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Multisource Signal Fusion using Dempster Shafer Evidence Accumulation Concept and its Applications to CMFD and Multimodal Biomedical Image Fusion

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Abstract: This paper addresses a soft computing approach of fusion of signals from different independent sources. The signals may be from different types of primary classifiers. The Dempster Shafer Evidence Accumulation (DSEA) theory provides a robust platform for evidence fusion and it incorporates uncertainty, imprecision and conflicting situations in the process of decision making into a mathematical framework. Primarily, Neuro-Fuzzy classifiers have been used on the signals of each individual source to classify them into meaningful clusters and to assign mass value to each cluster, then Dempster Shafer Evidence Accumulation engine (DSEAE) has been used to combine them for final output with proper classification to different admissible clusters. We have cited two experimental results of the use of this concept. Firstly, the concept has been studied on a diesel engine to fuse the coolant flow signals from three primary ANN classifiers; secondly, it has been used to fuse SPECT and MR-T2 registered brain images classified by fuzzy C-means method.

Keywords: Dempster-Shafer combination rule, data fusion, Multimodal medical Image fusion, CMFD

I. INTRODUCTION

Signal processing often requires combined studies of signals from independent sources. It might have spatial as well as temporal differences. These differences impede human experts to mentally fuse the signals in a consistent manner and often lead to a poor or wrong decision. In case, the signals are from different types of source, this task becomes more complex and error prone. It has also been found that, when the signals are from different sources, they potentially offer complementary information about the pattern to be classified and minimizes the weaknesses of individual source. Moreover, fusion often contains additional information which may be absent in individual signal. This leads to a synergistic study of signals and in turn improves the quality of the decision

Different fusion classifiers have recently been applied successfully in the areas of handwriting recognition [1], optical character recognition [2], speech recognition [3], multimodal medical image fusion [4], earthquake evaluation [5] and industrial fault diagnostics applications [6]. It has been found that the fusion of outcomes of primary classifiers provides better and robust results.

Primary classifiers perform classification by grouping the signals in different classes. Artificial neural network techniques like Multilayer Perceptron (MLP), Radial Basis Function (RBF), k Nearest Neighbor (kNN), Fuzzy C-means are very successful pattern recognition techniques and can be used as primary classifier [7, 8]. In the simplest form, frequency histogram under different operational conditions may also be used as primary classifier [3]

Depending upon the problem and pattern of outcome of primary classifiers, different fusion techniques have been tested to combine class the elements [9]. The following mathematical theories can be used as a fusion tool, as they can cope with uncertain, imprecise and vague data:

- probability theory
- fuzzy theory
- Dempster Shafer theory

Dempster Shafer evidence theory [10] is one such technique and has been used successfully in few cases [4, 10]. This approach is a powerful method of combining accumulative evidence and capable of changing prior evidence in the presence of new evidence [10].

This paper briefly presents the DSEA theory of evidence fusion followed by discussion on the methodology for classification and fusion of signals. A multisource Condition monitoring and Fault diagnosis (CMFD) module of a diesel engine to fuse the evidences of rate of coolant agent flow identified by three ANN classifiers and fusion of registered MR-SPECT brain images are adduced in support of the concept. We have considered these case studies from two different fields to show the strength and prospect of DSEA concept in diversified applications.

A. *Condition monitoring and Fault diagnosis*

CMFD requires study of numerous symptoms to predict possible failure of machines and to decide subsequent preventive mechanism. The study of symptoms requires classification and recognition of pattern of the outputs from the target machine. Various classification schemes can be used to achieve this goal. It has been observed from previous studies that one of the designs may yield the best performance but the sets of patterns wrongly classified by different classifiers may not necessarily improve the reliability of the total system. This suggests that different classifiers potentially offered complementary information about the pattern to be classified, combination of which could improve the performance of the selected classifier, which in term can improve the strength of the decision. These observations have motivated researchers to combine the output of multiple classifiers. The approach reduces the dependency of decision-making mechanism on a single scheme and derives a consensus decision [1]. Therefore to generate preventive maintenance mechanism, it is necessary to "fuse" the outcome of different primary classifiers.

B. Multimodal biomedical image fusion

Fusion is an important step in the process of image registration. It gives a synergistic view of two or more images [1, 11]. Medical image registration and fusion process increases the reliability of clinical decision-making mechanism [11]. In case of anatomical to functional image fusion, combined image provides complimentary functional information of the source images and provides anatomical localization of functional parameters. In all these situations, we have to deal with multiple information from different image modalities. Under this circumstance, image processing needs data fusion techniques based on exploiting redundant and complementary information from different sources. We propose here an active fusion concept for segmentation of the combined image according to the intensity pattern of the corresponding pixels of the registered images. The proposed method is an efficient tool for combining accumulative evidence or for changing prior evidence in the light of new evidence [10].

