MODEL BASED FUSION FOR MULTISENSOR TARGET RECOGNITION

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Abstract

A multisensor feature-based fusion approach to target recognition using a framework of model-theory is proposed. The Best Discrimination Basis Algorithm (BDBA) based on the best basis selection technique and the Sensory Data Fusion System (SDFS) based on logical models and theories are applied for feature extraction. The BDBA selects the most discriminant basis. The SDFS first selects features, which are interpretable in terms of symbolic knowledge about the domain, from the most discriminant basis determined for each sensor separately. Then, it fuses these features into one combined feature vector. The SDFS uses formal languages to describe the domain and the sensing process. Models represent sensor data, operations on data, and relations among the data. Theories represent symbolic knowledge about the domain and about the sensors. Fusion is treated as a goal-driven operation of combining languages, models, and theories related to different sensors into one combined language, one combined model of the world and one combined theory. The results of our simulations 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, while MDWC are selected from all the most discriminant bases determined for each sensor using a relative entropy measure.

Keywords— **backpropagation neural network, best basis, entropy, feature-based recognition, model-theory, multisensor, sensor/data fusion, target recognition, wavelet packet decomposition**

1 Introduction

In this work, we present a new methodology for multisensor feature-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 model-theory based fusion for multisensor feature selection.

By definition, 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. 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 [4, 7, 9]. 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 often results in suboptimal solutions which negatively affect the accuracy of the multisensor recognition systems. Additionally, fusion often increases processing time. 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.

The unifying fusion approach presented in this work is based on a framework of model-theory [1]. In particular, we apply and extend a model-theory based Sensory Data Fusion System (SDFS) (originally proposed by Kokar in [6]) to the wavelet-based recognition problems. The SDFS, which is the main part of the AMFRS, 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. In this work, we combine (fuse) feature vectors extracted from different sensors into one combined feature vector by utilizing the fused theory. 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.

The computational complexity of a recognition process is reduced by using a feature-based approach to recognition. In particular, we apply the Best Discrimination Basis Algorithm (BDBA) and a framework of model theory (SDFS) for feature extraction. The BDBA is based on a best basis selection technique proposed by Coifman and Wickerhauser in [2]. The BDBA selects the most discriminant basis. The SDFS selects features from the most discriminant basis. For the purpose of this work, the elements (wavelet coefficients) of the most discriminant basis are considered as features. The features extracted from input signals using the BDBA and the SDFS are used as inputs to a classifier. The output of the classifier gives a final recognition decision. In this work, we use a backpropagation neural network as a classifier.

To support the claim that the recognition accuracy is improved by using the AMFRS, we consider a simulated object recognition problem of distinguishing triangles from rectangles using a range and a vision sensor. The range and the vision sensors provide complementary information for recognition purposes. We specify feature-level models and theories for both range data and intensity data based on the most discriminant bases determined by the BDBA and based on a symbolic knowledge about the domain. Our goal is to fuse the range feature vector consisting of n_r range features and the intensity feature vector consisting of n_i intensity features into one combined feature vector consisting of n features. Effectively, n out of $n_r + n_i$ features need to be selected. By using only n features for recognition, the computational complexity of recognition is limited. However, the number of possible combinations of n features is big. To select the n features which have significant discriminant power and which are interpretable in terms of symbolic knowledge about the domain, we need to know the fused domain 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 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 [10].

Section 2 contains a conceptual description of the proposed recognition methodology (AMFRS). Section 3 presents a feature selection procedure for a recognition problem of distinguishing rectangles from triangles. Section 4 describes fusion of range and intensity features into one combined feature vector. The simulation results are shown in Section 5.

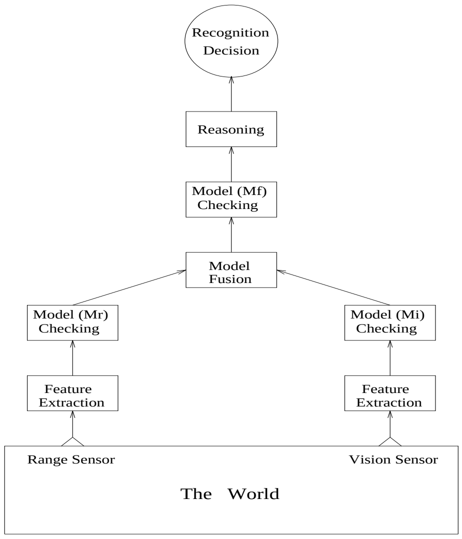

Figure 1: Automatic Multisensor Feature-based Recognition System (AMFRS)

2 Automatic Multisensor Feature-based Recognition System

Fig. 1 shows a conceptual view of the Automatic Multisensor Feature-based Recognition System (AMFRS) for two (range and vision) sensors.

