Handwritten Digit Recognition Based On a DSmT-SVM Parallel Combination

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***Abstract*—We propose in this work a new handwritten digit recognition system based on parallel combination of SVM classifiers for managing conflict provided between their outputs. Firstly, we evaluate different methods of generating features to train the SVM classifiers that operate independently of each other. To improve the performance of the system, the outputs of SVM classifiers are combined through the Dezert-Smarandache theory. The proposed framework allows combining the calibrated SVM outputs issued from a sigmoid transformation and uses an estimation technique based on a supervised model to compute the belief assignments. Decision making is performed by maximizing the new Dezert-Smarandache probability. The performance evaluation of the proposed system is conducted on the well known US Postal Service database. Experimental results show that the proposed combination framework improves the recognition rate even when individual SVM classifiers provide conflicting outputs.**

Keywords-Handwriting digit recognition; Support Vector Machines; Dezert-Smarandache theory; belief assignments; conflict management.

I. INTRODUCTION

The initial systems that have emerged in the optical character recognition (OCR) are the systems for reading postal addresses used for mail sorting, automatic reading of handwriting on the forms, etc. Despite the researches in this area, the recognition of handwriting remains an open and important problem.

The basic task of such system is the recognition of isolated handwritten digits, the idea is to focus on only one digit at a time. This method leads to several constraints such as variability in the size of digits that can occur even among the digits of the same class, the difference in writing between individuals, the complexity of the separation between the digit and background, the thickness of the writing, the inclination angle. All these parameters are variables which makes this task complex and difficult.

In fact, these constraints lead to develop a large number of classifiers and methods of generating features. Rather than trying to optimize a single classifier by choosing the best features for a given problem, researchers found more interesting to combine the recognition methods [1], [2]. Indeed, the combination of classifiers allows exploiting the redundant and complementary nature of the responses issued from different classifiers.

However, with the existence of the constraints mentioned before, an appropriate operating method using mathematical approaches is needed, which takes into account two notions: uncertainty and imprecision of the responses of classifiers.

In general, the non-probabilistic approaches such as Support Vector Machines (SVMs) [3], are able to represent the uncertain knowledge but are unable to model easily the information which is imprecise, incomplete, or not totally reliable. Moreover, they often lead to confuse both concepts of uncertainty and imprecision with the probability measure. Indeed, the modelling through these approaches allows the reasoning only on singletons, which represent the different hypotheses (classes), under the closed world assumption. Therefore, several theories for modelling both concepts of uncertainty and imprecision have been introduced [4], [5], [6], [7].

Researchers have proposed various approaches for combining classifiers increasingly numerous and varied, which led the development of several schemes in order to treat data in different ways [1], [2]. Generally, three approaches for combining classifiers can be considered: parallel approach, sequential approach and hybrid approach [1], [2]. Furthermore, these ones can be performed at a class level, at a rank level, or at a measure level [8], [9], [10]. In a class level combination, the opinion of the classifier is binary. We can then represent the response of classifier through a binary vector in which "1" indicates the proposed class by the classifier. A classifier can also produce a set of classes. It then considers a pattern belongs to a class of this set without giving other information, which allows discriminating between classes. A rank level combination performs a ranking on the classes. The classifier indicates the ranking by providing in the output a vector of ranks. The class placed at the first rank of the list by the classifier is

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considered as the most probable for a given pattern and the class of last rank is the less probable one. A measure level combination indicates the confidence factor of the classifier in its proposal. The output of the classifier is a vector of measures (normalized or not), which may be a distance, a posterior probability, a confidence value, a match score, belief function, a possibility, credibility or a fuzzy measure, etc.

In this research, we focus on parallel combination to efficiently combine two SVMs classifiers at measure level. Therefore, the combination framework that we propose in the context of recognition of isolated handwritten digits is based on Dezert-Smarandache theory (DSmT). We first evaluate different methods of generating features to train the SVMs classifiers that operate independently of each other. The outputs of SVMs classifiers provide the degrees of imprecision for the recognition task. We then transform these ones in posterior probabilities using a sigmoid transformation. Hence, in order to enhance the performances of handwritten digit recognition system, we propose a supervised model based on DSmT for managing significantly the conflict provided from the two SVMs classifiers.

The paper is organized as follows. We give in section 2 a review of Proportional Conflict Redistribution (PCR6) rule based on DSmT. In section 3, we present the description of proposed recognition system. Experiments conducted on the USPS database of isolated handwritten digits are presented in section 4. The last section gives a summary of the proposed combination framework and looks to the future research direction.

