SVM-DSmT Combination for Off-Line Signature Verification

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Abstract—**We propose in this work a signature verification system based on decision combination of off-line signatures for managing conflict provided by the SVM classifiers. The system is basically divided into three modules: i) Radon Transform-SVM, ii) Ridgelet Transform-SVM and iii) PCR5 combination rule based on the generalized belief functions of Dezert-Smarandache theory. The proposed framework allows combining the normalized SVM outputs and uses an estimation technique based on the dissonant model of Appriou to compute the belief assignments. Decision making is performed through likelihood ratio. Experiments are conducted on the well known CEDAR database using false rejection and false acceptance criteria. The obtained results show that the proposed combination framework improves the verification accuracy compared to individual SVM classifiers.**

Keywords-Off-line signature verification; Radon transform; Ridgelet transform; Support Vector Machines; Dezert-Smarandache theory.

I. INTRODUCTION

Biometrics is one of the most widely used approaches for person identification and verification. Hence, several biometric modalities have been proposed in the last decades [1], which are based on physiological and behavioral characteristics depending on their nature. Physiological characteristics are related to anatomical properties of a person, including, for instance, fingerprint, face, iris and hand geometry. Behavioral characteristics refer to how an individual performs an action, including, for instance, voice, signature and gait [1].

Usually, the handwritten signature is socially accepted for many government/legal/financial transactions such as validation of cheques, historical documents, etc [2]. Hence, an intense research field has been devoted to develop various robust verification systems [2] according the acquisition mode of the signature. Thus, two modes are used for capturing the signature, which are off-line mode and on-line mode, respectively. The off-line mode allows generating a handwriting static image from a document scanning. In contrast, the on-line mode allows generating from pen tablets or digitizers dynamic information such as velocity and pressure. For both modes, many Handwritten Signature Verification Systems (HSVS) have been developed in the past decades [2]. Generally, the off-line HSVS remains less robust compared to the on-line HSVS [2] because the importance of the signature variability. Indeed, signatures produced from the same user show considerable differences according different captures (high *intra-class* variability) and thus skilled forgers can perform signatures having high resemblance to the user's signature (low *inter-class* variability). Moreover, when a system is designed, only a fraction of information about skilled forgeries can be obtained as forgers. Therefore, unexpected skills can appear at any time once the system has been deployed. Hence, various methods have been developed to enhance performances of the off-line HSVS, which is generally composed of three modules: preprocessing, feature generation and classification. The most important module concerns the feature generation where many methods have been developed [2].

In order to enhance the performances of the off-line HSVS and ensure a better security, we propose a combination of two individual systems based on Dezert-Smarandache theory (DSmT) for managing the conflict provided from two Support Vector Machine (SVM) classifiers. Indeed, many works prove the useful of combining two systems for improving the performances of the individual systems. For instance, the combination method based on DST has been used by Arif and Vincent [3] for off-line signature verification problem. Nakanishi et al. proposed a parameter combination in Dynamic Time Warping (DTW) domain [4] for on-line signature verification. Mottl et al. [5] proposed a combination algorithm of on-line and off-line kernels for signature verification using SVM. Recently, combination of off-line image and dynamic information which are obtained from the same signature [6] has been proposed that exploit global and local information.

In this paper, we associate features based on Radon and ridgelet transforms for each individual system. Outputs of SVM classifiers are combined through a decision rule using the DSmT [7] for managing significantly the conflict generated from the individual systems.

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The paper is organized as follows. We give in section 2 a review of Proportional Conflict Redistribution (PCR5) rule based on DSmT. In section 3, we present the description of proposed verification system. Experiments conducted on the CEDAR database of off-line signatures 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 PCR5 COMBINATION RULE