The meaning of each block in the AMFRS is the following:

1. *The World* is a domain of the recognition problem with *Range Sensor* and *Vision Sensor* providing information about the domain to the AMFRS.

2. *Feature Extraction* extracts features from measurement data using the BDBA and a model-theory framework.

3. *Model (M_r) Checking* tests whether the measurement data represent a model M_r of a given theory T_r of the domain.

4. *Model (M_i) Checking* tests whether the measurement data represent a model M_i of a given theory T_i of the domain.

5. Model Fusion - the fusion operators for the models M_r and M_i.

6. *Model (M_f) Checking* tests whether the fused data represent a model M_f of a given theory T_f of the domain.

7. *Reasoning* uses the theory T_f to arrive with a final recognition decision.

There are three types of information available to the AMFRS:

- the target signatures $s_i \in S$, $i = 1, \cdots, K$, where S is a signal space;
- classes $c_j \in C$, $j = 1, 2$, of targets to be recognized, where C is a target class space;
- 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

$$recognition\ accuracy(\%) = \frac{number\ of\ correct\ recognition\ decisions}{total\ number\ of\ recognition\ decisions} * 100 \tag{1}$$

where the *total number of recognition decisions* is equal to the number of target signatures in a test set. Similarly, we define *misclassification rate* as

$$misclassification\ rate(\%) = \frac{number\ of\ incorrect\ recognition\ decisions}{total\ number\ of\ recognition\ decisions}*100 = 100-recognition\ accuracy \tag{2}$$

In this work, we investigate a method for extracting features $f_i \in F$ of the signal $s_i \in S$ represented in 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 $s_i \in S$ into a time/frequency (wavelet) representation $W_i \in W$. 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.

Assume that n_r features from the input signal of *Range Sensor* and n_i features from the input signal of *Vision Sensor* are extracted using the BDBA and a framework of model-theory. Our aim is to combine (fuse) features from both sensors into one feature vector consisting of exactly n features. Equivalently, we want to select n out of $n_r + n_i$ features which gives us

$$C(n_r + n_i, n) = \binom{n_r + n_i}{n} = \frac{(n_r + n_i)!}{(n_r + n_i - n)!n!} \tag{3}$$

possible combinations. This can be a big number. For example, for $n = n_r = n_i = 10$ we have 184,756 possible combinations. Therefore, we need a tool to select, from all these combinations, the combination of features which results in the most accurate recognition decision.

To select such a combination of features, we apply the model-theory based Sensory Data Fusion System (SDFS) as shown in Fig. 2. First, we specify a feature-level range model M_r and a theory T_r of a feature-level range language L_r, and a feature-level intensity model M_i and a theory T_i of a feature-level range language L_i. As can be seen from Fig. 1, in order to arrive at a recognition decision, we need to define the feature-level fused domain theory T_f for the AMFRS to perform reasoning. The fused theory is derived by using a theory fusion operator to fuse the feature-level theories for a range sensor and an intensity sensor as shown in Fig. 2. There is no physical law known and therefore there is no theory fusion operator known for fusing data from these two sensors. Instead, we derive a theory fusion operator manually from a 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 range theory and the intensity theory, we are able to derive the fused theory. In the same manner, we derive manually a model fusion operator and a language fusion operator.