II. REVIEW OF PCR6 COMBINATION RULE

Generally, the handwritten digit recognition is formulated as a ten-class problem where classes are associated to handwritten Arabic digits classes, namely $\theta_0, \theta_1, \ldots,$ and θ_9. Hence, the parallel combination of two classifiers, namely information sources S_1 and S_2, respectively, is performed through the PCR6 combination rule based on the DSmT. For ten-class problem, a reference domain also called the frame of discernment should be defined for performing the combination, which is composed of a finite set of exhaustive and mutually exclusive hypotheses.

In the context of the probabilistic theory, the frame of discernment, namely Θ, is composed of ten elements as: $\Theta = \{\theta_0, \theta_1, \ldots, \theta_9\}$, and a mapping function $m \in [0,1]$ is associated for each class, which defines the corresponding mass verifying $m(\varnothing) = 0$ and $\sum_{i=0}^{9} m(\theta_i) = 1$. When combining two sources of information, the combination rule defined in Bayesian framework [11], the weighted mean and consensus based methods [12], [13], [14] seem effective for non-conflicting responses. In the opposite case, an alternative approach has been developed in DSmT framework to deal with (highly) conflicting imprecise and uncertain sources of information [7]. Example of such approaches is PCR6 rule.

The main concept of the DSmT is to distribute unitary mass of certainty over all the composite propositions built from elements of Θ with $\cup$ (Union) and $\cap$ (Intersection) operators instead of making this distribution over the elementary hypothesis only. Therefore, the hyper-powerset D^Θ is defined as:

1. $\varnothing, \theta_0, \theta_1, \ldots, \theta_9 \in D^\Theta$.
2. If $A, B \in D^\Theta$, then $A \cap B \in D^\Theta$ and $A \cup B \in D^\Theta$.
3. No other elements belong to D^Θ, except those obtained by using rules 1 or 2.

The DSmT uses generalized basic belief mass, also known as the generalized basic belief assignment (gbba) computed on hyper-powerset of Θ and defined by a map $m(.): D^\Theta \to [0,1]$ associated to a given source of evidence which can support paradoxical information, as follows: $m(\varnothing) = 0$ and $\sum_{A \in D^\Theta} m(A) = 1$. The combined masses m_{PCR6} obtained from $m_1(.)$ and $m_2(.)$ by means of the PCR6 rule [7] is defined as:

$$m_{PCR6}(A_i) = \begin{cases} 0 & \text{if } A_i \in \Phi, \\ m_\wedge(A_i) + \sum_{k=1}^{2} m_k^2(A_i) L_k & \text{otherwise.} \end{cases} \quad (1)$$

Where

$$L_k = \sum_{\substack{Y_{\sigma_k(1)} \cap A_i \in \Phi \\ Y_{\sigma_k(1)} \in D^\Theta}} \frac{m_{\sigma_k(1)} Y_{\sigma_k(1)}}{m_k(A_i) + m_{\sigma_k(1)} Y_{\sigma_k(1)}} \quad (2)$$

$\Phi = \{\Phi_M, \varnothing\}$ is the set of all relatively and absolutely empty elements, Φ_M is the set of all elements of D^Θ which have been forced to be empty in the hybrid model M defined by the exhaustive and exclusive constraints, $\varnothing$ is the empty set, the denominator $m_k(A_i) + m_{\sigma_k(1)} Y_{\sigma_k(1)}$ is different to zero, and where $\sigma_k(1)$ counts from 1 to 2 avoiding k, i.e.: $\sigma_1(1) = 2$ and $\sigma_2(1) = 1$. Thus, the term $m_\wedge(A_i)$ represents a conjunctive consensus, also called DSm Classic (DSmC) combination rule [7], which is defined as:

$$m_\wedge(A_i) = \begin{cases} 0 & \text{if } A_i = \varnothing, \\ \sum_{(X, Y \in D^\Theta, X \cap Y = A_i)} m_1(X) m_2(Y) & \text{otherwise.} \end{cases} \quad (3)$$

III. SYSTEM DESCRIPTION

The system shown in Fig. 1 is composed of two individual systems using SVMs classifiers, which are combined through the PCR6 rule. In the following, we give a description of each module composed our system.

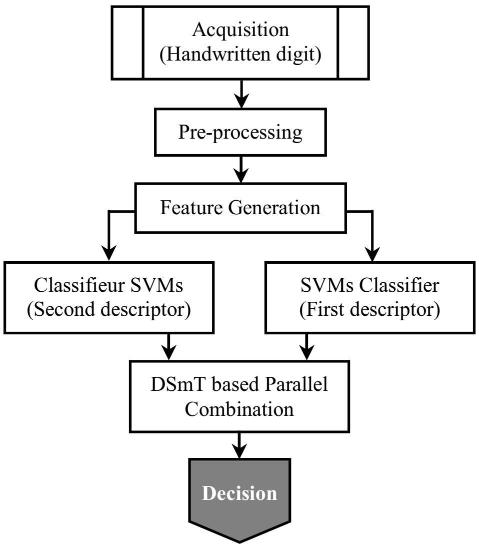

Figure 1. Structure of the recognition system.

