COMPARISON AND ANALYSIS OF REMOTE SENSING DATA FUSION TECHNIQUES AT FEATURE AND DECISION LEVELS

Yu ZENG [a,b] , Jixian ZHANG [a], J.L.VAN GENDEREN [c]

[a] Chinese Academy of Surveying and Mapping, Beijing, 100039, P.R.China, zengyu@casm.ac.cn
[b] College of Geo-Information Science and Engineering, Shandong University of Science and Technology, Qingdao, Shandong Province, 266510, P.R.China
[c] International Institute for Aerospace Survey and Earth Sciences (ITC), P.O. Box 6, 7500 AA Enschede, The Netherlands

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ABSTRACT:

Image fusion is the combination of two or more different images to form a new image by using a certain algorithm. The aim of image fusion is to integrate complementary data in order to obtain more and better information about an object or a study area than can be derived from single sensor data alone. Image fusion can be performed at three different processing levels which are pixel level, feature-level and decision-level according to the stage at which the fusion takes place. This paper explores the major remote sensing data fusion techniques at feature and decision levels implemented as found in the literature. It compares and analyses the process model and characteristics including advantages, limitations and applicability of each technique, and also introduces some practical applications. It concludes with a summary and recommendations for selection of suitable methods.

1. INTRODUCTION

Data fusion is a process dealing with data and information from multiple sources to achieve refined/improved information for decision making (Hall 1992). A general definition of image fusion is given by Genderen and Pohl (1994) as "Image fusion is the combination of two or more different images to form a new image by using a certain algorithm". The aim of image fusion is to integrate complementary data in order to obtain more and better information about an object or a study area than can be derived from single sensor data alone. Image fusion can be performed at three different processing levels which are pixel level, feature-level and decision-level according to the stage at which the fusion takes place. An in-depth research on pixel-level image fusion has been carried out, and new techniques are constantly developed. Pohl and Genderen (1998) gave a rather detailed summarization and review at pixel-level image fusion techniques. At the same time, image fusion techniques based on feature-level and decision-level have been studied and applied in some fields to a certain extent also; they are especially applicable for images from different sensors and with different characteristics, for example, optical image data and SAR data. However, there is no review on this topic available in remote sensing related fields.

This paper explores the major remote sensing data fusion techniques at feature and decision levels implemented as found in the literature. It compares and analyses the process model and characteristics including advantages, limitations and applicability of each technique, and also introduces some practical applications. It concludes with a summary and recommendations for selection of suitable methods.

2. IMAGE FUSION TECHNIQUES

Other than pixel-level fusion, feature/decision-level fusion is performed at a higher processing level. In the feature-level fusion, each sensor observes an object, and a feature extraction is performed to yield a feature vector from each sensor. After using an association process to sort feature vectors into meaningful groups, these feature vectors are then fused and an identity declaration is made based on the joint feature vector. In the decision-level approach, each sensor performs independent processing to produce a declaration of identity, and then the declarations of identity from each sensor are subsequently combined via a fusion process. Techniques involved in feature/decision-level data fusion are drawn from a wide range of areas including artificial intelligence, pattern recognition, statistical estimation, information theory, and other areas. These techniques are listed as follows in Table 1.

Feature-level fusion	Decision-level fusion
Cluster Analysis	Classical Inference
Neural Networks	Bayesian Inference
Bayesian Inference	Dempster-Shafer's Method
Dempster-Shafer's Method	Voting Strategies
Expert Systems	Expert Systems
Logical Templates	Logical Templates
	Neural Networks
	Fuzzy Logic
	Blackboard
	Contextual Fusion
	Syntactic Fusion

Table 1. Fusion techniques based on fusion levels

These techniques can be classified into two groups, which are knowledge-based methods and methods with the identity fusion concepts (ITC, 1998). Expert Systems, Logical Templates, Neural Networks, Fuzzy Logic, Blackboard, Contextual Fusion and Syntactic Fusion belong to the former; Classical Inference, Bayesian Inference, Dempster-Shafer approach and Voting Strategies belong to the latter. In the field of remote sensing, the widely used techniques are Bayesian inference, Dempster-