In the presented AMFRS methodology, fusion operators are derived by using reduction, expansion and union operators [1]. 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

$$L = L^r \cup X, \tag{4}$$

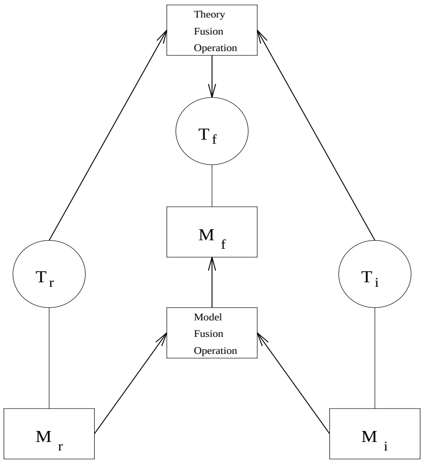

Figure 2: Model-Theory Based SDFS

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

$$M^r =< A, I^r > \tag{5}$$

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
  $$L^e = L \cup X, \tag{6}$$
  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
  $$M^e =< A, I \cup I_x > \tag{7}$$
  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_r and L_i if the language L can be written as
  $$L = L_r \cup L_i. \tag{8}$$
  A model $M =< A; R, G, x; I >$ for the language L is a union of the model $M_r =< A_r; R_r, G_r, X_r; I_r >$ for the language L_r and the model $M_i =< A_i; R_i, G_i, x_i; I_i >$ for the language L_i if the model M can be written as
  $$M = M_r \cup M_i =< A_r \cup A_i; R_r \cup R_i, G_r \cup G_i, x_r \cup x_i; I_r \cup I_i >, \tag{9}$$
  where R, R_r, R_i are relations; G, G_r, G_i are functions; x, x_r, x_i are constants; and I, I_r, I_i are interpretation functions.

  A theory T for the language L is a union of the theory T_r for the language L_r and the theory T_i for the language L_i if the theory T can be written as
  $$T = T_r \cup T_i. \tag{10}$$

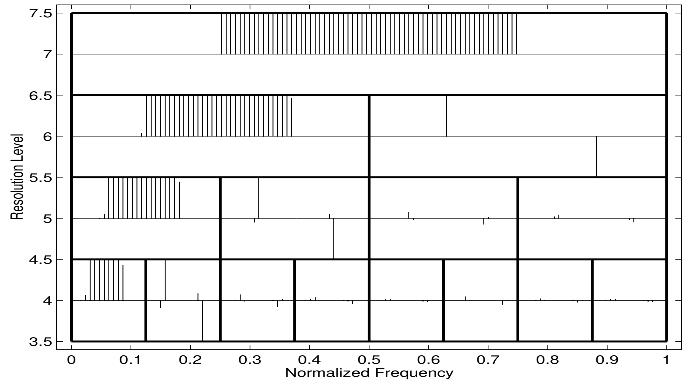

Figure 3: DWPD of a Rectangle Range Signal

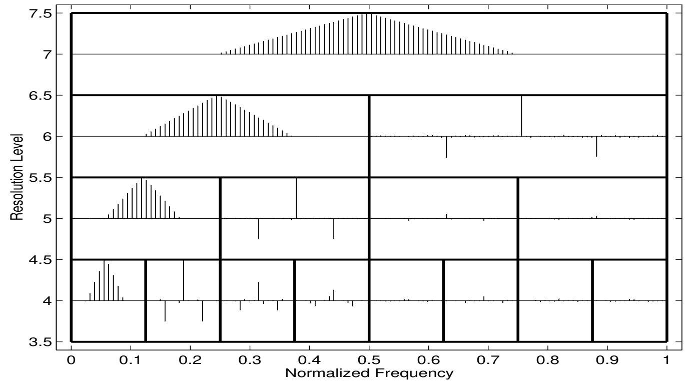

Figure 4: DWPD of a Triangle Range Signal

3 Feature Selection for Range and Intensity Data

A problem of distinguishing triangles from rectangles using a range sensor and a vision sensor is described in detail in [8]. Each of the triangle/rectangle (target) signatures in the 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 [3]. Figs. 3 and 4 show examples of the DWPD performed on a range signal corresponding to a rectangle and to a triangle respectively.

A complete orthonormal most discriminant basis 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 a complete orthonormal most discriminant basis for a given range reference database and the discriminant value of each component determined by using a relative entropy measure. For the range reference database, the most discriminant basis is the basis at the finest resolution level of the DWPD. In order to limit computational complexity of recognition, we apply a framework of model-theory to select $k_f < 128$ wavelet coefficients (features) from the complete basis. Our aim is to select k_f features that, in addition to significant discriminant power, are interpretable in terms of symbolic target features. A domain theory for the range reference database enables us to select appropriate features.

The $k_f = 9$ selected features by using the range domain theory are shown in Fig. 6. The first three features correspond to the rising edge of a rectangle, the next three features correspond to the vertex of a triangle, and the last three features correspond to the falling edge of the rectangle.