Generally, the signature verification is formulated as a two-class problem where classes are associated to *genuine* user and *impostor*, namely θ_{gen} and θ_{imp}, respectively. Hence, the combination of two individual systems, namely information sources S^1 and S^2, respectively, is performed through the PCR5 combination rule based on the DSmT. For two-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, let $\Theta = \{\theta_{gen}, \theta_{imp}\}$ be the frame of discernment that represents a finite set of exhaustive and mutually exclusive hypothesis and $m \in [0,1]$ be the mapping function associated for each class, which defines the corresponding mass verifying $m(\emptyset) = 0$ and $m(\theta_{gen}) + m(\theta_{imp}) = 1$. When combining two sources of information, the sum rule [8] seems effective for non-conflicting responses. In the opposite case, an alternative approach has been developed by Dezert and Smarandache to deal with (highly) conflicting imprecise and uncertain sources of information [7]. Example of such approaches is PCR5 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 $D^\Theta = \{\emptyset, \theta_{gen}, \theta_{imp}, \theta_{gen} \cup \theta_{imp}, \theta_{gen} \cap \theta_{imp}\}$. The DSmT uses the generalized basic belief mass, also known as the generalized basic belief assignment (gbba) computed on hyper-powerset of Θ and defined by a map $m(.) : D^\Theta \longrightarrow [0,1]$ associated to a given source of evidence, which can support paradoxical information, as follows: $m(\emptyset) = 0$ and $m(\theta_{gen}) + m(\theta_{imp}) + m(\theta_{gen} \cup \theta_{imp}) + m(\theta_{gen} \cap \theta_{imp}) = 1$. The combined masses m_{PCR5} obtained from $m_1(.)$ and $m_2(.)$ by means of the PCR5 rule [7] is defined as:

$$m_{PCR5}(A) = \begin{cases} 0 & \text{if } A \in \Phi \\ m_{DSmC}(A) + m_{A\cap X}(A) & \text{otherwise} \end{cases} \tag{1}$$

Where

$$m_{A\cap X}(A) = \sum_{\substack{X \in D^\Theta \setminus \{A\} \\ c(A\cap X)=\emptyset}} \left[\frac{\{m_1(A)\}^2\, m_2(X)}{m_1(A) + m_2(X)} + \frac{\{m_2(A)\}^2\, m_1(X)}{m_2(A) + m_1(X)} \right]$$

and $\Phi = \{\Phi_{\mathcal{M}}, \emptyset\}$ is the set of all relatively and absolutely empty elements, $\Phi_{\mathcal{M}}$ is the set of all elements of D^Θ which have been forced to be empty in the Shafer's model $\mathcal{M}$ defined by the exhaustive and exclusive constraints, $\emptyset$ is the empty set, and $c(A \cap X)$ is the canonical form (conjunctive normal) of $A \cap X$ and where all denominators are different to zero. If a denominator is zero, that fraction is discarded. Thus, the term $m_{DSmC}(A)$ represents a conjunctive consensus, also called DSm Classic (DSmC) combination rule [7], which is defined as:

$$m_{DSmC}(A) = \begin{cases} 0 & \text{if } A = \emptyset \\ \sum_{(X,Y \in D^\Theta, X\cap Y = A)} m_1(X) m_2(X) & \text{otherwise} \end{cases} \tag{2}$$

III. SYSTEM DESCRIPTION

The system shown in Fig. 1 is composed of two individual systems: Radon Transform-SVM classifier and Ridgelet Transform-SVM classifier, which are combined through the PCR5 rule. In the following, we give a description of each module composed our system.

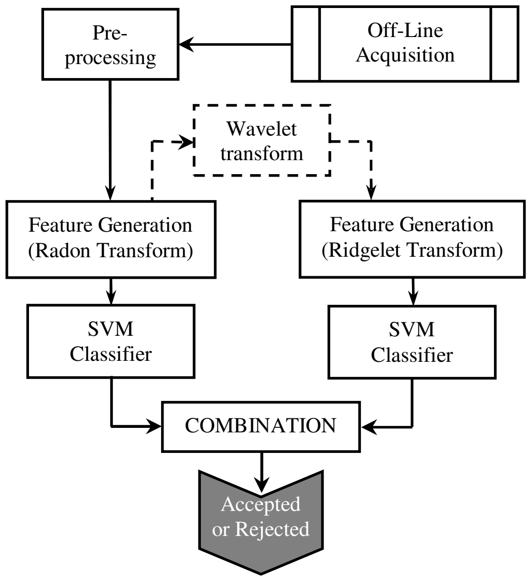

Figure 1. Structure Of The Verification System

A. Pre-processing

The acquired image of off-line signature should be processed to facilitate the feature generation. In our case, the pre-processing module includes two steps: Binarization using the local iterative method [9] and elimination of the useless information around the signature.

B. Feature Generation

In our system, we use the Radon and ridgelet transforms for generating features from the same signature. The Radon transform is well adapted for detecting linear features. In contrast, the ridgelet transform allows representing linear singularities [10]. Therefore, Radon and ridgelet coefficients provide complementary information about the signature.

