)}{\kappa}} \tag{27}$$

The new measures provide the advantages of considering the important features of local decisions, i.e. commission or omission errors, and they depend on only to the local classifier performances. Therefore, the calculation of these new tools compare with the basic DS method probability masses is very easier. If we use the commission or omission errors tools for improving the DS method, then the improved method name is DS (PM) or DS (CM). Although, using these new measures, we can considerably improve the fusion results in DS method, in this section; we present the DMDF algorithm, which is based on the parallel usage of these measures. Supposing the decision fusion results, using commission and omission errors measures are as follows:

$$\mu cm_{c_{i,j}}^{1\oplus 2}(c_h) = \max_{c_k}\{\mu c_{c_{i,j}}^{1\oplus 2}(c_k)\} \tag{28}$$

$$\mu om_{c_{i,j}}^{1\oplus 2}(c_f) = \max_{c_l}\{\mu o_{c_{i,j}}^{1\oplus 2}(c_l)\} \tag{29}$$

In which, $\mu cm_{c_{i,j}}^{1\oplus 2}(c_h)$ and $\mu om_{c_{i,j}}^{1\oplus 2}(c_f)$ respectively are the values of $\mu c_{C_{i,j}}^{1\oplus 2}$ and $\mu o_{C_{i,j}}^{1\oplus 2}$ at $c = c_h$ and $c = c_f$, and they are equal to:

$$\mu cm_{c_{i,j}}^{1\oplus 2}(c_h) \triangleq \alpha c_{i,j}\ mc_{c_h c_i} mc^*_{c_h c_j} \tag{30}$$

$$\mu om_{c_{i,j}}^{1\oplus 2}(c_f) \triangleq \alpha o_{i,j}\ mo_{c_f c_i} mo^*_{c_f c_j} \tag{31}$$

In which, $\alpha c_{i,j}$ and $\alpha o_{i,j}$ are $\alpha_{a,b}$ coefficient that defined in Eq. (25). In the DMDF method, the final decision for selected (winner) class is considered as follow:

$$X \in \begin{cases} \omega_h & \text{if} \quad \mu ocm_{c_{i,j}}^{1\oplus 2}(c_h) > \mu ocm_{c_{i,j}}^{1\oplus 2}(c_f) \\ \omega_f & \text{if} \quad \mu ocm_{c_{i,j}}^{1\oplus 2}(c_f) > \mu ocm_{c_{i,j}}^{1\oplus 2}(c_h) \\ \omega_h / \omega_f & \text{if} \quad \mu ocm_{c_{i,j}}^{1\oplus 2}(c_h) = \mu ocm_{c_{i,j}}^{1\oplus 2}(c_f) \end{cases} \tag{32}$$

In which, $\mu ocm_{c_{i,j}}^{1\oplus 2}(c_h)$ and $\mu ocm_{c_{i,j}}^{1\oplus 2}(c_f)$ respectively are the extracted joint measures from fusion results, by applying the commission and omission errors vectors, and defined as follows:

$$\mu ocm_{c_{i,j}}^{1\oplus 2}(c_h) \triangleq \mu om_{c_{i,j}}^{1\oplus 2}(c_h) + \mu cm_{c_{i,j}}^{1\oplus 2}(c_h) \tag{33}$$

$$\mu ocm_{c_{i,j}}^{1\oplus 2}(c_f) \triangleq \mu om_{c_{i,j}}^{1\oplus 2}(c_f) + \mu cm_{c_{i,j}}^{1\oplus 2}(c_f) \tag{34}$$

Figure 3, illustrates the decision fusion procedure in DMDF algorithm.