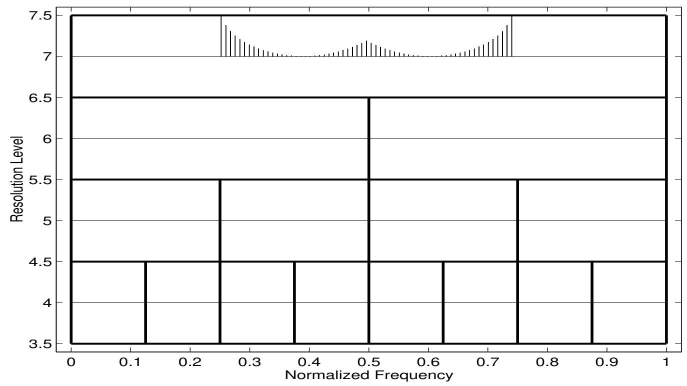

Figure 5: Most Discriminant Basis (MDB) for Range Data

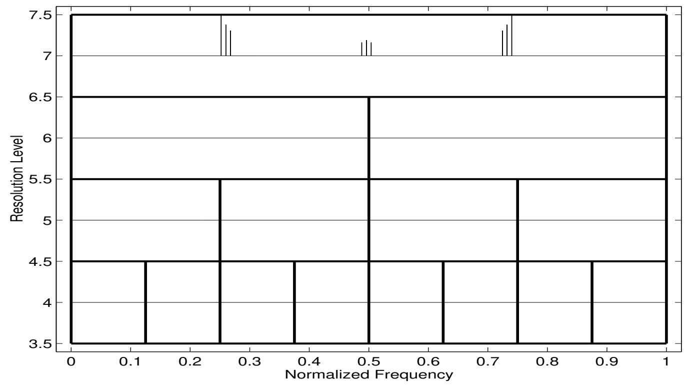

Figure 6: Range Features Selected from the MDB for Range Data Using the Domain Theory

Below, we describe an appropriate formal language, a model, and a range domain theory for the range sensor. In our formalization we assume that the symbol $\leq$ is a *logical symbol* with the usual interpretation as a linear order relation on the universe [5]. Consequently, this symbol is not included in the definition of the language but it appears in the theory.

1. **Language** L_r
   A feature-level range language L_r is the following:
$$L_r = \{rect_r, trian_r, f_r, C_{r_0}, C_{r_1}, \ldots, C_{r_7}, C_{r_8}\}, \quad (11)$$
   where
   - $rect_r$ is a 9-placed relation symbol (rectangle object to be recognized using range data),
   - $trian_r$ is a 9-placed relation symbol (triangle object to be recognized using range data),
   - f_r is an 1-placed function symbol (a function that maps range features' indices into features' values),
   - $C_{r_0}, C_{r_1}, \ldots, C_{r_7}, C_{r_8}$ are constant symbols (range features' indices).

2. **Model** M_r
   A feature-level range model M_r is defined as
$$M_r =< A; rect_r, trian_r, f_r, 0, 1, \ldots, 8; I_r >, \quad (12)$$
   where

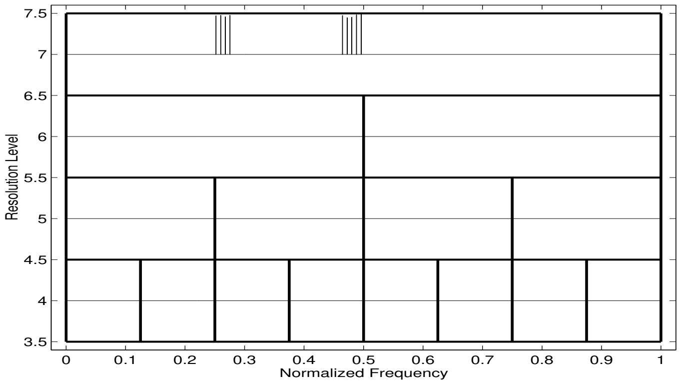

Figure 7: Intensity Features Selected from MDB for Intensity Data Using the Domain Theory

- $A = \{0, \ldots, 8\}$ is a universe of the model M_r,
- $rect_r \subset A^9$ is a relation,
- $trian_r \subset A^9$ is a relation,
- $f_r : A \rightarrow A$ is a function,
- I_r is an interpretation function (for more details see [8]).