The Radon transform of each off-line signature is calculated by establishing the number of projection points N_r and orientations N_θ, which define the length of the radial and angular vectors, respectively. Hence, we obtain a radon matrix of size $[N_r \times N_\theta]$ which provides in each point the cumulative intensity of pixels forming the image of the off-line signature. Since the Radon transform is redundant, we take into account only positive radial points $[(N_r/2) \times N_\theta]$. Then after, for each angular direction, the energy of Radon coefficients is computed to form the feature vector x_1 of dimension $[1 \times N_\theta]$. For generating complementary information of the Radon features, the wavelet transform (WT) is performed along the radial axis allowing generating the ridgelet coefficients [11]. Hence, for each angular direction, the energy of ridgelet coefficients is computed taking into account only the details issued from the decomposition level L of the WT. Therefore, the different values of energy are finally stored in a vector x_2 of dimension $[1 \times N_\theta]$.

C. Classification Based On SVM

The SVM, a learning method introduced by Vapnik et al. [12], tries to find an optimal hyperplane for separating two classes. Therefore, the misclassification error of data both in the training set and test set is minimized. Basically, SVM have been defined for separating linearly two classes. When data are non linearly separable, a kernel function is used as polynomial function, radial basis function (RBF) or multi layer perceptron. The classification based on SVM involves training and testing stages. The training stage consists to find the optimal parameters. Hence two parameters should be determined: the kernel parameter and the regularization parameter. These two parameters are found experimentally depending on the dataset. The testing stage allows evaluating the robustness of the classifier.

In order to decide if a signature is genuine or forgery, a decision rule is performed on the outputs of the SVMs where values are positive or negative. Hence, the output of the SVMs should be transformed to the objective evidences expressed as the membership degree. In practice, no standard form is defined for the membership degree. The only constraint is that it must be limited in the range of $[0, 1]$ whereas SVM produce a single output. In this paper, we use a fuzzy model [13] to assign memberships for SVM outputs in both genuine and impostor classes. Let $h_d(\theta_i), i = \{gen, imp\}$ membership models associated to genuine and impostor classes obtained for a feature vector based on Radon $(d = 1)$ or ridgelet $(d = 2)$ transforms, a signature is considered genuine or forgery through the following decision rule:

if $\frac{h_d(\theta_{gen})}{h_d(\theta_{imp})} \geq t$ **then** $s_d \in \theta_{gen}$
else $s_d \in \theta_{imp}$
end if

where t is the threshold value, s_1 and s_2 designate the j-th off-line signature characterized by both Radon and ridgelet features, respectively.

D. Classification Based On DSmT

The proposed combination module consists of three steps: i) transform membership degrees of the SVM outputs into belief assignments using estimation technique based on the dissonant model of Appriou, ii) combine masses through an algorithm based on DSmT and iii) make a decision for accepting or rejecting a signature.

1) Estimation of Masses: In this paper, the mass functions are estimated using a dissonant model of Appriou, which is defined for two classes [14]. Therefore, the extended version of Appriou's model in DSmT framework is given as:

$$m_{id}(\emptyset) = 0 \tag{3}$$

$$m_{id}(\theta_i) = \frac{(1-\beta_{id})\, h_d(\theta_i)}{1+h_d(\theta_i)} \tag{4}$$

$$m_{id}(\overline{\theta_i}) = \frac{1-\beta_{id}}{1+h_d(\theta_i)} \tag{5}$$

$$m_{id}(\theta_i \cup \overline{\theta_i}) = \beta_{id} \tag{6}$$

$$m_{ib}(\theta_i \cap \overline{\theta_i}) = 0 \tag{7}$$

where $i = \{gen, imp\}$, $h_d(\theta_i)$ is the membership degree of j-th off-line signature provided by the corresponding source S^d $(d = 1, 2)$, $(1 - \beta_{id})$ is a confidence factor of i-th class, and β_{id} defines the error provided by each source $(d = 1, 2)$ for each class θ_i. In our approach, we consider β_{id} as the verification accuracy prior computed on the training database for each class [15]. Since both SVM models have been validated on the basis that errors during training phase are zero, β_{id} is fixed to 0.001 in the estimation model.