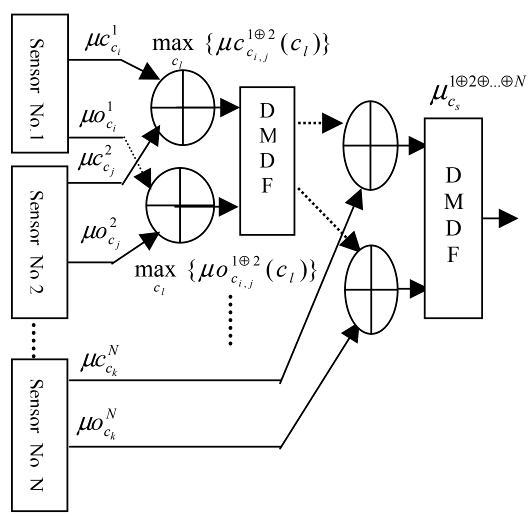

Figure 3. The multiple classifiers decision fusion scheme in DMDF method.

4. Deployments and Comparing the Methods

In this section, we have deployed the decision fusion methods including MVF, rank based, Bayesian inference, Dempster-Shafer and DMDF for fusing the local classifier decisions. Then we compared the decision fusion results, considering their commission and omission classification errors those defined as follows:

$$eo_{c_i} \underline{\underline{\Delta}} (1 - n_{ii} \Big/ \sum_{j} n_{ij}) \tag{35}$$

$$ec_{c_i} \underline{\underline{\Delta}} (1 - n_{ii} \Big/ \sum_{i} n_{ij}) \tag{36}$$

In which, eo_{c_i} and ec_{c_i} respectively are the omission and commission classification errors for c_i data class (Petrakos *et al.*, 2000, Rashidi& Ghassemian, 2003). In addition, the total commission and omission errors and reliability factor (re_{tot}) for all data classes are defined as follows:

$$eo_{tot} \underline{\underline{\Delta}} M^{-1} \sum_{i=1}^{M} eo_{c_i} \tag{37}$$

$$ec_{tot} \underline{\underline{\Delta}} M^{-1} \sum_{i=1}^{M} ec_{c_i} \tag{38}$$

$$re_{tot} \underline{\underline{\Delta}} \{1 - 0.5(ec_{tot} + eo_{tot})\} \tag{39}$$

The experiments have done for more than 15 available remote sensing data classification results. In all of these experiments, we have found that the DMDF performances are higher than other methods. In this section we show the decision fusion results related the data described in example (we called C12 data). In tables 3 and 4, there are comparisons for percentages of the omission and commission classification errors for the final classification in different methods versus data classes. In addition, Figures 4 and 5 and table 5 show the percentages of the total omission and commission errors and reliabilities for all data classes of data.

Table 3. The decision fusion methods omission error percentages (eo_{c_i}) for C12 data.

Classes \ Methods	MVF	Rank	Bayesian	DS(PM)	DS(CM)	DMDF
Corn	1.64	0.45	13.3	2.41	2.11	2.89
Soybeans	0.43	0.62	6.31	3.05	0.47	2.63
Woods	77.8	75.2	94.0	36.0	50.9	23.9
Wheat	23.8	30.0	71.5	20.9	30.6	14.6
Sudex	2.12	1.92	11.6	3.55	3.32	3.56
Oats	38.2	54.1	62.9	30.6	51.1	13.6
Pasture	2.15	2.14	47.5	2.14	2.14	0.32
Hay	25.8	35.1	66.6	16.5	32.8	15.4
Unclassified	2.25	5.56	1.41	3.53	3.58	3.68

Table 4. The decision fusion methods commission error percentages (ec_{c_i}) for C12 data.

Classes \ Methods	MVF	Rank	Bayesian	DS(PM)	DS(CM)	DMDF
Corn	8.15	5.67	7.82	1.87	3.52	1.69
Soybeans	20.1	11.2	50.9	3.19	7.82	1.92
Woods	14.0	5.7	25.4	55.0	6.84	15.7
Wheat	17.5	16.4	50.1	11.4	11.3	14.4
Sudex	3.51	6.09	6.76	2.59	2.84	2.67
Oats	31.6	15.8	34.3	23.9	13.2	36.0
Pasture	2.74	2.44	8.84	2.44	2.44	4.88
Hay	26.8	8.63	45.3	14.6	9.06	15.8
Unclassified	15.1	8.04	30.4	7.6	11.1	7.28