3. **Theory T_r**
   A feature-level range theory T_r is the following.

$$\begin{aligned} rect_r(y_0 \ldots y_8) &\iff (\forall_{y_0, \ldots, y_8})\ ((y_0 = f_r(C_{r_0}) \wedge \ \ldots \ \wedge y_8 = f_r(C_{r_8})) \Rightarrow (y_0 = \ \ldots \ = y_8)), \quad (13) \\ trian_r(y_0 \ldots y_8) &\iff (\forall_{y_0, \ldots, y_8})\ ((y_0 = f_r(C_{r_0}) \wedge \ \ldots \ \wedge y_8 = f_r(C_{r_8})) \Rightarrow \\ & \qquad (y_0 \leq y_1 \leq y_2 \leq y_3 \leq y_4 \wedge y_0 = y_8 \wedge y_1 = y_7 \wedge y_2 = y_6 \wedge y_3 = y_5)), \quad (14) \end{aligned}$$

$$C_{r_0} \leq C_{r_1} \leq C_{r_2} \leq C_{r_3} \leq C_{r_4} \leq C_{r_5} \leq C_{r_6} \leq C_{r_7} \leq C_{r_8}. \quad (15)$$

In the same way as for the range reference database, each of the target signatures in the intensity reference database is transformed into the wavelet domain using the DWPD. The $k_f = 9$ selected features using the intensity domain theory are shown in Fig. 7. The first four features correspond to the rising edge of a rectangle and the last five features correspond to the vertex of a triangle.

A feature-level intensity language L_i is defined as

$$L_i = \{rect_i, trian_i, f_i, 0, 1, C_{i_0}, C_{i_1}, \ldots, C_{i_7}, C_{i_8}\}. \quad (16)$$

A feature-level intensity model M_i is defined as

$$M_i =< A; rect_i, trian_i, f_i, 0, 1, \ldots, 8; I_i > . \quad (17)$$

The feature-level intensity theory T_i is the following:

$$\begin{aligned} rect_i(y_0 \ldots y_8) &\iff (\forall_{y_0, \ldots, y_8})\ ((y_0 = f_i(C_{i_0}) \wedge \ \ldots \ \wedge y_8 = f_i(C_{i_8})) \Rightarrow (1 \leq y_0 = \ \ldots \ = y_8)), \quad (18) \\ trian_i(y_0 \ldots y_8) &\iff (\forall_{y_0, \ldots, y_8})\ ((y_0 = f_i(C_{i_0}) \wedge \ \ldots \ \wedge y_8 = f_i(C_{i_8})) \Rightarrow (y_0 = \ \ldots \ = y_8 = 0)), \quad (19) \end{aligned}$$

$$C_{i_0} \leq C_{i_1} \leq C_{i_2} \leq C_{i_3} \leq C_{i_4} \leq C_{i_5} \leq C_{i_6} \leq C_{i_7} \leq C_{i_8}. \quad (20)$$

4 Fusion of Range and Intensity Features

In this section, we describe a language fusion operator used to combine feature-level range and intensity languages into one fused language for triangle/rectangle recognition. The description of model and theory fusion operators can be found in [8]. We also present the resulting fused language, the fused model, and the fused theory for the triangle/rectangle recognition problem.

Our goal is to fuse the range feature vector consisting of $n_r = 9$ range features and the intensity feature vector consisting of $n_i = 9$ intensity features into one combined feature vector consisting of $n \leq n_r + n_i$ features. Effectively, n out of $n_r + n_i = 18$ features need to be selected. We selected $n = 9$ fused features using the fused theory. The first three fused features are the first three intensity features corresponding to the rising edge of the rectangle. The next three fused features are the last three intensity features corresponding to the vertex of the triangle. And the last three fused features are the last three range features corresponding to the falling edge of a rectangle.

To select these $n = 9$ fused features which have significant discriminant power and which are interpretable in terms of symbolic knowledge about the domain, we needed to know the fused theory. But to derive the fused theory, we needed to know a theory fusion operator. We derived a theory fusion operator manually from a symbolic knowledge about the domain and a relation between the symbolic knowledge and features determined by applying the BDBA to range and intensity data. In the same manner, we derived manually a language fusion operator and a model fusion operator by using reduction, expansion, and union operators.

