Model Theory Based Fusion Framework with Application to Multisensor Target Recognition

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Abstract

In this work, we present a model theory based fusion methodology for multisensor wavelet-features based recognition called Automatic Multisensor Feature-based Recognition System (AMFRS). The goal of this system is to increase accuracy of the commonly used wavelet-based recognition techniques by incorporating symbolic knowledge (symbolic features) about the domain and by utilizing a model theory based fusion framework for multisensor feature selection.

1 Introduction

Fusion is a process of combining (fusing) information from different sensors when there is no physical (fusing) law indicating the correct way to combine this information [7]. A fusion problem can be defined in terms of finding such a fusing law. Current solutions to the fusion problem consist of numerous clever, problem-specific algorithms [5, 11]. It is not clear what unifying theory exists behind all the fusion algorithms which would guide algorithm development. The lack of an unifying theory results in a difficulty in comparing various fusion solutions and in suboptimal solutions which negatively affect the accuracy of the multisensor recognition systems. Additionally, a computer system can be easily overloaded with data from different sensors to the degree that it cannot perform its task within the time constraints dictated by the application. Therefore, it has become important to develop an unifying approach for fusing/combining data from multiple sensors or from multiple measurements with minimal computational complexity.

One of the recent research efforts to develop a unifying fusion approach is described in [7], where a model-theory based Sensory Data Fusion System (SDFS) is proposed. The SDFS uses formal languages to describe the world and the sensing process. Models represent sensor data, operations on data, and relations among the data. Theories represent symbolic knowledge about the world and about the sensors. Fusion is treated as a goal-driven operation of combining languages, models, and theories, related to different sensors into one fused language, one fused model of the world and one fused theory. However, no specific algorithm for sensor data fusion is presented in [7], and the proposed sensor data fusion approach is not tested on real tasks and real noisy data.

In this work, we apply and extend the model theory based SDFS to a multisensor wavelet-features based target recognition by using the AMFRS. The Discrete Wavelet Packet Decomposition (DWPD) is used for feature extraction, and the Best Discrimination Basis Algorithm (BDBA) and a domain theory for feature selection for each sensor. The BDBA [10] is based on a best basis selection technique proposed by Coifman and Wickerhauser in [3]. The BDBA selects the most discriminant basis. For the purpose of this work, the elements (wavelet coefficients) of the most discriminant basis are considered as features. Then, the domain theories for each sensor select interpretable wavelet features from the most discriminant basis. The wavelet features are interpretable in terms of symbolic target features. And finally, the wavelet features are combined (fused) into one fused vector by utilizing the fused theory. The fused theory is derived from a symbolic knowledge about the domain and a relation between the symbolic knowledge and the most discriminant basis determined by using the BDBA. We show that the knowledge of a fused theory allows us to select the combination of features (out of many possible combinations) which results in the increased recognition accuracy of the AMFRS. In particular, we show that the recognition accuracy of the proposed Automatic Multisensor Feature based Recognition System (AMFRS) is better than the recognition accuracy of a system that performs recognition using Most Discriminant Wavelet Coefficients (MDWC) as features. The AMFRS utilizes a model-theory framework (SDFS) for feature selection as described above, while MDWC are selected from the range and intensity most discriminant bases using a relative entropy measure [12].

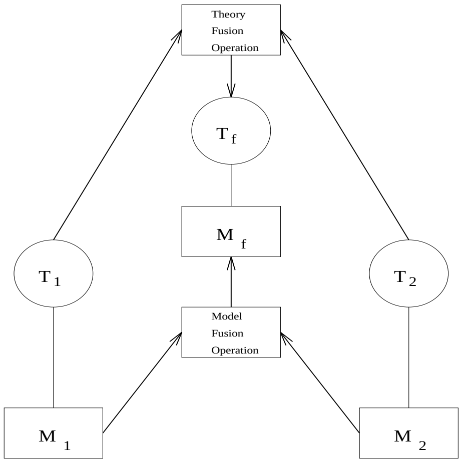

Figure 1: Model Theory Based Fusion Framework

Section 2 presents a feature selection (fusion) methodology. Section 3 contains a conceptual description of the AMFRS. Section 4 describes a target recognition scenario considered in this work, while Section 5 presents a feature fusion procedure for this target recognition scenario. The simulation results are shown in Section 6.

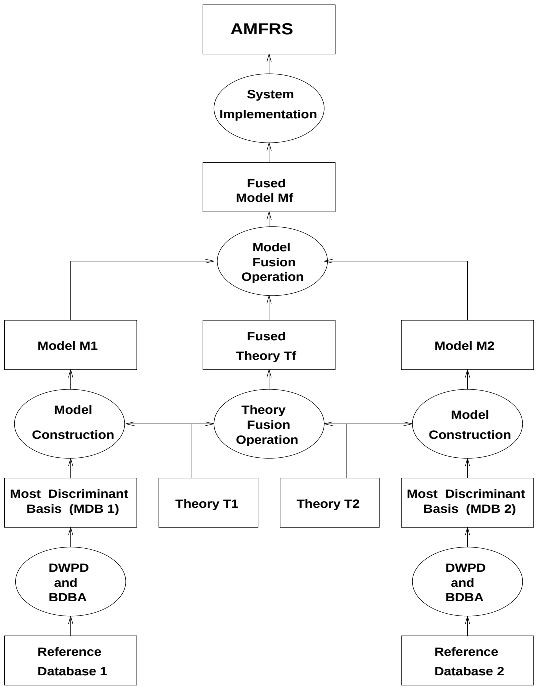

Figure 2: Feature Fusion for Automatic Multisensor Feature based Recognition System (AMFRS)