II. DEMPSTER SHAFER THEORY OF EVIDENCE FUSION

This model generalizes the Bayesian inference method. Analogous to the Bayesian method, the DS technique updates a prior mass density function to obtain a posterior evidence interval. The evidential interval quantifies the measure of belief of a proposition and its plausibility. Mass density functions provide the analogy to Bayesian probability.

It starts by assuming mutually exhaustive sets of propositions θ, also called a Frame of Discernment (FOD) and the power set (2^θ). The elements of 2^θ are the class of general propositions in the domain. DS approach assigns evidence mass "m" (basic probability assignment) on the subsets A of the power set 2^θ. The subset A can be singleton (or single proposition) such as $\{A_i\}$, or a composed proposition such as $\{A_i, A_j\}=A_{ij}$. The evidence mass "m" allows the set of symbolic classes of 2^θ to be mapped into the numerical values of the interval [0 1]:

$m: 2^\theta \rightarrow [0, 1]$

$A \rightarrow m(A)$

This mass function satisfies the following properties:

$m(\phi) = 0$ where ϕ is a null set and

$$\sum_{A \subset \theta} m(A) = 1$$

The value m(A) represents the degree of evidential support with which a specific element of θ belongs to the set A.

A salient characteristic of the DS theory is its powerful combination operator to create a pool of evidences coming in from various sources into a single belief figure for each hypothesis. In case of two bpas m_1 and m_2 associated with a FOD θ , a new distribution of 'bpa' $m_{1,2}$ on θ is defined as

$$m_{1,2}(S) = \sum m_1(A) \circ m_2(B) \quad (1)$$

$S=A \cap B$

A belief function assigns a measure of our total belief to the propositions represented by the subsets of θ. A function m: $2^\theta \rightarrow [0, 1]$ is called a belief function if it satisfies conditions $Bel(\phi) = 0$ and $Bel(\theta) = 1$, for any collection A_1, A_2,.. A_n of subsets of θ. Corresponding to each belief function there is one and only one basic probability assignment. Thus,

$$Bel(A) = \sum_{B \subseteq A} m(B), \forall A \subseteq \theta \quad (2)$$

and Bel(not A) is the Bel of the complement of A. Bel(A) and Bel(not A) form only a part of all the subsets of θ. Hence,

$$Bel(A) + Bel(not\ A) \le 1.0 \quad (3)$$

i.e. one can assign belief neither to A nor to its negation but in case of classical probability model P(A) + P(not A) = 1.0

Belief interval characterizes the unassigned belief and hence the uncertainty associated with the hypothesis. The belief interval of a set θ is defined as:

$$I = [Bel(A), 1-Bel(not\ A)] \quad (4)$$

with the properties as follows:

max-length[I] = 1.0, and min-length[I] = 0.0

Maximum length is attained when one has belief neither in A nor in its negation, whereas minimum length is obtained where there is full belief to A or its negation. But if one has equal belief to A and to its negation then also the interval is of zero length and it is not possible to take any decision.

Plausibility Pl(A) is defined as the measure of belief that the true hypothesis is not contained in the complementary set of A and is written as

$$Pl(A) = \sum_{A \cap B \neq \phi} m(B) \forall A \subset \theta \quad (5)$$

A new parameter K emerges when the assignment of evidence is made to conflicting propositions [11]. K is interpreted as a measure of conflict between the sources and is directly taken into account in the combination as a normalization factor. To evaluate the quality of the combination, K value is taken into consideration.

Let m_1 and m_2 be two bpas over same FOD, and

$m_1(A).m_2(B) < 1$ and $A \cap B = C$

Then the combined bpa, is

$$M(C) = m_1(A) \oplus m_2(B) = \frac{\sum_{A \cap B = C} m_1(A) m_2(B)}{1 - \sum_{A \cap B = \phi} m_1(A) m_2(B)} \quad (6)$$

and for $C = \phi$ $m(C) = 0$

The conflict or normalization factor 'K' appears for the assignment of evidence to conflicting propositions. If sensor S1 assigns evidence $m_1(A)$ to proposition A and sensor S2 assign evidence $m_2(B)$ to a conflicting proposition B then

$$K = \sum_{A \cap B = \phi} m_1(A).m_2(B) < 1 \quad (7)$$

DS rule is consistent with the law of probability and the combination also results in a Bayesian mass function. Thus probability appears as a limit to DS, in the case where no ambiguity or imprecision exists [8]

III. CASE STUDY

A. *Fusion of the coolant flow signals of diesel engine*

The schematic diagram of signal fusion scheme is shown in figure 1. The figure depicts the whole idea about the fusion control of CMFD of a (mechanical) system [6, 12].

