A DSmT Based System for Writer-Independent Handwritten Signature Verification

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***Abstract*—We propose in this chapter a new writer-independent off-line handwritten signature verification (HSV) system using only genuine signatures. This system is based on a combination of two off-line individual HSV systems through the plausible and paradoxical reasoning theory of Dezert-Smarandache (DSmT). Firstly, we propose to evaluate the performances of both off-line HSV systems through using one-class SVM classifiers (OC-SVM) that operate independently of each other, which are associated to DCT and Curvelet transform based descriptors. To improve system performance, the outputs of both individual HSV systems are combined in DSmT framework, where a new decision making criterion is proposed. Experimental results conducted on the well known CEDAR database show the effective use of the proposed DSmT based combination for improving the verification accuracy comparatively to individual systems.**

Keywords*—Conflict management; Dezert-Smarandache theory; Writer-independent off-line signature verification; One-class SVM.

I. INTRODUCTION

The handwritten signature is one of the oldest behavioral biometric modalities employed for authentication of an individual or a document. Despite technological advances in the modern digital era, signature remains one of the popular means for the authentication of official documents like bank checks, credit card transactions, certificates, contracts and bonds. Hence, its use is more relevant for the verification on a system. The main objective of a handwritten signature verification (HSV) system is to verify the identity of an individual based on the analysis of signature employing the unique personal characteristics of his or her writing [1], [2], [3]. Indeed, signatures are a special case of handwriting in which special characters and flourishes occur and therefore most of the time they can be unreadable. Furthermore, intrapersonal variations and interpersonal differences make it necessary to analyze them as complete images (or subsequent sampled trajectory points including the signature's shape and the dynamic information issued from the ballistic movements of the signer) and not as letters and words put together [4], [3].

Depending on the mode of signature acquisition, such a HSV problem can be categorized into on-line and off-line [3], [4]. In general, on-line HSV systems achieve better performance since they deal with dynamic features like time, speed, pressure and order of strokes, which can be easily generated from a signature acquired through the on-line devices [2]. Off-line HSV systems, on the other hand, rely only on static features generated from signature images [1]. Although an efficient off-line HSV system is comparatively difficult to design, as many desirable dynamic features are not available, its wide application in the area of forensics and biometrics has made it an intense research field.

Signature verification methods fall into two broad categories: *writer-dependent* versus *writer-independent* methods [5]. The *writer-dependent* methods are the commonly used for HSV, where a specific model is build for each writer [6], [4], [7]. These methods therefore require selecting at each time the parameters of the model, when a new writer should be included in the system [8], [9]. The *writer-independent* HSV methods go for a generic and more economic system which can be tested on any writer. A set of writers, producing a minimal amount of handwriting signatures, is necessary for generating a unique model in order to mitigate the effect of large inter-class variability. In the testing phase, one or more reference signatures of any arbitrary writer can be used, comparing with which the system would conclude whether a questioned signature belongs to this particular writer or not. Our approach falls in this latter category. From the application point of view, the notable advantage is that classifier parameters remain the same whenever a new writer is added to the system.

In order to improve writer-independent off-line HSV performances, we propose an effective combination scheme of OC-SVM classifiers in DSmT framework [10], [11], [12], [13]. Indeed, few works have been recently focused on the classifier combination for dealing with the writer-independent off-line HSV. For instance, Oliveira *et al*. [8] take into account the framework initially proposed by Santos *et al*. [14] for improving the performance of a writer-independent off-line HSV system. Two contributions have been proposed in this work for designing the system. Firstly, authors analyze the impacts of choosing different fusion strategies to combine the partial decisions provided by the SVM classifiers. Hence, they have found that the Max rule is more effective than the original Voting proposed in [14]. Then Receiver Operating Characteristic (ROC) curves produced by different classifiers are combined using maximum likelihood analysis, producing an ROC combined classifier. Bertolini *et al*. [9] resume work in depth investigation of writer-independent off-line HSV problem, which has already been studied in [8], by reducing forgeries through ensemble of classifiers. In [15], an hybrid generative-discriminative ensembles of classifiers (EoCs) approach is investigated for addressing the challenge of designing off-line HSV systems form a limited amount of genuine signature samples, where the classifier selection process is performed dynamically. Later, two different learning approaches, namely global and writer-dependent SVMs, are proposed in [16] for performing the verification. The global SVM classifiers, which are writer-independent classifiers, are combined at score level with writer-dependent SVM classifiers through weighted sum rule, for improving overall verification accuracy. However, the problem of designing a robust writer-independent off-line HSV system, through an effective classifier combination approach, using only few genuine signatures, is research challenge that still need to be addressed.

The contribution of this paper is twofold. First, we introduce a new intelligent learning technique which allows us to build a unique model, while reducing the pattern recognition problem to a two-class problem, by introducing the concept of (dis) similarity representation [17] using only genuine signatures. Therefore, makes it possible to build robust individual HSV systems even when few signatures per writer are available. In this vein, we propose firstly to evaluate the performances of two writer-independent off-line HSV systems through using OC-SVM classifiers that operate independently of each other, which are associated to DCT and Curvelet transform based descriptors, respictively.