2 Model-Theory Based Feature Fusion

Assume that n_1 features are selected from the measurement data of *Sensor 1* and n_2 features are selected from the measurement data of *Sensor 2*. The goal is to combine (fuse) these features into one feature vector consisting of exactly n features. Since we want to select n out of $n_1 + n_2$ features, we have

$$C(n_1 + n_2, n) = \left(\begin{array}{c} n_1 + n_2 \\ n \end{array} \right) = \frac{(n_1 + n_2)!}{(n_1 + n_2 - n)!n!}$$

possible combinations. For example, for $n = n_1 = n_2 = 10$ we have 184,756 possible combinations. Therefore, we need a tool to select, from all these combinations, the combination of features which results in most accurate recognition decisions.

To select such a combination of features, we apply a model theory based fusion framework shown in Fig. 1. In particular, the knowledge of a fused theory allows us to select the right combination of features. The fused theory is derived by using a theory fusion operator to fuse the theory T_1 for $Sensor_1$ and the theory T_2 for $Sensor_2$. In this experiment we derived a theory fusion operator manually from symbolic knowledge about the domain and a relation between the symbolic knowledge and features determined by using the BDBA. By applying the theory fusion operator to the theory T_1 and the theory T_2, we derived the fused theory T_f. In the same manner, we derived manually a model fusion operator. By applying the model fusion operator to the model M_1 and the model M_2, we derived the fused model M_f.

Fig. 2 shows a complete block-diagram design framework for Automatic Multisensor Feature-based Recognition System (AMFRS). The meaning of the blocks in this figure is as follows. *Reference Database 1* and *Reference Database 2* are databases of target signatures used to train a recognition system. *DWPD & BDBA* selects the most discriminant basis for both reference databases by using Discrete Wavelet Packet Decomposition (DWPD) and Best Discrimination Basis Algorithm (BDBA). *Most Discriminant Basis (MDB 1 & MDB 2)* are bases with maximum discriminant power with regard to each of the two reference databases (sensors) as determined by a relative entropy discriminant measure. *Theory 1 & Theory 2* contain domain knowledge about relationship between features in the MDB's which are interpretable in terms of symbolic target features. *Model Construction* creates a model for a given domain theory. *Model 1 & Model 2* represent features selected from both sensor data, operations on these features, and relations among these features. *Theory Fusion Operation* fuses domain theories: $Theory1$ and $Theory2$. *Model Fusion Operation* fuses models for given theories: *Model*1 and *Model*2. *Fused Theory & Fused Model* represent the fused domain knowledge and the fused features respectively. *System Implementation* implements Automatic Multisensor Feature-based Recognition System (AMFRS) using the knowledge of the fused theory and the fused model. *AMFRS* is the Automatic Multisensor Feature-based Recognition System using a framework of model theory for feature-level fusion.

In our AMFRS methodology, fusion operators are derived by using reduction, expansion and union operators [2]. These reduction, expansion and union operators are defined as follows:

Reduction Operator A language L^r is a reduction of the language L if the language L can be written as

$$L = L^r \cup X, \tag{1}$$

where X is the set of symbols not included in L^r. We form a model M^r for the language L^r as a reduction of the model $M =< A, I >$ for the language L by restricting the interpretation function $I = I^r \cup I_x$ on $L = L^r \cup X$ to I^r. Therefore

$$M^r =< A, I^r > \tag{2}$$

We form a theory (subtheory) T^r for the language L^r as a reduction of the theory T for the language L by removing sentences from the theory T which are not legal sentences of the language L^r.

Expansion Operator A language L^e is an expansion of the language L if the language L can be written as

$$L^e = L \cup X, \tag{3}$$

where X is the set of symbols not included in L. We form a model M^e for the language $L^e = L \cup X$ as an expansion of the model $M =< A, I >$ for the language L by giving appropriate interpretation I_x to symbols in X. Therefore

$$M^e =< A, I \cup I_x > \tag{4}$$

We form a theory T^e for the language L^e as an expansion of the theory T for the language L by adding a set of new legal sentences of the language L^e to the theory T.