Below, we describe the language fusion operations for our recognition problem. The description of the model and the theory fusion operations can be found in [8].

First, we create a language L_r^e as an expansion of the range language L_r by the language $X_r = \{rect_r', trian_r', f_r'\}$. Therefore

$$L_r^e = \{rect_r, rect_r', trian_r, trian_r', f_r, f_r', C_{r_0}, C_{r_1}, \ldots, C_{r_8}\}. \tag{21}$$

where $rect_r'$ is a 3-placed relation symbol, $trian_r'$ is a 3-placed relation symbol, and f_r' is an 1-placed function symbol.

Next, we define a language

$$L_r^{er} = \{rect_r', trian_r', f_r', C_{r_6}, C_{r_7}, C_{r_8}\}. \tag{22}$$

to be a reduction of the language L_r^e.

In a similar manner, we create a language L_i^e as an expansion of the intensity language L_i by the language $X_i = \{rect_i', trian_i', f_i'\}$. Therefore

$$L_i^e = \{rect_i, rect_i', trian_i, trian_i', f_i, f_i', C_{i_0}, C_{i_1}, \ldots, C_{i_7}, C_{i_8}\}. \tag{23}$$

where $rect_i'$ is a 6-placed relation symbol, $trian_i'$ is a 6-placed relation symbol, and f_i' is an 1-placed function symbol.

Then, we define a language

$$L_i^{er} = \{rect_i', trian_i', f_i', 0, 1, C_{i_0}, \ldots, C_{i_5}\}. \tag{24}$$

to be a reduction of the language L_i^e.

Next, we create a language L_{ri}, by applying a union operator to the languages L_r^{er} and L_i^{er}. Therefore

$$L_{ri} = \{rect_r', rect_i', trian_r', trian_i', f_r', f_i', 0, 1, C_{r_6}, C_{r_7}, C_{r_8}, C_{i_0}, \ldots, C_{i_5}\}, \tag{25}$$

Then, we create a language L_{ri}^e, as an expansion of the language L_{ri} by the language $X_{ri} = \{rectangle, triangle, f_f, C_{f_0}, C_{f_1}, \ldots, C_{f_8}\}$. Therefore

$$\begin{aligned} L_{ri}^e \ = \ & \{rectangle, rect_r', rect_i', triangle, trian_r', trian_i', \\ & f_f, f_r', f_i', 0, 1, C_{f_0}, \ldots, C_{f_8}, C_{r_6}, C_{r_7}, C_{r_8}, C_{i_0}, \ldots, C_{i_5}\}, \end{aligned} \tag{26}$$

where *rectangle* is a 9-placed relational symbol, *triangle* is a 9-placed relational symbol, f_f is an 1-placed function symbol, and $C_{f_0}, C_{f_1}, \ldots, C_{f_8}$ are constant symbols.

And finally, we create a fused language L_f, as a reduction of the language L_{ri}^e

$$L_{ri}^e = L_f \cup \{rect_r', rect_i', trian_r', trian_i', f_i', f_r', C_{r_6}, C_{r_7}, C_{r_8}, C_{i_0}, \ldots, C_{i_5}\} \quad (27)$$

4.1 Fused Language, Model and Theory

The fused language L_f, the fused model M_f, and the fused theory T_f created by applying reduction, expansion, and union operators are the following.

1. **Language** L_f
   A feature-level fused language L_f is defined as

   $$L_f = \{rectangle, triangle, f_f, 0, 1, C_{f_0}, \ldots, C_{f_8}\}, \quad (28)$$

   where

   - *rectangle* is a 9-placed relational symbol (rectangle object to be recognized using fused data),
   - *triangle* is a 9-placed relational symbol (triangle object to be recognized using fused data),
   - f_f is an 1-placed function symbol (a function that maps fused features' indices into features' values),
   - 0, 1 are constant symbols (special constants needed in the fused theory T_f),
   - $C_{f_0}, \ldots, C_{f_8}$ - are constant symbols (fused features' indices).

2. **Model** M_f
   A feature-level fused model M_f is defined as

   $$M_f =< A; rectangle, triangle, f_f, 0, \ldots, 8; I_f >, \quad (29)$$

   where

   - $A = \{0, \ldots, 8\}$ is a universe of the model M_f,
   - $rectangle \subset A^9$ is a relation,
   - $triangle \subset A^9$ is a relation,
   - $f_f : A \rightarrow A$ is a function,
   - I_f - is an interpretation function.