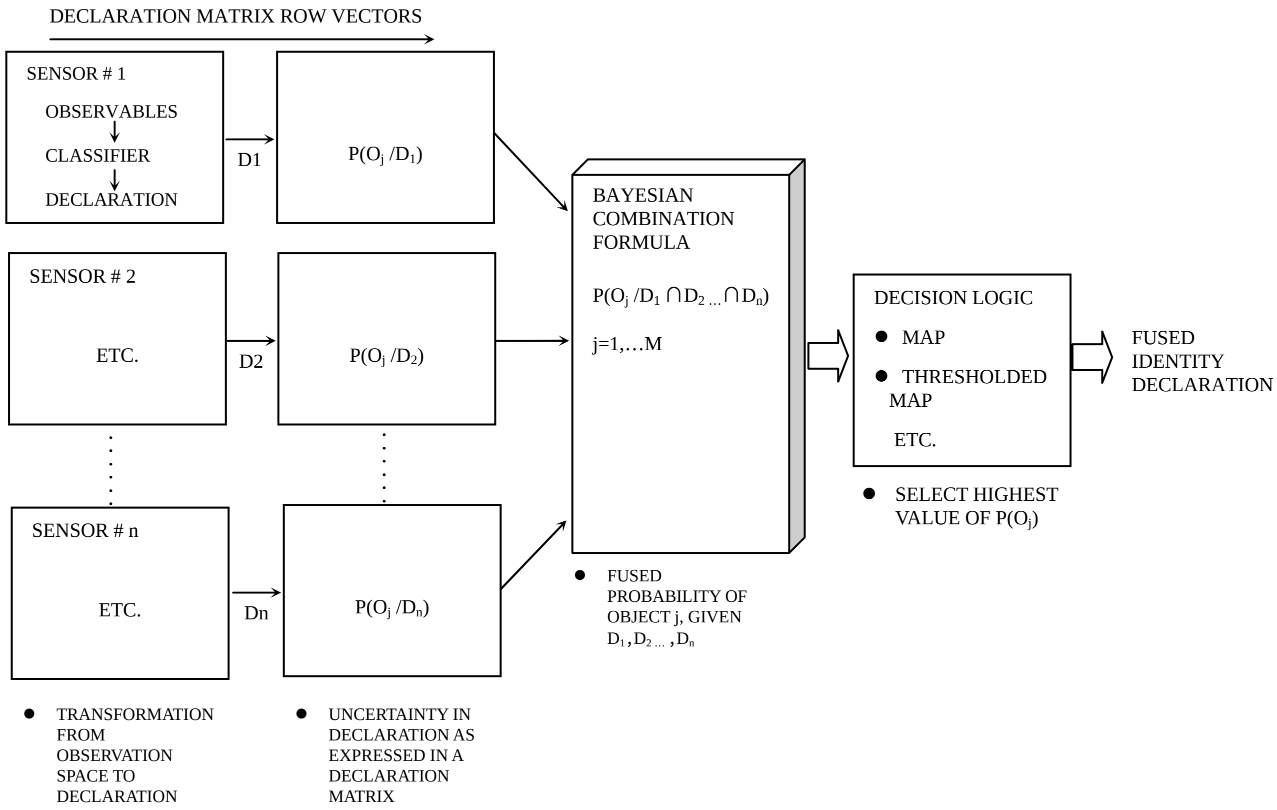

Figure 1. Summary of Bayesian fusion (Hall, 1996)

Shafer evidence theory, Fuzzy logic, Neural networks and Expert Systems. Because of the limited space, here we just summarize the basic principles of the major three techniques and their practical applications.

2.1 Bayesian Inference

Bayesian inference takes its name from the English clergyman Thomas Bayes. A paper published by Bayes contains the inequality that is known today as Bayes's theorem in 1763. The Bayesian inference technique resolves some of the difficulties with classical inference methodology. Bayesian inference allows multisensor information to be combined according to the rules of probability theory. Bayes'formula provides a relationship between the *a priori* probability of a hypothesis, the conditional probability of an observation given a hypothesis, and the *a posteriori* probability of the hypothesis. It updates the probabilities of alternative hypotheses, based on observational evidence. New information is used to update the *a priori* probability of the hypothesis.