Union Operator A language L is a union of the languages L_1 and L_2 if the language L can be written as

$$L = L_1 \cup L_2. \tag{5}$$

A model $M =< A; R, G, x; I >$ for the language L is a union of the model $M_1 =< A_1; R_1, G_1, X_1; I_1 >$ for the language L_1 and the model $M_2 =< A_2; R_2, G_2, x_2; I_2 >$ for the language L_2 if the model M can be written as

$$M = M_1 \cup M_2 = \\ < A_1 \cup A_2; R_1 \cup R_2, G_1 \cup G_2, x_1 \cup x_2; I_1 \cup I_2 >, \tag{6}$$

where R, R_1, R_2 are relations; G, G_1, G_2 are functions; x, x_1, x_2 are constants; and I, I_1, I_2 are interpretation functions. We form a theory T for the language L by applying a union operator to the theory T_1 for the language L_1 and to the theory T_2 for the language L_2. Therefore

$$T = T_1 \cup T_2. \tag{7}$$

3 Automatic Multisensor Feature-based Recognition System

Fig. 3 shows a conceptual view of the Automatic Multisensor Feature-based Recognition System (AMFRS) for two sensors. The meaning of each block in the AMFRS is the following: *The World* is a domain of the recognition problem with *Sensor1* and *Sensor2* providing information about the domain to the AMFRS. *Feature Extraction* extracts features from measurement data using the BDBA and a model theory framework. *Model (M_1) Checking* tests whether the measurement data represent a model M_1 of a given theory T_1 of the domain. *Model (M_2) Checking* tests whether the measurement data represent a model M_2 of a given theory T_2 of the domain. Model Fusion - the fusion operators for the models M_1 and M_2. *Model (M_f) Checking* tests whether the fused data represent a model M_f of a given theory T_f of the domain. *Classification* uses the theory T_f to arrive with a final recognition decision.

There are three types of information available to the AMFRS: (1) the target signatures $s_2 \in S$, $i = 1, \cdots, K$, where S is a signal space; (2) classes $c_j \in C$, $j = 1, 2$, of targets to be recognized, where C is a target class space; (3) symbolic features $b_j \in B$ for each class $c_j \in C$ of targets, where B is a set of symbolic features.

The goal of the AMFRS is to increase the recognition accuracy by using all three types of information in an interpretable way. The *recognition accuracy* is defined as the ratio of *number of correct recognition decisions* to *total number of recognition decisions* multiplied by 100, where the *total number of recognition decisions* is equal to the number of target signatures in a test set. Similarly, we define *misclassification rate.*

In this work, we investigate a method for extracting features $f_2 \in F$ of the signal $s_2 \in S$ represented in

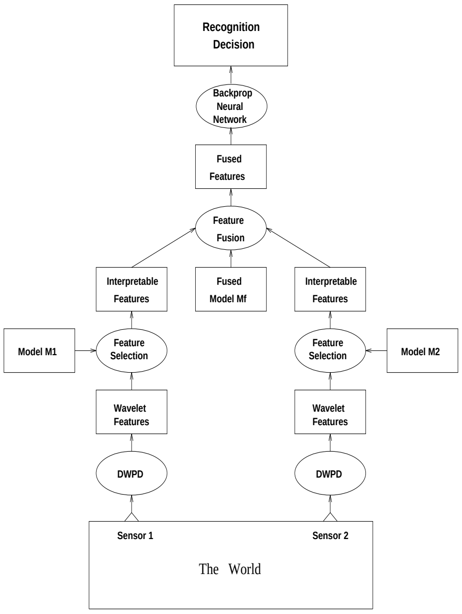

Figure 3: Automatic Multisensor Feature-based Recognition System (AMFRS)

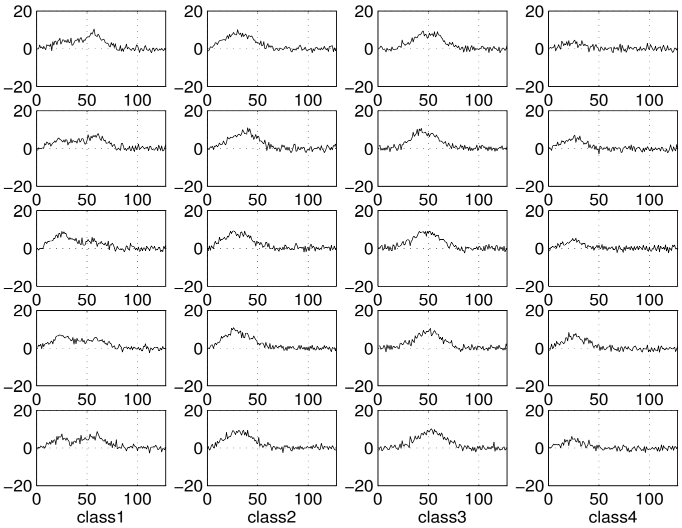

Figure 4: Five Target Signatures for Each of the Four Classes of Targets in DT_1

the wavelet domain, such that these features are interpretable in terms of the symbolic features $b_j \in B$ for every target class $c_j \in C$. We define a recognition problem as a mapping $S \rightarrow C$. This mapping is composed of three mappings: (i) $S \rightarrow W$, (ii) $W \rightarrow F$, and (iii) $F \rightarrow C$. The mapping $S \rightarrow W$ is determined by the Discrete Wavelet Packet Decomposition (DWPD). The DWPD transforms a sensor signal $s_2 \in S$ into a time/frequency (wavelet) representation $W_2 \in W$. The mapping $W \rightarrow F$ is determined by the Best Discrimination Basis Algorithm (BDBA) and a model-theory framework. The BDBA selects the most discriminant basis. The model checker selects features from the most discriminant basis. Conceptually, a mapping $F \rightarrow C$ is determined by a domain theory. The domain theory is an optimal classifier for deterministic target signatures. To apply the domain theory to noisy target signatures, we implement it by using a backpropagation neural network.