A. Pre-processing

The acquired image of isolated digit should be processed to facilitate the feature generation. In our case, the pre-processing module includes a binarization step using the method of Otsu [15], which eliminates the homogeneous background of the isolated digit and keeps the foreground information.

B. Feature Generation

The objective of the feature generation step is to underline the relevant information that initially exists in the raw data. Thus, an appropriate choice of the descriptor improves significantly the accuracy of the recognition system. In this study, we use a collection of popular feature generation methods, which can be categorized into background features [16], [17], foreground features [16], [17], geometric features [2], and uniform grid features [18], [19].

C. Classification Based On SVM

Currently, SVMs are widely used in many pattern recognition applications as the handwritten digit recognition [2]. Its concept is based on the underlying structural risk minimization principle [3]. They proceed by mapping data into a high dimensional dot product space via a kernel function. In this space an optimal hyperplane, that maximizes the margin of separation between the two classes, is calculated.

Let D a set of N learning samples which are separable in n classes $\{\theta_0, \theta_1, \ldots, \theta_{n-1}\}$, such that $\mathrm{D} = \{(x_i, y_i), x_i \in \mathrm{R}^p; i = 1, \ldots, \mathrm{N}, y_i \in \{0, 1, \ldots, n\}\}$. In this paper, the combination of binary SVMs is performed using the multi-class implementation based on One Against All (OAA) method [20], in which each SVM is designed to separate a class from all the others (n SVMs are performed to solve a n-class problem). Thus, to solve a handwritten digit recognition problem, 10 SVMs trained over the full database are required.

D. Classification Based On DSmT

The proposed combination module consists of three steps: i) transformation of the SVM outputs into belief assignments using estimation technique based on a calibration method and a supervised model, ii) combination of masses through a combination rule and iii) decision rule.

1) Estimation of Masses: In this paper, the SVM outputs are calibrated using a sigmoidal transformation of Platt [21], and the masses of simple classes and their complementary classes are estimated using a supervised model, respectively. Let note $m_1(.)$ and $m_2(.)$ the gbba provided by two distinct information sources S_1 (First descriptor) and S_2 (Second descriptor), F is the set of focal elements for each source, such that $F = \{\theta_0, \theta_1, \ldots, \theta_{n-1}, \bar{\theta}_0, \bar{\theta}_1, \ldots, \bar{\theta}_{n-1}\}$, the classes θ_i are separable (One relatively to its complementary class $\bar{\theta}_i$) using the SVM multi-class implementation (OAA): they correspond to different singletons of the handwritten digits assumed to be known. Therefore, each compound element $A_i \notin F$ has a mass m_1 equal to zero, on the other hand, the mass of the complementary element $\bar{\theta}_i = \bigcup_{\substack{0 \le j \le n-1 \\ j \ne i}} \theta_j$ is different from zero, which represents the mass of the partial ignorance. The same reasoning is applied to the classes issued from the second source S_2 and $m_2(.)$. Hence, both gbba $m_1(.)$ and $m_2(.)$ are given as follows:

$$m_b(\theta_i) = \frac{\hat{P}_b(\theta_i|x)}{Z_b}, \forall \theta_i \in F, \quad (4)$$

$$m_b(\bar{\theta}_i) = \frac{\sum_{\substack{j=0 \\ j \ne i}}^{n-1} \hat{P}_b(\theta_j|x)}{Z_b}, \forall \bar{\theta}_i \in F, \quad (5)$$

$$m_b(A_i) = 0, \forall A_i \in \Phi = \mathrm{D}^{\Theta} \setminus F. \quad (6)$$

where $Z_b = \sum_{j=0}^{n-1} \hat{P}_b(\theta_j|x)$ represent normalization factors that are introduced in the axiomatic approach in order to respect the mass definition, $\hat{P}_b$ are the posterior probabilities issued from the first source $(b=1)$ and the second source $(b=2)$ respectively. They are given for a test digit x as follows [21]:

$$\hat{P}_b(\theta_i|x)=\frac{1}{1+\exp(A_{ib}\times f_{ib}(x)+B_{ib})}. \quad (7)$$

A_{ib} and B_{ib} are the parameters of the sigmoidal function tuned by minimizing the negative log-likelihood of the learning samples for each class of digits θ_i, and $f_{ib}(x)$ is the i-th output of binary SVM classifier issued from the source S_b, such that $i=0,1,\ldots,n-1$ and $b\in\{1,2\}$.