2) Combination of Masses: The combined masses are computed in two steps. First, the belief assignments $(m_{id}(.), i = \{gen, imp\})$ are combined for generating the belief assignments for each source as follows:

$$m_1 = m_{\{gen\}1} \oplus m_{\{imp\}1} \tag{8}$$

$$m_2 = m_{\{gen\}2} \oplus m_{\{imp\}2} \tag{9}$$

where $\oplus$ represents the DSmC combination rule.

Finally, the belief assignments for the combined sources $(m_d(.), d = 1, 2)$ are then computed as:

$$m_c = m_1 \oplus m_2 \tag{10}$$

where $\oplus$ represents the PCR5 based combination algorithm.

3) Decision Rule: A decision for accepting or rejecting an off-line signature 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:

$$DSmP_{\epsilon}(\theta_i) = m_c(\theta_i) + (m_c(\theta_i) + \epsilon)w_{\mathcal{M}} \quad (11)$$

where $w_{\mathcal{M}}$ is a weighting factor defined as:

$$w_{\mathcal{M}} = \sum_{\substack{A_j \in 2^{\Theta} \\ A_j \supset \theta_i \\ C_{\mathcal{M}}(A_j) \geq 2}} \frac{m_c(A_j)}{\sum_{\substack{A_k \in 2^{\Theta} \\ A_k \subset X \\ C_{\mathcal{M}}(A_k)=1}} m_c(A_k) + \epsilon\, C_{\mathcal{M}}(A_j)}$$

such that $i = \{gen, imp\}$, $\epsilon \geq 0$ is a tuning parameter, $\mathcal{M}$ is the Shafer's model for Θ, and $C_{\mathcal{M}}(A_k)$ denotes the DSm cardinal [7] of the set A_k. Therefore, the likelihood ratio test is used with a threshold t for decision making as follows:

if $\frac{DSmP_{\epsilon}(\theta_{gen})}{DSmP_{\epsilon}(\theta_{imp})} \geq t$ **then** $s \in \theta_{gen}$
else $s \in \theta_{imp}$
end if

where $s = \{s_1, s_2\}$ is the j-th off-line signature characterized by both Radon and ridgelet features.

IV. Experimental Results

A. Data Description and Performance Criteria

The Center of Excellence for Document Analysis and Recognition (CEDAR) signature dataset [16] is a commonly used dataset for off-line signature verification. The CEDAR dataset consists of 55 signature users, each one provided 24 genuine and forgery samples, respectively. In total, 1320 genuine and 1320 skilled forgery signatures are built from 55 users, respectively. For evaluating the performances of the signature verification system, two popular errors are considered, which are *False Accepted Rate* (*FAR*) and *False Rejected Rate* (*FRR*).

B. Feature generation

The main problem for generating features is the appropriate number of the angular direction N_{θ} for the Radon transform and the number of the decomposition level L of the WT (Haar Wavelet) in the ridgelet domain. Hence, many experiments are conducted for searching the optimal values. In the case of the CEDAR database, N_{θ} and L are fixed to 32 and 3, respectively.

C. SVM model

The SVM model is produced for each individual system according the Radon and ridgelet transforms, respectively. For each user, 2/3 and 1/3 samples are used for training and testing, respectively. In our system, the RBF kernel is selected for the experiments. The optimal parameters (C, σ) of each SVM are tuned experimentally, which are fixed as $(C = 19.1, \sigma = 4)$ and $(C = 15.1, \sigma = 4.6)$, respectively.

D. Verification Results and Discussion

Decision making will be only done on the simple classes. Hence, we consider the masses associated to all classes belonging to the hyper power set $D^{\Theta} = \{\emptyset, \theta_{gen}, \theta_{imp}, \theta_{gen} \cup \theta_{imp}, \theta_{gen} \cap \theta_{imp}\}$ in both combination process and decision making.

In the context of signature verification, we take as constraint the proposition that $\theta_{gen} \cap \theta_{imp} = \emptyset$ in order to separate between genuine and impostor classes. Therefore, the hyper power set D^{Θ} is simplified to the power set 2^{Θ} as $2^{\Theta} = \{\emptyset, \theta_{gen}, \theta_{imp}, \theta_{gen} \cup \theta_{imp}\}$, which defines the Shafer's model [7].

Indeed, the task of the proposed combination module is to manage the conflicts generated between the two SVM classifiers for each signature using the PCR5 combination algorithm. For that, we compute the verification errors of both SVM classifiers and the proposed combination framework with PCR5 rule. Figure 2 shows the FRR and FAR computed for different values of decision threshold using the SVM classifiers on both Radon and ridgelet features, respectively and the PCR5 combination rule.