4 Target Recognition Scenario

As an example of a target recognition problem, we consider a version of the waveform recognition problem, originally examined and applied to a ship recognition project in [1] and then analyzed in [12]. The goal of this problem is to recognize the class to which a given target signature belongs, knowing a reference database of target signatures. The reference database is synthesized using different combinations of three basic waveforms to form three classes of target signatures. Our formulation of the recognition problem differs from the original waveform recognition problem in that (1) the number of the measurements in the target signatures is increased from 21 in [1] and 32 in [12] to 128; (2) one additional class of target signatures is added, so that we have a four-class problem instead of a three-class problem; (3) symbolic features characteristic for each class of targets are assumed to be known; (4) the recognition problem is extended to a multisensor scenario by using two reference databases of target signatures (one for each sensor). Fig. 4 shows five examples of target signatures for each of the four classes of targets in DT_1. The DT_2 reference database of target signatures (corresponding to $Sensor_2$) was synthesized in a similar way [9].

5 Feature Selection

Each of the target signatures in the DT_1 reference database is transformed into the wavelet domain using the DWPD with the Daubechies_6 compactly supported wavelets with extreme phase and highest number of vanishing moments compatible with their support width. A complete orthonormal Most Discriminant Basis (MDB) is selected using the BDBA. The total number of components (wavelet coefficients) in this basis is equal to 128, i.e., it is equal to the number of samples in the target signature. Fig. 5 shows the MDB for the DT_1 reference database and the discriminant value of each component as determined by a relative entropy measure. The MDB consists of the

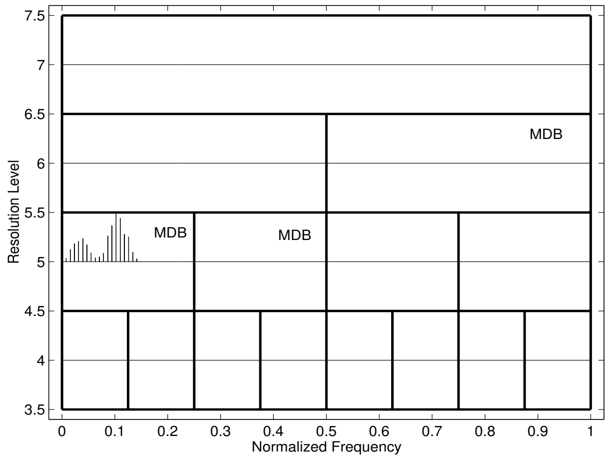

Figure 5: Most Discriminant Basis (MDB) for the DT_1 Reference Database

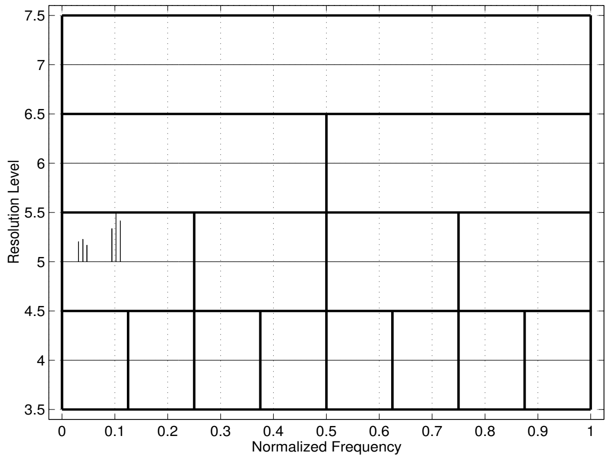

Figure 6: Features Selected From the MDB for the DT_1 Database Using the Domain Theory

two subbases on the third level of the DWPD decomposition and one subbasis on the second level of the decomposition. In order to limit the computational complexity of recognition, we apply a domain theory for the DT_1 reference database to select $n_1 < 128$ wavelet coefficients (features) from the complete MDB. Our aim is to select n_1 features that, in addition to significant discriminant power, are interpretable in terms of the following symbolic target signature features: *rising edges*, where the value of the signal is increasing within a given time interval; *falling edges*, where the value of the signal is decreasing within a given time interval; *zero edges*, where the value of the signal remains around zero within a given time interval; *peaks*, where the value of the signal has its local maximum. The value of selected features indicates which one of the four symbolic features described above is present in the target signature, while the position of selected features in the MDB indicates the time interval within which a given symbolic feature is present in the target signature.

Below, we describe a language, a model, and a theory for $Sensor_1$. The symbol $\leq$ is a *logical symbol* with the usual interpretation as a linear order relation on the universe.

Language L_1

$L_1 = \{class1_1, class2_1, class3_1, class4_1, f_1, 0, 1, C_{r_0}, C_{r_1}, \ldots, C_{r_4}, C_{r_5}\}$,
where $class1_1$, $class2_1$, $class3_1$, $class4_1$ are 6-placed relation symbols (classes of targets to be recognized using $Sensor_1$), f_1 is an 1-placed function symbol (a function that maps features' indices into features' values), $0, 1$ are constant symbols, $C_{r_0}, C_{r_1}, \ldots, C_{r_4}, C_{r_5}$ are constant symbols (features' indices).