The Bayesian inference process proceeds as follows: Suppose $H_1, H_2, \dots, H_i$, represent mutually exclusive and exhaustive hypotheses that can explain an event E (an observation) that has just occurred. Then,

$$P(H_i/\mathrm{E}) = \frac{P(\mathrm{E}/H_i)P(H_i)}{\sum_i P(\mathrm{E}/H_i)P(H_i)} \qquad (1)$$

and

$$\sum_i P(H_i) = 1 \qquad (2)$$

where,

$P(H_i/\mathrm{E}) =$ the *a posteriori* probability of hypothesis H_i being true given the evidence E.

$P(H_i)$ = *a priori* probability of hypothesis H_i being true.

$P(\mathrm{E}/H_i)$ = the probability of observing evidence E, given that H_i is true.

Figure 1 illustrates the process of using a Bayesian formulation for data fusion. Bayesian methods are probably the most widely used in probabilistic image fusion. Mascarenhas et al. (1996) proposed a new data fusion method using Bayesian statistical estimation theory, that uses the multispectral and panchromatic bands of the SPOT satellite to generate the fused multispectral image with 10m spatial resolution. Zaniboni et al. (1998) adapted the Bayesian method to work with locally adaptive correlation coefficients to generate fused multispectral images from the SPOT satellite.

2.2 Dempster-Shafer (DS) Evidence Theory

The Dempster-Shafer (DS) evidence theory was proposed by Dempster (A.Dempster, 1967) and extended by Shafer (Shafer G., 1976). It is a generalization of Bayesian theory that allows for a general level of uncertainty (Lowrance and Garvey, 1982). Hence, unlike the Bayesian approach, the DS method provides a means to account explicitly for unknown possible cause of observational data (Hall, 1996). This method utilizes probability intervals and uncertainty intervals to determine the likelihood of hypotheses based on multiple evidence. In addition, it computes a likelihood that any hypothesis is true. These two methods produce identical results when all of the hypotheses considered are mutually exclusive and the set of hypotheses is exhaustive.