3. **Theory** T_f
   A feature-level fused theory T_f is defined as

$$\begin{aligned} rectangle(y_0 \ldots y_8) \iff & (\forall_{y_0, \ldots, y_8}) \ ((y_0 = f_f(C_{f_0}) \wedge \ldots \wedge y_8 = f_f(C_{f_8})) \Rightarrow \\ & (1 \leq y_0 = \ldots = y_5 \wedge y_6 = y_7 = y_8)), \quad (30) \\ triangle(y_0 \ldots y_8) \iff & (\forall_{y_0, \ldots, y_8}) \ ((y_0 = f_f(C_{f_0}) \wedge \ldots \wedge y_8 = f_f(C_{f_8})) \Rightarrow \\ & (y_0 = \ldots = y_5 = 0 \wedge y_8 \leq y_7 \leq y_6)), \quad (31) \end{aligned}$$

$$C_{f_0} \leq C_{f_1} \leq C_{f_2} \leq C_{f_3} \leq C_{f_4} \leq C_{f_5} \leq C_{f_6} \leq C_{f_7} \leq C_{f_8}. \quad (32)$$

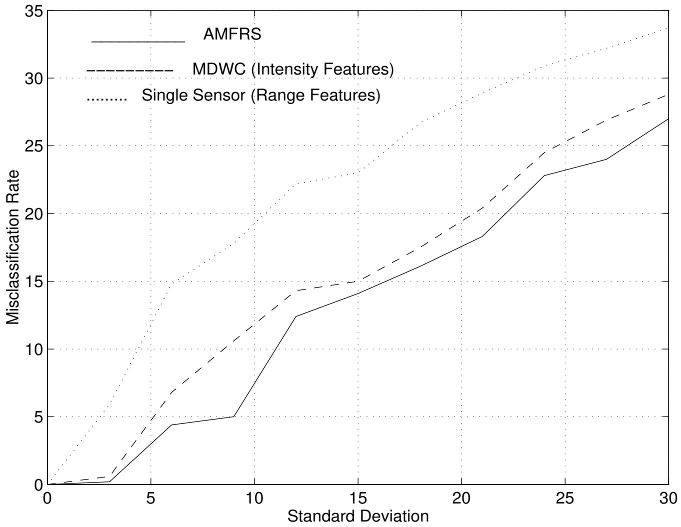

Figure 8: Misclassification Rates Using a Framework of Model-Theory for Feature Selection (AMFRS) and Using Most Discriminant Wavelet Coefficients (MDWC) as Features.

5 Results of Experiments

We test the recognition accuracy of the AMFRS by using a range and an intensity test database with triangle/rectangle signatures. Each of the target signatures in the test databases is transformed into the wavelet domain using the DWPD. A framework of model theory (SDFS) is used to extract range and intensity features, and to fuse them into one combined feature vector. This feature vector is used as an input vector into backpropagation neural network. The backpropagation neural network arrives with a final recognition decision.

Fig. 8 shows the resulting misclassification rates for different levels of noise for unisensor and multisensor (using range and intensity data) triangle/rectangle recognition. This figure also shows the misclassification rate of a recognition system using Most Discriminant Wavelet Coefficients (MDWC) as features. MDWC are selected, from among the features in the range and intensity most discriminant bases, using a relative entropy measure [10]. For our recognition problem the MDWC are the same as the intensity features, because all nine intensity features have more discriminant power than any of the range features.

6 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 the model-theory based Sensory Data Fusion System (SDFS). The symbolic knowledge about the domain is incorporated into the AMFRS through a domain theory using a framework of model-theory (SDFS). 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 recognition system adapts well to a set of features characteristic to the range and intensity reference databases, but it does not have enough generalization power to perform equally well with the range and intensity test databases. MDWC are the same as intensity features, because all nine intensity features have more discriminant power than any of the range features. Therefore, the MDWC used to train a classifier are concentrated in one time/frequency area.

We are able to increase the generalization power of the recognition system by using features which are more spread across the time/frequency domain. To select such features, we utilize the symbolic knowledge (fused domain theory) specific to a class of triangles and to a class of rectangles.

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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