2) Combination of Masses: In order to manage the conflict generated from the two information sources S_1 and S_2 (i.e. both SVM classifications), the combined masses are computed as follows:

$$m_c = m_1 \oplus m_2. \quad (8)$$

where $\oplus$ defines the PCR6 combination rule.

3) Decision Rule: A decision of membership of a handwritten digit to one of the simple classes of Θ is made using the statistical classification technique. First, the combined beliefs are converted into probability measure using a new probabilistic transformation, called Dezert-Smarandache probability (DSmP), that maps a belief measure to a subjective probability measure [7] defined as:

$$\begin{aligned} &DSmP_\varepsilon(\theta_i)= \\ &m_c(\theta_i)+ \\ &(m_c(\theta_i)+\varepsilon)\sum_{\substack{A_j\in 2^\Theta \\ A_j\supset\theta_i \\ C_M(A_j)\geq 2}}\frac{m_c(A_j)}{\sum_{\substack{A_k\in 2^\Theta \\ A_k\subset A_j \\ C_M(A_k)=1}} m_c(A_k)+\varepsilon\, C_M(A_j)}. \end{aligned} \quad (9)$$

where $i=\{0,1,\ldots,9\}$, $\varepsilon\geq 0$ is a tuning parameter, M is the Shafer's model for Θ, and $C_M(A_k)$ denotes the DSm cardinal [7] of A_k. Therefore, the maximum likelihood (ML) test is used for decision making as follows:

$$x\in\theta_i \text{ if } DSmP_\varepsilon(\theta_i)=\max\left\{DSmP_\varepsilon(\theta_j), 0\leq j\leq 9\right\}. \quad (10)$$

where x is the handwritten digit test characterized by both descriptors, which are used during the feature generation step, and ε is fixed to 0.001 in the decision measure given by (8).

IV. EXPERIMENTAL RESULTS

A. Database Description and Performance Criteria

Experiments are conducted on the well-known US Postal Service (USPS) handwriting recognition task. This database contains normalized grey-level handwritten digit images of 10 numeral classes, extracted from US postal envelopes. All images are segmented and normalized to a size of 16×16 pixels. There are 7291 training data and 2007 test data where some of them are corrupted and difficult to classify correctly. For evaluating the performances of the handwritten digit recognition system, a popular error is considered, which is the *Error Rate (ER)* for each class and *Mean Error Rate (MER)* for all classes.

B. SVM Model Used for Validation

The SVM model is produced for each class according the used descriptor. Hence, the training dataset is partitioned into two equal subsets of samples: the first one is the learning subset used to learn each binary SVM classifier and the second one is the validation subset. Thus, the validation phase allows finding the optimal hyperparameters for the ten SVM models. In our system, the RBF kernel is selected for the experiments. Indeed, the regularization and RBF kernel parameters (C,σ) of each SVM are tuned experimentally at the time of learning phase, in such way that the misclassification error of data in the learning subset is zero and the validation test gives a minimal error during validation phase for each SVM separating between a simple class and its complementary class.

C. Recognition Results and Discussion

The test phase has been performed using all samples from the test dataset. Hence, the performance of the handwritten digit recognition system will be evaluated on an appropriate choice of descriptors using the SVMs classifier and then we evaluate the combination of the SVMs classifiers through DSmT framework.

1) Performance Evaluation of the Proposed Descriptors: In these experiments, we compute the test error rate of the SVMs classifier using Foreground Features (FF), Background Features (BF), Geometric Features (GF), Uniform Grid Features (UGF), and the descriptors which result from a concatenation between at least two simple descriptors such as (BF,FF), (BF,FF,GF), and the (UGF,BF,FF,GF) descriptor. Indeed, the experiments have shown that the appropriate choice of both descriptors and concatenation in order to represent each digit class in the feature generation step provides an interesting recognition performance. In table 1, FF and UGF-based descriptors using SVM classifiers are evaluated. When using (BF,FF)-based descriptors, we observe a significant improvement in the recognition performance when we concatenate background and foreground features in the same vector, respectively. In fact, a gain of 6.71% in the error rate has been obtained using the new (BF,FF)-based descriptor. A reduction of 1.5% in the error rate is obtained in the experiment (c) for the new (BF,FF,GF)-based descriptor, which is constructed by a concatenation of (BF,FF)-based descriptor and geometric features in the same vector, respectively.