Theory T_1

$class1_1(y_0\ \ldots\ y_5) \iff (\forall_{y_0, \ldots, y_5})\ \ ((y_0 = f_1(C_{r_0}) \wedge \ldots \wedge y_5 = f_1(C_{r_5})) \Rightarrow (1 \leq y_0 \leq y_2 \leq y_1\ \wedge\ 1 \leq y_3 \leq y_5 \leq y_4))$,

$class2_1(y_0\ \ldots\ y_5) \iff (\forall_{y_0, \ldots, y_5})\ \ ((y_0 = f_1(C_{r_0}) \wedge \ldots \wedge y_5 = f_1(C_{r_5})) \Rightarrow (1 \leq y_0 \leq y_1\ \wedge\ y_0 \leq y_2\ \wedge\ 1 \leq y_5 \leq y_4 \leq y_3))$,

$class3_1(y_0\ \ldots\ y_5) \iff (\forall_{y_0, \ldots, y_5})\ \ ((y_0 = f_1(C_{r_0}) \wedge \ldots \wedge y_5 = f_1(C_{r_5})) \Rightarrow (0 = y_0 \leq y_1 \leq y_2\ \wedge\ 1 \leq y_5 \leq y_4 \leq y_3))$,

$class4_1(y_0\ \ldots\ y_5) \iff (\forall_{y_0, \ldots, y_5})\ \ ((y_0 = f_1(C_{r_0}) \wedge \ldots \wedge y_5 = f_1(C_{r_5})) \Rightarrow (1 \leq y_0 \leq y_2 \leq y_1\ \wedge\ y_3 = y_4 = y_5 = 0))$,

$C_{r_0} \leq C_{r_1} \leq C_{r_2} \leq C_{r_3} \leq C_{r_4} \leq C_{r_5}$.

Model M_1

$M_1 =< A_1; class1_1, class2_1, class3_1, class4_1, f_1, 0, 1, \ldots, 5; I_1 >$, where $A_1 = \{0, \ldots, 5\}$ universe of the model M_1, $class1_1, class2_1, class3_1, class4_1 \subset A_1^6$, $f_1 : A_1 \rightarrow A_1$, I_1 - interpretation function.

The $n_1 = 6$ selected features from the most discriminant basis (MDB) using the domain theory are shown in Fig. 6. Fig. 7 shows the relationship between the selected features and symbolic target features in ideal, not noisy conditions. All six features carry information about the type of symbolic target features and their position in a target signature. The features selected from the MDB using the theory T_1 are different from the Most Discriminant Wavelet Coefficients (MDWC) which are shown in Fig. 8.

In the same manner as for the $Sensor_1$, we define

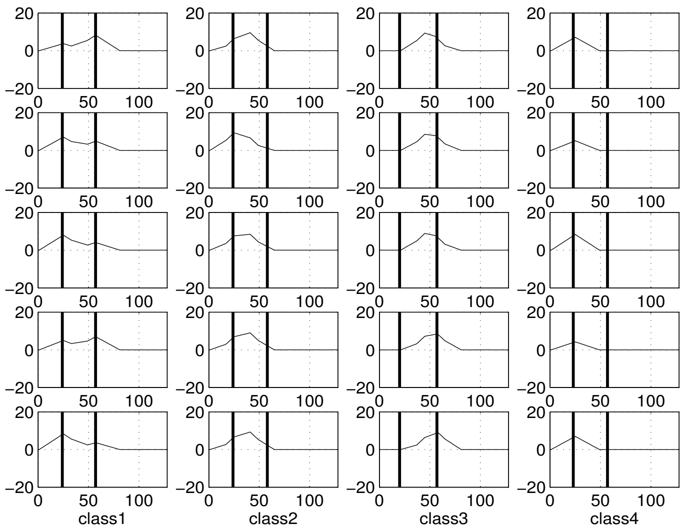

Figure 7: Relationship Between the Selected Features and Symbolic Target Features for the DT_1 Database

an appropriate language, a model, and a theory for $Sensor_2$.

$L_2 = \{class1_2, class2_2, class3_2, class4_2, f_2, 0, 1, 2, C_{i_0}, C_{i_1}, \ldots, C_{i_7}, C_{i_8}\}$.

Theory T_2

$class1_2(y_0 \;...\; y_8) \iff (\forall_{y_0,\,\ldots\,,y_8}) \quad ((y_0 = f_2(C_{i_0}) \wedge \ldots \wedge y_8 = f_2(C_{i_8})) \Rightarrow (2 \le y_0 \le y_2 \le y_1 \;\wedge\; 2 \le y_5 \le y_3 \le y_4 \;\wedge\; 2 \le y_6 \le y_7 \;\wedge\; 2 \le y_8 \le y_7))$,

$class2_2(y_0 \;...\; y_8) \iff (\forall_{y_0,\,\ldots\,,y_8}) \quad ((y_0 = f_2(C_{i_0}) \wedge \ldots \wedge y_8 = f_2(C_{i_8})) \Rightarrow (1 \le y_2 \le y_1 \le y_0 \;\wedge\; 2 \le y_3 \le y_4 \le y_5 \;\wedge\; y_7 \le y_6 \le 1 \;\wedge\; y_8 = 0))$,