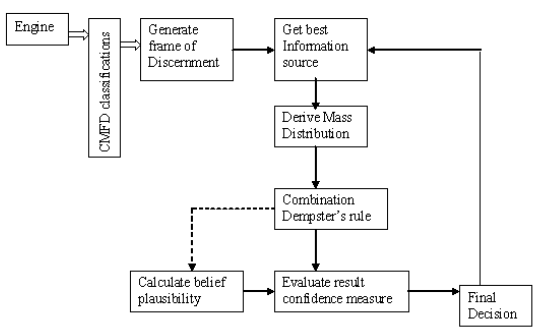


Figure 1. Schematic diagram of evidence fusion scheme

Primary classifiers classify the output signals into mutually exclusive exhaustive sets and form the FOD. Classifiers assign each signal to one of the classes of $\theta = \{C_1, C_2, \dots C_n\}$ according to the measured signal patterns. This pattern classification can be done by grouping status signals from the system. The classification process needs knowledge about the definition of the classes according to the numerical values of $x \in \theta_x$. This knowledge can be achieved in different supervised and unsupervised ways.

The priori knowledge of classification can be collected from the human expert. The usual tools used in this case are the fuzzy sets. A set of labels describing the relation between the measure x and the class i by means of fuzzy sets or more frequently by Gaussian distribution on θ_x (supervised classification). The fault signal histogram of the system is often used when no information about the classes of the signal is available (unsupervised).

It is also possible to classify the signals in a unsupervised sense by grouping the entire range of the frequency histogram in mutually exclusive classes [5]. This type of method leads to the definition of classes C_i according to the measure x, taking values in the finite set $\theta_x = [x_{min}, x_{max}]$. Measuring the fault condition levels of each state of the system yields a histogram defined on the set θ_x. Each $x \in \theta_x$ corresponds to a value h(x) that represents the number of different fault situations. Figure 2 depicts a simulated histogram.

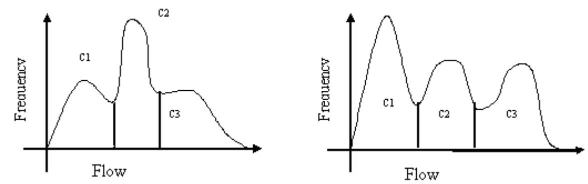


Figure 2. Simulated fault histogram of three different classifiers.

Many recent papers have examined the application of expert system in condition monitoring and fault diagnosis. Parikh et. al. [6] has discussed the supervised classification of signals from a thermostatic coolant flow value of a diesel engine using MLP, RBF and non parametric k-NN ANN classifiers. The primary classifications were done under 30, 50, 65 and 80 % of the normal (100%) coolant flow through the thermostatic value [6]. It has been found that with MLP, RBF, k-NN as primary classifier the success rate is around 76% [6].

A simplified case of CMFD of a cooling system of a diesel engine has been considered here. The study has been carried out on a fusion system with MLP, RBF and k-NN as its three different primary classifiers. The combined evidence, belief and plausibility measures are presented in Table II. For simplicity, only the normal flow is considered as input and the outputs, which are obtained through the three ANN primary classifiers.

Table I. Outcome of 100 test input data from three primary classifiers

Input	Classifier	Output		
Normal flow (100 input)		N	m(N)	m(~N)
	MLP	98	0.98	0.02
	RBF	86	0.86	0.14
	KNN	69	0.69	0.31

From the Table I it is clear that none of the ANN primary classifiers is able to classify all the normal flow at a high level of accuracy. To improve the performance DS evidence unification strategy is used.

The FOD (θ) consists of two (N and ~N) mutually exclusive and exhaustive propositions. In order to obtain the normalized $m_{1,2,3}$, Bel and Pl of the normal flow only, we have combined the outcomes of three classifiers using the equation 6. The K parameter of the equation 6 eliminates the conflicting elements form the confusion matrix of the primary 'm' values.

$$M(N) = m_{MLP}(N) \oplus m_{RBF}(N) \oplus m_{kNN}(N)$$

The result of combining the three classifiers is presented in the Table II.

Table II. Fused bpa and Bel and Pl measures for classified normal flow data

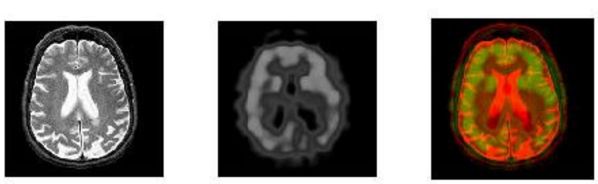
	m_{MLP}(N)	m_{RBF}(N)	m_{KNN}(N)
N	0.98	0.86	0.69
~N	0.02	0.14	0.31
	$m_{MLP,RBF,KNN}$(N)	Bel(N)	Pl(N)
N	.998509615	.998509615	.998509615
~N	.001490385	.001490385	.001490385

The result of normal flow after combination has shown a higher reliability of the classification task. In this study as the two outcomes (i.e. N, ~N) were considered, Bel and Pl are same as m_{123}. In DS implementation, a signal would remain unclassified after combination if two or more proposition has equal belief (in this case, say for example, if both the N and ~N have equal bpas). Moreover, if two classifiers assign contradictory bpas to a signal, then also combination would result in unclassified condition.