Furthermore, UGF-based descriptor yields a recognition error of 6.98% which 3.68% less than the recognition error of (BF,FF,GF)-based descriptor. Finally, the combination of UGF and (BF,FF,GF)-based descriptors through a concatenation allows decreasing the recognition performance, which is expressed by an increase of 2.73% in the error recognition.

TABLE 1. MEAN ERROR RATES OF THE SVM CLASSIFIERS USING DIFFERENT METHODS OF FEATURE GENERATION

	MER (%)
(a) FF	18.87
(b) (BF,FF)	12.16
(c) (BF,FF,GF)	10.66
(d) UGF	6.98
(e) (UGF,BF,FF,GF)	9.71

As we can see, it is difficult to improve the recognition performance by a concatenation of features since most of the time the combined descriptors does not take into account the complementary, which can be exist between both descriptors.

Hence, we propose a combination of SVMs classifiers based on DSmT for a better exploitation of the complementary, which is obtained from the descriptors. In this way, it is possible to improve the recognition performance when the concatenation of descriptors can fail to provide the correct solution for some specific handwritten digit recognition problems.

2) Performance Evaluation of the Proposed Combination Framework: In these experiments, we evaluate a handwritten digit recognition system based on a combination of SVMs classifiers through DSmT. In fact, the proposed combination framework allows to exploit the redundant and complementary nature of the (BF,FF,GF) and UGF-based descriptors and manage the conflict provided from the outputs of SVMs classifiers.

Decision making will be only done on the simple classes belonging to the frame of discernment. Hence, we consider in both combination process and calculation of the decision measures the masses associated to all classes representing the partial ignorance $\overline{\theta_i} = \bigcup_{\substack{0 \le j \le n-1 \\ j \ne i}} \theta_j$ and $\overline{\theta_i} \cap \overline{\theta_j}$ such that $i \ne j$.

For better comparison, table 2 shows the mean recognition rate computed separately on test samples belonging to each simple class using the SVM classifiers and PCR6 combination rule. Therefore, results corresponding to the error rates are determined and given in the last line of table 2 for each algorithm.

As shown in table 2 the PCR6 algorithm yield in the case of the digits belonging to θ_6 a recognition rate of 96.47%, which is 1.76% greater than the recognition accuracy of SVMs classifier trained with UGF-based descriptor, but it is less than 0.59% compared to the recognition accuracy obtained when training the SVMs classifier with (BF,FF,GF)-based descriptor. This is because there are some digits of the class θ_6 which are wrongly characterized by both UG and (BF,FF,GF)-based descriptors. In other words, the PCR6 combination based algorithm is not reliable when the complementary information provided from both descriptors is wrongly preserved.

Except the samples belonging to class θ_6, the PCR6 combination based algorithm kept the same recognition performance when considering the best individual SVMs classifier trained with UGF-based descriptor and taking into account the samples belonging to θ_0 and θ_3, and it improves the recognition accuracy when considering other samples belonging to classes θ_1, θ_2, θ_4, θ_5, θ_7, θ_8, and θ_9.

Therefore, the proposed framework with PCR6 combination rule yields a recognition error of 5.43% corresponding to a decrease of 1.55%. This is because the efficient redistribution of the partial conflicting mass only to the elements involved in the partial conflict when using PCR6 combination rule.

V. CONCLUSION AND FUTURE WORK

We proposed and presented a new system which allows improving the handwritten digit recognition performance by combining the outputs issued from two SVM classifiers. The proposed parallel combination is performed through DSmT framework using an estimation technique based on sigmoid transformation and supervised model, PCR6 combination rule and DSmP based maximum likelihood (ML) test. Experimental results show that the proposed combination framework with PCR6 rule yields the best recognition accuracy even when the individual SVMs classifications provide conflicting outputs.

In continuation to the present work, the next objectives consist to incorporate two complementary descriptors using the same proposed handwritten digit recognition system in order to attempt to reduce the MER.

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TABLE 2. MEAN ERROR RATES OF THE PROPOSED FRAMEWORK WITH PCR6 COMBINATION ALGORITHM USING BF-FF-GF AND UGF DESCRIPTORS

Class	(BF,FF,GF)+SVMs	UGF+SVMs	PCR6 Combination Rule
0	93.31	98.05	98.05
1	95.45	96.21	96.97
2	87.37	91.92	93.94
3	82.53	89.16	89.16
4	80.00	88.50	91.00
5	83.13	90.00	92.50
6	97.06	94.71	96.47
7	91.16	91.84	95.24
8	87.95	89.16	93.37
9	89.27	93.79	94.35
MER (%)	10.66	6.98	5.43