$class3_2(y_0 \;...\; y_8) \iff (\forall_{y_0,\,\ldots\,,y_8}) \quad ((y_0 = f_2(C_{i_0}) \wedge \ldots \wedge y_8 = f_2(C_{i_8})) \Rightarrow (2 \le y_0 = y_1 \;\wedge\; y_2 \le y_1 \;\wedge\; 1 \le y_3 \le y_4 \le y_5 \;\wedge\; 2 \le y_6 \le y_7 \;\wedge\; 2 \le y_8 \le y_7))$,

$class4_2(y_0 \;...\; y_8) \iff (\forall_{y_0,\,\ldots\,,y_8}) \quad ((y_0 = f_2(C_{i_0}) \wedge \ldots \wedge y_8 = f_2(C_{i_8})) \Rightarrow (y_0 = y_1 = y_2 = y_6 = y_7 = y_8 = 0 \;\wedge\; 2 \le y_3 \le y_4 \;\wedge\; 2 \le y_5 \le y_4))$, .

$C_{i_0} \le C_{i_1} \le C_{i_2} \le C_{i_3} \le C_{i_4} \le C_{i_5} \le C_{i_6} \le C_{i_7} \le C_{i_8}$.

Model M_2

$M_2 =< A_2; class1_2, class2_2, class3_2, class4_2, f_2, 0, 1, \ldots, 8; I_2 >$.

The $n_2 = 9$ selected features from the MDB using the domain theory (symbolic knowledge about the target signatures in the DT_2 database) are shown in Fig. 9. More details on feature selection for $Sensor_2$ can be found in [9].

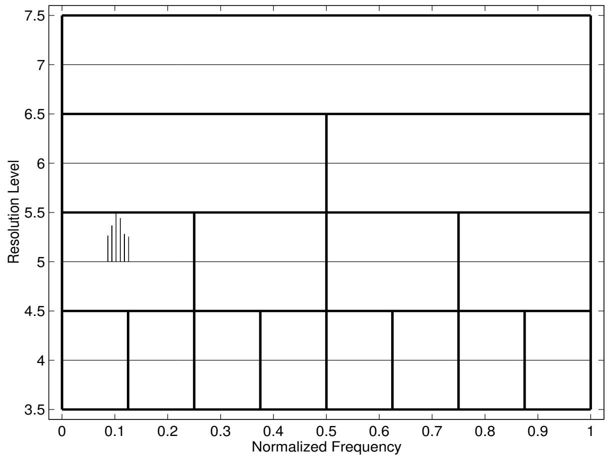

Figure 8: Most Discriminant Wavelet Coefficients (MDWC) Selected from the MDB for the DT_1 Database as Features

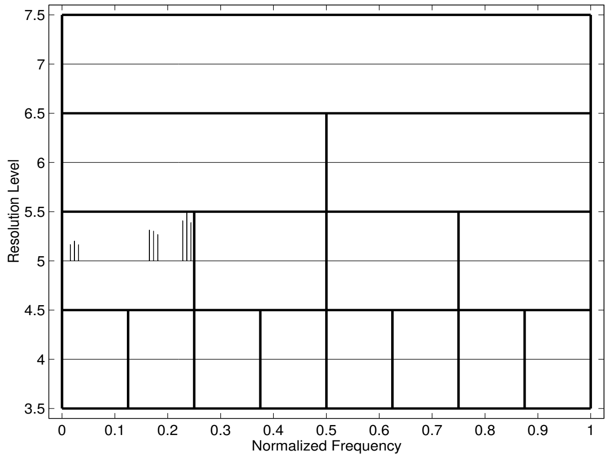

Figure 9: Features Selected From the MDB for the DT_2 Database Using the Domain Theory

Using the operators of *reduction, expansion* and *union* (ref. [9]), we were able to derive the following fused language, fused theory and fused model.

Fused Language L_f

$L_f = \{class1, class2, class3, class4, f_f, 0, 1, 2, C_{f_0}, C_{f_1}, \ldots, C_{f_7}, C_{f_8}\}$,
where $class1, class2, class3, class4$ are 9-placed relation symbols (classes of targets to be recognized using fused data), f_f is an 1-placed function symbol (a function that maps features' indices into features' values), $0, 1, 2$ are constant symbols, $C_{f_0}, C_{f_1}, \ldots, C_{f_7}, C_{f_8}$ are constant symbols (features' indices).

Fused Theory T_f

$class1(y_0 \;...\; y_8) \iff (\forall_{y_0,\,\ldots\,,y_8}) \quad ((y_0 = f_f(C_{f_0}) \wedge$

$\ldots \wedge y_8 = f_f(C_{f_8})) \Rightarrow (1 \leq y_0 \leq y_2 \leq y_1 \ \wedge \ 1 \leq y_3 \leq y_5 \leq y_4 \ \wedge \ 2 \leq y_6 \leq y_7 \ \wedge \ 2 \leq y_8 \leq y_7)),$

$class2(y_0 \ \ldots \ y_8) \iff (\forall_{y_0, \ldots, y_8}) \ \ ((y_0 = f_f(C_{f_0}) \wedge \ldots \wedge y_8 = f_f(C_{f_8})) \Rightarrow (1 \leq y_0 \leq y_1 \ \wedge \ y_0 \leq y_2 \ \wedge \ 1 \leq y_5 \leq y_4 \leq y_3 \ \wedge \ y_7 \leq y_6 \leq 1 \ \wedge \ y_8 = 0)),$