B. Fusion of MR and SPECT brain images

The fusion of multimodal biomedical images is achieved by assigning the pair of pixels which represents the same physical coordinate point, into one class C_i of class set =. $\{C_i\}_{i=1..N}$ This classification is performed by combining the 'bpa' measures of the pixel pair of two images. The numerical measures correspond to the grey levels of the physical point p in their respective images. The point p may be of two different classes (C_i and C_j) in two images with no prior connections. The combined field of discernment is obtained by the Cartesian product of the focal elements of two fields of discernments (FOD). Each class $\{C_k^{12}\}$ of the resulting FOD is formed by a logical AND operation of corresponding classes of the component images. Then the combined 'bpa' is obtained by using the DSEAE. Since the combined mass value is in normalized form, the sum of mass values is also 1 [8].

The original images to be segmented and fused are shown in figure 3. The dimensions of MR T2 and SPECT images are 256×256. The image pixels are primarily classified into GM, WM, CSF and ventricular regions. Grey and white matters are grouped into class C_1 and C_2; rests are grouped into class C_3.



(a) MR-T2 (I1) (b) SPECT (I2) (c) Fused Image

Figure 3. MR-T2 and SPECT image fusion

Here the FOD $\theta = \{C_1, C_2, C_3\}$ and the power set 2^{θ} is $\{\theta, C_1, C_2, C_3, C_1 \cup C_2, C_1 \cup C_3, C_2 \cup C_3, C_1 \cup C_2 \cup C_3\}$. The mass function 'm' is assigned to each pixels of each individual class of the power set using a FCM clustering mechanism.

$$m_1 : 2^{\theta_1} \to [0,1], m_2 : 2^{\theta_2} \to [0,1]$$
$$\theta_1 = \{C_1^1, C_2^1, C_3^1\}, \theta_2 = \{C_1^2, C_2^2, C_3^2\}$$

To explain the method we have considered an example point p. The mass value of the given point p of two images I1 and I2 are given in Table III and arranged in a conflict matrix form in Table IV. Using this mass value distribution of Table IV, the combined mass distributions of point p are calculated (Table V) using the equation 6.

Table III. Fuzzy mass values to a pixel p

	C_1	C_2	C_3	□
M1	0	0.8988	0.1012	0
M2	0.0063	□	0.9937	0

Table IV. Combined mass values of the point

		2nd image		
		C_1^2	C_2^2	C_3^2
1st image		.0063	0.0	.9937
C_1^1	.0	0	0	.0
C_2^1	.8988	.0056	0	.8931
C_3^1	.1012	.0006	0	.1000

The final distribution of masses $m_{1,2} = m_1 \oplus m_2$ are calculated using the values of Table IV as follows:

Table V. Membership values of n x m clusters

FUSED CLASSES	SYMBOLIC REPRESENTATION	BPA
$C_1^1 \cap C_1^2$	$C_{1,1}$	**0**
$C_1^1 \cap C_2^2$	$C_{1,2}$	**0**
$C_1^1 \cap C_3^2$	$C_{1,3}$	**0**
$C_2^1 \cap C_1^2$	$C_{2,1}$	**.0056**
$C_2^1 \cap C_2^2$	$C_{2,2}$	**0**
$C_2^1 \cap C_3^2$	$C_{2,3}$	**.8931**
$C_3^1 \cap C_1^2$	$C_{3,1}$	**.0006**
$C_3^1 \cap C_2^2$	$C_{3,2}$	**0**
$C_3^1 \cap C_3^2$	$C_{3,3}$	**.1000**

Since classes $C_{i,j}$ and $C_{j,i}$ are not same, there will be nine clusters and the pixel of our interest will belong to the class $C_{3,1}$, as the bpa value is the highest.

The proposed approach of fusion of two multimodal images provides us a method of combining the evidences with uncertainty and impression. This also shows us a way to eliminate the conflicting conditions. But, if the conflict matrix provides bpa's with equal values or two contradictory mass values, in two different classes, a region would remain unclassified.

IV. CONCLUSION

The paper has discussed a soft computing approach of CMFD of diesel engine on the basis of combined coolant flow signals from three primary ANN classifiers and fusion of two registered multimodal medical images classified using a primary FCM classifier. This method provides us a mathematical framework for measuring uncertainty, imprecision and conflicting situations. The study presented here shows that this method of evidence fusion is robust in the sense that only inputs from different primary classifiers are needed for the classification. If the conflict matrix produces equal or contradictory bpa's for a region, the region remains unclassified.

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