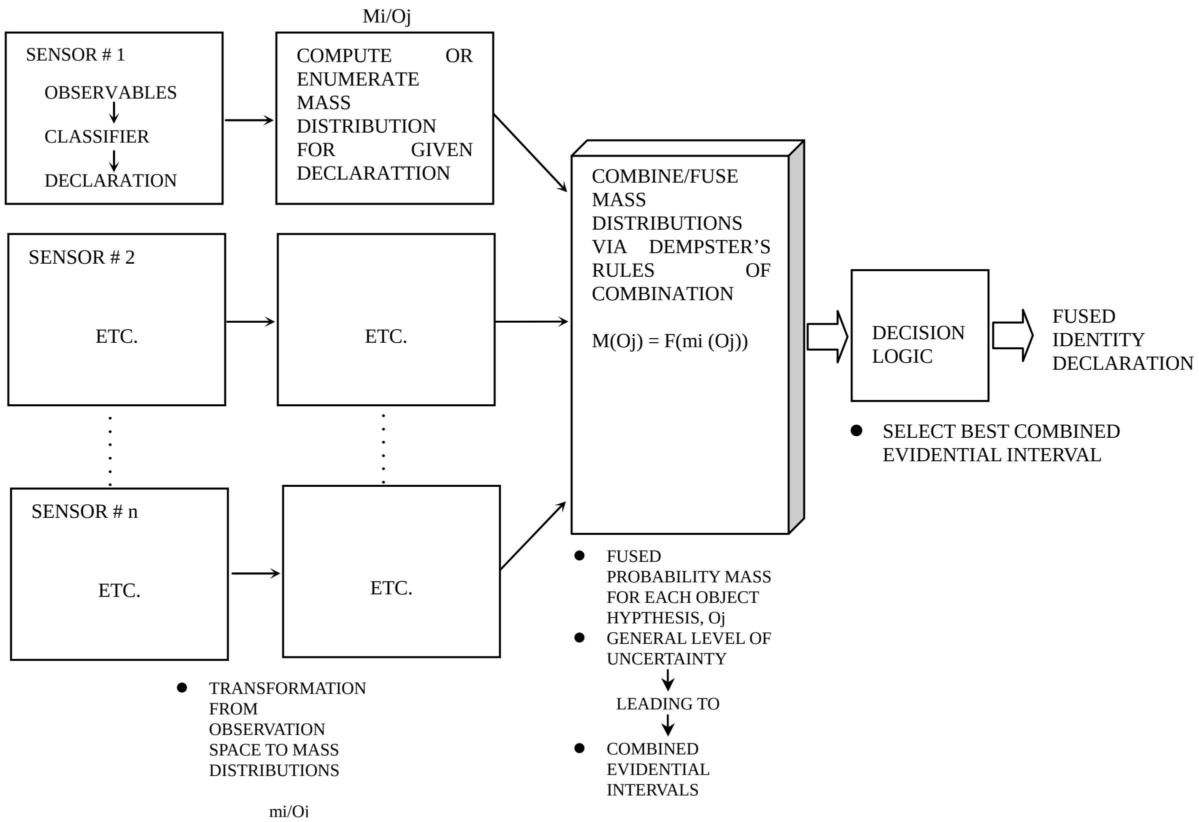

Figure 2. Summary of Dempster-Shafer fusion (Hall, 1996)

The basic principles of Dempster-Shafer evidence theory are: Assume the frame of discernment θ represents the set of image classes. An elementary mass function is defined by

$$m : 2^{\theta} \rightarrow [0,1]; \sum_{B \subset 2^{\theta}} m(B) = 1; \; m(\phi) = 0 \qquad (3)$$

The belief function *Bel*(B) gives the amount of evidence which implies the observation of B. This function is defined on the frame of discernment by the relation

$$Bel(B) = \sum_{C \subset B} m(C) \qquad (4)$$

And the plausibility function *Pl*(B) can be seen as the amount of evidence which does not refute B:

$$Pl(B) = \sum_{C \cap B \neq 0} m(C) \qquad (5)$$

This function can be represented according to the belief function *Bel*(B)

$$Pl(B) = 1 - Bel(\bar{B}) \qquad (6)$$

The interest of DS theory is to combine pieces of evidence/information from various sources. The combination, which is also called the orthogonal sum, is defined as follows:

$$if \;\; K \neq 1, and \; \forall A \subseteq \theta, \; A \neq \phi,$$

$$(m_1 \oplus m_2)(A) = \frac{\sum_{B_1 \cap B_2 = A} m_1(B_1) m_2(B_2)}{1 - K} \qquad (7)$$

$$K = \sum_{B_1 \cap B_2 = \phi} m_1(B_1) m_2(B_2) \qquad (8)$$

$$(m_1 \oplus m_2)(\phi) = 0 \qquad (9)$$

The concept of using a Dempster-Shafer approach to fuse multisensor data is illustrated in Figure 2. Dempster-Shafer evidence theory allows the representation of both imprecision and uncertainty, has already shown its suitability for remote sensing data fusion problems. Based on this theory, Le Hégarat-Mascle S. et al. improved the land cover classification accuracy using multisource remote sensing data (2000, 2003); Mickaël Germain et al. (2002) classified the forest area using Landsat TM data while introducing the spatial contextual information; Fang Yong (2000) demonstrated that evidential reasoning has extensive applications in the classification of remote sensing images through the fusion analysis of ERS SAR and TM image; Foucher. S. et al. (2002) presented the result in the fusion of an optical (Spot) and the SAR image (Radarsat).

2.3 Neural Networks

Neural networks are the systems that seek to emulate the process used in biological nervous systems. A neural network consists in layers of processing elements, or nodes, which may be interconnected in a variety of ways. The neural network performs a non-linear transformation of an input vector. This theory is used when the relation between output and input data is unknown. A neural network can be trained using a sample or training data set (supervised or unsupervised depending on the training mode) to perform correct classifications by systematically adjusting the weights in the activation function. This activation function defines the processing in a single node. The ultimate goal of neural network training is to minimize the cost or error function for all possible examples through the input-output relation (X. Dai and S. Khorram, 1998). The neural networks can be used to transform multisensor data into a joint declaration of identity for an entity. Figure 3 illustrates a four-layer network with each layer having multiple processing elements. The applications of neural networks to image data fusion included A. Chiuderi et al. (1994) used a neural network approach for data fusion of land cover classification of remote sensed images on an agricultural area. By using supervised and unsupervised neural network, the optical-infrared data and microwave data were fused for land cover classification. L. Yiyao et al. (2001) adopted a knowledge-based neural network for fusing edge maps of multi-sensor remote sensing images. He Mingyi and Xia Jiantao (2003) proposed DPFNN (Double Parallel Feedforward Neural Networks) used to classify the high dimensional multispectral images. Other applications can be found in crop classification, forest type classification, recognition of typhoon clouds etc.