$class3(y_0 \ \ldots \ y_8) \iff (\forall_{y_0, \ldots, y_8}) \ \ ((y_0 = f_f(C_{f_0}) \wedge \ldots \wedge y_8 = f_f(C_{f_8})) \Rightarrow (0 = y_0 \leq y_1 \leq y_2 \ \wedge \ 1 \leq y_5 \leq y_4 \leq y_3 \ \wedge \ 2 \leq y_6 \leq y_7 \ \wedge \ 2 \leq y_8 \leq y_7)),$

$class4(y_0 \ \ldots \ y_8) \iff (\forall_{y_0, \ldots, y_8}) \ \ ((y_0 = f_f(C_{f_0}) \wedge \ldots \wedge y_8 = f_f(C_{f_8})) \Rightarrow (1 \leq y_0 \leq y_2 \leq y_1 \ \wedge \ y_3 = y_4 = y_5 = y_6 = y_7 = y_8 = 0)),$

$C_{f_0} \leq C_{f_1} \leq C_{f_2} \leq C_{f_3} \leq C_{f_4} \leq C_{f_5} \leq C_{f_6} \leq C_{f_7} \leq C_{f_8}.$

$C_{f_0} = C_{r_0} \wedge C_{f_1} = C_{r_1} \wedge C_{f_2} = C_{r_2} \wedge C_{f_3} = C_{r_3} \wedge C_{f_4} = C_{r_4} \wedge C_{f_5} = C_{r_5} \wedge C_{f_6} = C_{i_6} \wedge C_{f_7} = C_{i_7} \wedge C_{f_8} = C_{i_8},$

$f_f(C_{f_0}) = f_1(C_{r_0}) \wedge f_f(C_{f_1}) = f_1(C_{r_1}) \wedge f_f(C_{f_2}) = f_1(C_{r_2}) \wedge f_f(C_{f_3}) = (f_1(C_{r_3}) \wedge f_f(C_{f_4}) = f_1(C_{r_4}) \wedge f_f(C_{f_5}) = f_1(C_{r_5}) \wedge f_f(C_{f_6}) = f_2(C_{i_6}) \wedge f_f(C_{f_7}) = f_2(C_{i_7}) \wedge f_f(C_{f_8}) = f_2(C_{i_8}).$

Fused Model M_f

$M_f =< A; class1, class2, class3, class4, f_f, 0, 1, \ldots, 8; I_f >$, where $A = \{0, \ldots, 8\}$ the universe of the model M_f, $class1 \subset A^9$, $class1 = class1'_2 \times class1_1$, $class1'_2 = class1_2 \cap (A \cap \{6,7,8\})^3$, $class2 \subset A^9$, $class2 = class2_1 \times class2'_2$, $class2'_2 = class2_2 \cap (A \cap \{6,7,8\})^3$, $class3 \subset A^9$, $class3 = class3_1 \times class3'_2$, $class3'_2 = class3_2 \cap (A \cap \{6,7,8\})^3$, $class4 \subset A^9$, $class4 = class4_1 \times class4'_2$, $class4'_2 = class4_2 \cap (A \cap \{6,7,8\})^3$, $f_f : A \rightarrow A$, $f_f = f_1 \cup f'_2$, $f'_2 = f_2 \mid_{A \cap \{6,7,8\}}$, I_f - interpretation function.

The fused theory and fused model are used to fuse the feature vector consisting of $n_1 = 6$ features from the DT_1 database and the feature vector consisting of $n_2 = 9$ features from the DT_2 database into one fused feature vector consisting of $n_f = 9$ interpretable features. In particular, the first three fused features of this fused feature vector are the first three features selected for $Sensor_1$, whose value indicates the existence of the first peak characteristic for target signatures belonging to $class1$ and $class4$, the existence of a rising edge characteristic for target signatures belonging to $class2$, or the existence of a zero edge characteristic for target signatures belonging to $class3$. The next three fused features are the last three features selected for $Sensor_1$, whose value indicates the existence of the second peak characteristic for target signatures belonging to $class1$, the existence of a falling edge characteristic for target signatures belonging to $class2$ and $class3$, or the existence of a zero edge characteristic for target signatures belonging to $class4$. The last three fused features of this fused feature vector are the first three features selected for $Sensor_2$, whose value indicates the existence of a peak characteristic for target signatures belonging to $class1$ and $class3$, or the existence of a zero edge characteristic for target signatures belonging to $class2$ and $class4$.

6 Results of Experiments

We test the recognition accuracy of the AMFRS by using two test databases with target signatures corresponding to the DT_1 and DT_2 reference databases. Each of the target signatures in these databases is transformed into the wavelet domain using the DWPD. Then, we select one target signature from each of the test databases in such a way that these two target signatures correspond to the same target. A framework of model theory (SDFS) is used to extract features from each of these two target signatures, and to fuse them into one combined feature vector. This feature vector is used as an input vector into a backpropagation neural network. The backpropagation neural network arrives with a final recognition decision.