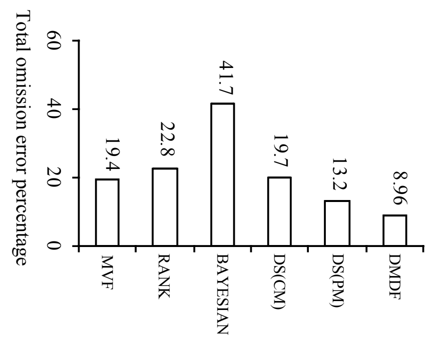

Figure 4. The total omission errors for the decision fusion methods.

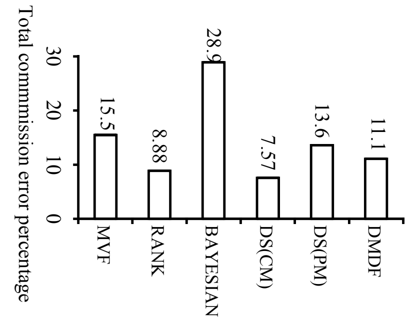

Figure 5. The total commission errors for the decision fusion methods.

Table 5. The reliability factors for the decision fusion methods.

Methods	**Reliability (C12 data)**
MVF	%82.55
Rank	%84.20
Bayesian	%64.70
DS(CM)	%86.36
DS(PM)	%86.56
DMDF	%89.70

Considering the mentioned results in the tables and figures, it is cleared that the DMDF method, has lower commission and omission errors and higher reliability than other methods. This superiority is raised from the better combination rules and extraction the new tools such as commission and omission errors distribution vectors in the DMDF algorithm. Another important point about the presented method is that, we just need to hard decision for extraction the commission and omission errors matrixes of classifier results as the fuser inputs, while the other methods such as rank based and Bayesian methods, need soft decisions which are high volume data and complex inputs. Therefore, we confirm that the new method has a desirable condition for all classes in commission and omission errors, and reliability viewpoints. Of course, for any data fusion and classification, we should note that we have to evaluate the commission and omission errors of the whole classes jointly, and improving in only one of them is not sufficient. So, table 5 shows that the DMDF is superior in this aspect(reliability) comparing the all other methods.

5. Conclusion

In this article, we described at first, the most useable methods of decision fusion such as MVF, rank based, Bayesian inference and Dempster-Shafer theory of evidence. Meanwhile, we referred to the related problems and insufficiency of mentioned methods as the formal methods of decision fusion. It was also showed that it is the main problem in voting methods that they use only the local classification results for local winner class in only one defined pixel. This causes an intensive increasing in commission and omission errors of decision fusion results for correlated data, and also for class correlated classifiers errors. Also, the rank based methods, which use the local classification results in the order of the rank of all classes in a defined pixel, the volumes of transferred data and data, which should be processed, will be intensively increased. Improvements in performances for voting and rank based methods are related to the degree of error diversity among combined classifiers. Unfortunately, in classification applications, it may be difficult to design an ensemble to exhibit a high degree of error diversity. The Bayesian method does not consider uncertainty and may have error and complexity in the posterior probabilities measurements. We explain that the Dempster-Shafer method, which is an extension of Bayesian inference, overcomes some of the difficulties. This method can be used without prior probability distributions and is able to deal with uncertainty. The main and common problem in suggested fusion methods is the ignorance of nature of local data classifiers and similarity of classes. Also, these methods use only the local classification results in one point (pixel), without attention on result distribution for all classes and other different pixels. For solving these problems and accessing desirable results, by using the mathematical features and distribution of multi-sensor local classifications results, we introduced commission and omission errors functions. Formulation the similarity and correlation of local classification results and errors for different classes and need to hard decision, can be considered as the main features of these new tools. Finally, by using the common features of the mentioned tools, we presented the dual measure decision fusion (DMDF) method. The assumption of uncorrelated errors is not necessary for DMDF because an optimal class selector always selects the most appropriate class for each pixel. In previous section, we deployed these methods for fusion of three local classifier results. After comparing the results, we showed that the DMDF, which uses the special features of multi-sensor local decisions, has lower commission and omission errors and higher reliability than other methods. Of course, the DMDF method is a flexible method that can use for any decision fusion problem and any application. Although we obtained desirable results through developing the DMDF, extraction the new measures and distribution, and applying of some tools such as: fuzzy measures and methods, and neural network for accession the better reliability are considered as the next interest research of the writer.