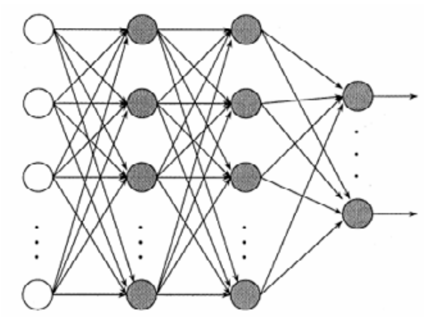

Figure 3. Architecture graph of a neural network with two hidden layers (L. Yiyao et al., 2001)

3. ADVATAGES AND LIMITATIONS

In this section, we compare and analysis the benefits and limitations of the above mentioned theories.

Bayes's framework is exceptionally fruitful in decision theory. It has several advantages. First it provides a determination of the probability of a hypothesis being true, given the evidence. Second, Bayes's formulation allows incorporation of a priori knowledge about the likelihood of a hypothesis being true at all. The final feature of Bayes's formulation is the ability to use subjective probabilities for a priori probabilities for hypothesis, and for the probability of evidence given a hypothesis (Hall, 1996). Isabelle Bloch and Henri Maitre (1994) pointed out that Bayesian inference faces two major limits. First of all, it is quite demanding since it requires that all the dependencies between measures and underlying phenomena be set in the same statistical framework. Specifically, it requires the knowledge of a priori and conditional probabilities which are very rarely known. Because of these requirements probabilistic methods have several weaknesses which are well known such as: their practical implementation often relies on simplified assumptions (for instance events independency), or on arbitrary choices (Gaussian or uniform distributions). Thus all the available information, since it can hardly be set in this framework, is often not completely used. Second, it can hardly manage spatial uncertainty or imprecision. Direct methods where spatial uncertainty is introduced by means of statistical distribution functions become very complex and time consuming to implement as soon as it is combined with other sources of uncertainty and, in practice, are never used in ordinary complex situations.

Dempster-Shafer evidence theory is often described as an extension of the probability theory or a generalization of the Bayesian inference method. Unlike Bayesian inference theory, Dempster–Shafter evidential reasoning can present both imprecision and uncertainty through the definition of belief and plausibility functions; It has the capability to take into account compound hypotheses. In the Bayesian framework, the degree of belief we have on a union of classes (without being able to discriminate between them) should be shared by all the simple hypotheses, thus penalizing the good one (Florence Tupin et al, 1999). In Dempster-Shafer evidence theory, the definition of mass functions is a crucial step and it is the most difficult part in the implementation of Dempster-Shafer evidence theory. Lots of research work has been done on it, however, there still remains unsolved problems in the definition of mass functions, which did not yet find a general answer.

Neural network approach can exhibit properties analogous to adaptive biological learning; it has good pattern recognition capabilities, and once learned, information recall resistant to hardware or data failure. It has the following advantages over the statistical approaches: distribution-free; and degree of belief in each data source is represented by the weights of the network and determined by the training process. It is not necessary to estimate the reliability function during the fusion process (X. Dai and S. Khorram, 1998). Bowman (1988) and Priebe and Marchette (1988) suggest that neural networks are superior to traditional cluster methods for identity fusion, especially when the input data are noisy and when data are missing. However, the theoretical basis of neural networks is still evolving, during the implementation of a neural network, the problem of local extremum, convergence speed of the training, and misclassification when the data dimensions increase still should be considered.

4. CONCLUSIONS

From the recent literature in image fusion, we can see that researchers have now acquired a better understanding of the data fusion techniques and of how they can be used in higher level image fusion. Each image fusion technique has its pros and cons. The degree of success is always case-dependent. Non-probabilistic methods are getting more and more popular, and their main features are better exploited. Inference performance, required computer resources, requirement of a priori information, and general utilities should be the tradeoffs when applying a higher level image fusion technique. In order to achieve an overall objective, a combination of techniques and a significant amount of ancillary measures may be employed.

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