Fig. 10 shows the resulting misclassification rates for different levels of noise for the multisensor (using the DT_1 and DT_2 target signatures) target recognition problem. This figure also shows the misclassification rate of the target recognition system using Most Discriminant Wavelet Coefficients (MDWC) as features. The misclassification results show that the AMFRS has a better recognition accuracy than a MDWC based target recognition system.

7 Conclusions and Future Research

A multisensor recognition methodology (AMFRS) is proposed based on features selected by utilizing the Best Discrimination Basis Algorithm (BDBA), symbolic knowledge about the domain, and a model-theory based fusion framework. The symbolic knowledge about the domain is incorporated into the AMFRS through a domain theory using a model-theory based fusion framework. A model of a domain theory represents a bridge between a symbolic knowledge about the domain and measurement data.

The simulation results show that the AMFRS has a better recognition accuracy than a MDWC based recognition system with respect to the test databases. The MDWC based target recognition system adapts well to the training set of target signatures, but it does not have enough generalization power to perform

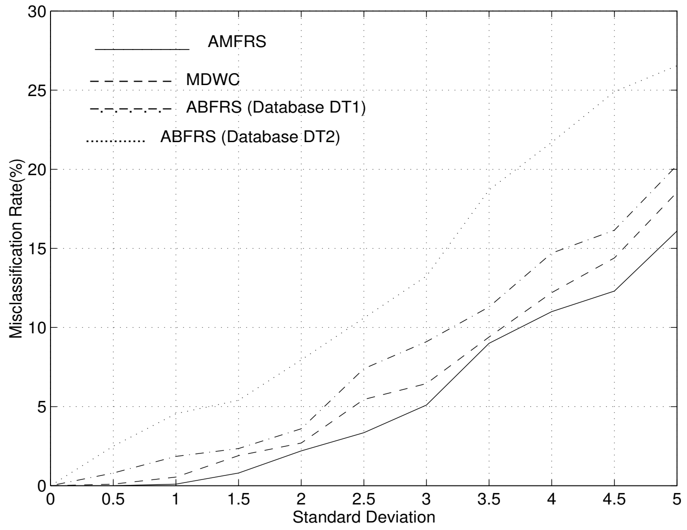

Figure 10: Misclassification Rates for the Multisensor Target Recognition Using Model Theory (AMFRS) and Most Discriminant Wavelet Coefficients (MDWC) for Feature Selection

equally well with the test data. The MDWC used to train a classifier, in the discussed recognition problem, are concentrated only in one time/frequency area. We are able to increase the generalization power of the target recognition system by selecting interpretable features which are more spread across the time/frequency domain and which capture more of symbolic target features. To select such interpretable features, we utilize the symbolic knowledge (fused theory) specific to the recognition problem domain.

In this work, we build the domain theory manually based on the analysis of the target signatures in the reference database (symbolic knowledge) and the most discriminant bases determined by using the BDBA. In the future research we are going to incorporate learning capabilities into the AMFRS.

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References

[1] L. Breiman, J. H. Friedman, R. A. Olshen and C. J. Stone, *Classification and Regression Trees.* Belmont, California: Wadsworth International Group, 1984.

[2] C. C. Chang and H. J. Keisler. *Model Theory.* Amsterdam, New York, Oxford, Tokyo: North Holland, 1992.

[3] R. R. Coifman and M. V. Wickerhauser, "Entropy-Based Algorithms for Best Basis Selection," *IEEE Transactions on Information Theory,* vol.38, no.2, pp. 713–718, March 1992.

[4] I. Daubechies, *Ten Lectures on Wavelets.* Philadelphia, Pennsylvania: Society for Industrial and Applied Mathematics, 1992.

[5] D. L. Hall, *Mathematical Techniques in Multisensor Data Fusion.* Boston-London: Artech House, 1992.

[6] N. Immerman, "Languages Which Capture Complexity Classes," in *Proc. 15th Ann. ACM Symp. on the Theory of Computing,* pp. 347–354, 1983.

[7] M.M. Kokar and J. Tomasik, *Towards a Formal Theory of Sensor/Data Fusion.* Progress Report, Northeastern University, May 1994.

[8] Z. Korona and M.M. Kokar, "Multiresolution Multisensor Target Identification," in *Proc. IEEE Int'l Conf. Multisensor Fusion and Integration for Intelligent Systems (MFI'94),* pp. 501–506, Las Vegas, Nevada, Oct. 1994.

[9] Z. Korona, "Model Theory Based Feature Selection for Multisensor Recognition," *Ph.D. Dissertation,* Northeastern University, 1996.

[10] "Wavelet-Based Recognition Using Model Theory for Feature Selection," in *Proc. SPIE Aerospace/Defense Sensing and Controls Symposium: Wavelet Applications III,* pp. 256–266, Orlando, FL, April 1996.

[11] R. C. Luo and M. G. Kay, "Multisensor Integration and Fusion in Intelligent Systems," *IEEE Transactions on Systems, Man and Cybernetics,* vol. 19, no. 5, pp. 901–931, 1989.

[12] N. Saito, "Local Feature Extraction and Its Applications Using a Library of Bases," *Ph.D. Dissertation,* Yale University, Dec. 1994.