6. References

Achermann, B. and Bunde, H., 1996, "Combination of classifiers on the decision level for face recognition," *Technical reports IAM-96-002*, University of Bern.

Benediktsson, J. A. and Kanellopoulos, I., 1999, *IEEE Transactions on Geoscience and Remote Sensing* 37(3), 1367-1377.

Bhanu, B., 1986, *IEEE Trans. Aerosp. Elect. Systems* 22 (4), 364-376.

Bond, A., Francesco, G. and Longhi, S., 2002, "A Bayesian approach to the hough transform for video and ultrasonic data fusion in mobile robot navigation," *IEEE International Conference on Systems, Man and Cybernetics*, 3, 354-359.

Chen, S. and Jen, Y.W., 2000, *International Journal of Machine Tools and Manufacture*, 40(3), 381- 400.

Dempster, A. P., 1968, *Journal of Royal Statistical Socie* 30, 205-247.

Djafari, A. M., 2002, "Hierarchical Markov modeling for fusion of X ray radiographic data and anatomical data in computed tomography," in *Proc. of the IEEE International Symposium on Biomedical Imaging*, 401- 404.

Foucher, S., Germain, M., Boucher, J. M. and Benie, G. B., 2002, *IEEE Transactions on Instrumentation and Measurement* 5, 277–281.

Hall, D. L., 1992, *Mathematical Techniques in Multi-Sensor Data Fusion* (Artech House, Norwood).

Hernandez, A., Basset, O., Magnin, I., Bremond, A. and Gimenez, G., 1996, "Fusion of ultrasonic and radiographic images of the breast," *in Proc. of the IEEE Ultrasonic Symposium*, 1437-1440.

Hongwei, Z., Basir, O. and Karray, F., 2002, "Data fusion for pattern classification via the dempster-shafer evidence theory," *IEEE International Conference on Systems, Man and Cybernetics*, 7,109 –110.

Jimenez, L. O. and Creus, A. ,1999, *IEEE Transactions on Geoscience and Remote Sensing* 37(3), 1360-1366.

Mirjalily, G., Zhi-Quan, L., Davidson, T. N. and Bosse, E., 2003, *IEEE Transactions on Aerospace and Electronic Systems* 39, 34-52.

Parker, J. R., 1998, "Multiple sensors, voting methods and target value analysis," *Technical report 1998-615-06,* University of Calgary, CANADA.

Petrakos, M., Kannelopoulos, I., Benediktsson, J. A. and Pesaresi, M., 2000, "The effect of correlation on the accuracy of the combined classifier in decision level fusion," *Proc. of International IEEE Geoscience and Remote Sensing Symposium*, 6, 2623 –2625.

Rashidi, A. J., Ghassemian, M. H. and Dehghani, H., 2002, "Decision fusion in remote sensing systems," in *Proce. of the 10th Iranian Conference on Electrical Engineering,* 2, 234-241.

Rashidi, A. J. and Ghassemian, M. H., 2003, "Extended Dempster-Shafer theory for multi-system/sensor decision fusion," in *Proc. of the ISPRS Commission IV Joint Workshop (Challenges in Geospatial Analysis, Integration and Visualization II), Stuttgart, Germany*.

Sweet, B. T. and Tiana, C. L., 1996, "Image processing and fusion for landing guidance," in *Proc. of SPIE*, 2736, 84-95.

Trankler, H. R. and Kanoun, O., 2001, "Recent advances in sensor technology," in *Proc. of the 18th IEEE Conference on Instrumentation and Measurement Technology*, 1, 309-316.