The off-line verification system based on Radon Transform yields an error rate of 7.72% corresponding to the optimal value of threshold $t = 1.11$ while the off-line verification system based on Ridgelet Transform provides the same result with an optimal value of threshold $t = 0.991$. When using the PCR5 rule, our proposed framework allows improving the verification error rate by 2.27% for an optimal value of the threshold $t = 0.986$. This is due to the efficient redistribution of the partial conflicting mass only to the elements involved in the partial conflict.

V. Conclusion And Future Work

The objective of this paper is to present a new system for improving the performance of the off-line signature verification by associating Radon and ridgelet features in order to ensure a greater security. Hence, a combination framework is proposed using an estimation technique based on the dissonant model of Appriou, DSmT and likelihood ratio. Experimental results show that the proposed combination framework with PCR5 rule yields the best verification accuracy even when the individual off-line classifications provide conflicting outputs.

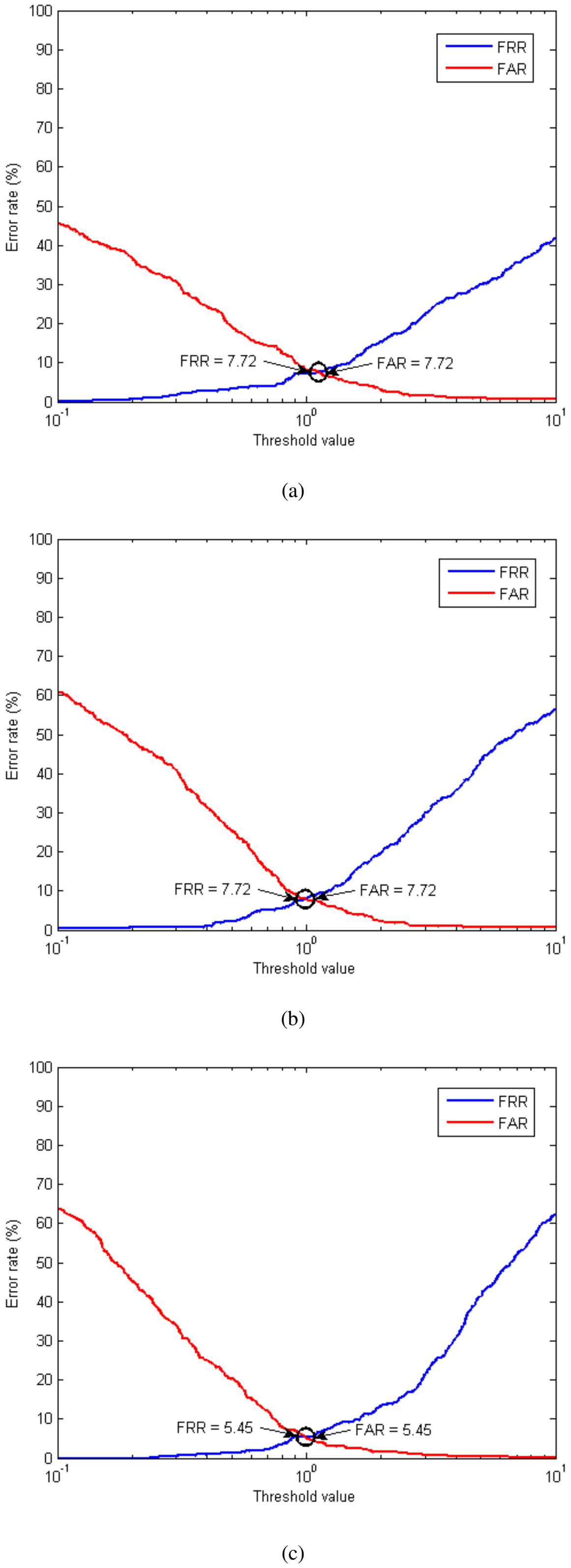

Figure 2. Performance Evaluation of the Off-Line Verification System
(a) Radon transform-SVM (b) Ridgelet transform-SVM
(c) PCR5 combination rule

In continuation to the present work, the next objectives consist to explore other alternative combinations of individuals off-line classifications based on DSmT framework in order to attempt to reduce the FRR and FAR.

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