Second, for a given test signature during verification, both OC-SVM classifiers are considered using a static selection strategy, where a single ensemble of OC-SVM classifiers is selected before operations, and applied to all input samples, and then all the corresponding outputs of this ensemble provide the degrees of imprecision for the verification task. We then transform these ones in generalized basic belief assignments (gbba) using an inspired version of Appriou's model. To improve the performance of the proposed system, the gbba issued from both OC-SVM classifiers are combined through an effective combination scheme within DSmT framework, where a new decision making criterion has been implemented, while managing significantly the conflict provided from the corresponding individual HSV systems.

The paper is organized as follows. We give in Section II a review of Proportional Conflict Redistribution (PCR5) rule based on DSmT. Section III describes the proposed verification system. The dataset of the off-line handwritten signatures and experimental protocol used for validation are described in Section IV. The experimental and statistical results are summarized in Section V.

II. Review of PCR5 Combination Rule

Let $\Theta = \{\theta_1, \theta_2\}$ the *discernment space* of the two-class classification problem under consideration having 2 *exhaustive elementary* hypotheses θ_i, which are not necessarily mutually *exclusive* in DSmT. 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 [18]. The main concept of the DSmT is to distribute unitary mass of certainty over all the composite propositions built from elements of with (Union) and (Intersection) operators instead of making this distribution over the elementary hypothesis only. Therefore, the hyper-powerset D^Θ is defined as $D^\Theta = \{ø, \theta_1, \theta_2, \theta_1 \cup \theta_2, \theta_1 \cap \theta_2\}$. 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 $m(.): D^\Theta \to [0,1]$ associated to a given source of evidence, which can support paradoxical information, as follows: $m(ø) = 0$ and $m(\theta_1) + m(\theta_2) + m(\theta_1 \cup \theta_2) + m(\theta_1 \cap \theta_2) = 1$. The combined masses m_{PCR5} obtained from $m_1(.)$ and $m_2(.)$ by means of the PCR5 rule [18] is defined as:

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

Where

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

and $\Phi = \{\Phi_M, ø\}$ 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 Shafer's model M defined by the exhaustive and exclusive constraints, ø 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, which is defined as [10], [10]:

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

III. System Description

The structure of the combined system for writer-independent HSV is depicted in Fig. 1, which is composed of two individual off-line HSV systems and a DSmT based combination module. Each individual HSV system is generally composed of three modules: pre-processing, feature generation for constructing descriptors and classification.

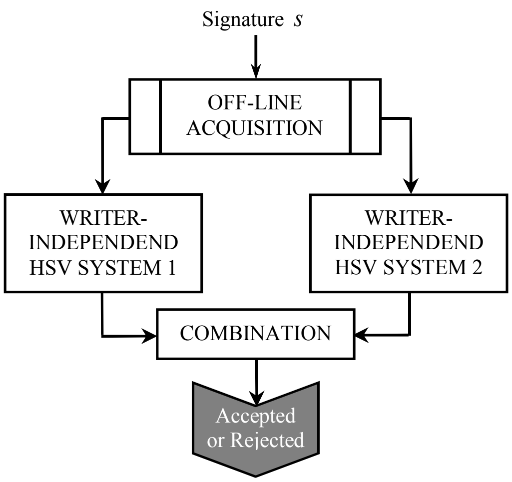

Fig. 1. Structure of the global system for writer-independent HSV.

A. Pre-processing

Any image-processing application suffers from noise like touching line segments, isolated pixels and smeared images. Hence, pre-processing is one of the crucial stages for solving any document analysis problem. In our case, the pre-processing will be only performed on signature images for which we have applied the descriptor issued from the feature generation method, namely Curvelet transform (CT), except the signature images which are to be submissive to DCT based feature generation method. A normalization of size is performed on scanned signature images, which are available in the form of grey-level images, as required by CT-based descriptor. This normalization is performed by adding zeros around these images to make them in a square matrix of dimensions $[R \times R]$, such that $R = 2^l$ and l is an integer, without distorting the signature image.

B. Features Used for Training Individual Classifiers

To evaluate the verification performance of the global system, we use two kinds of features generated from a signature image using two suitable methods whose each one of them allows constructing a descriptor: (1) Discrete Cosine Transform (DCT)-based descriptor and (2) Curvelet Transform (CT)-based descriptor. In this section, we briefly describe descriptors used for training both individual classifiers, respectively.

1) Discrete Cosine Transform: In the 2D-DCT based descriptor, the input signature image is transformed into frequency domain. Hance, we obtain a matrix of size $[R \times R]$ which includes DCT coefficients. Thus, the most significant information of the original signature image will be concentrated on the upper left part of the DCT matrix (energy compaction property). Due to this property, the input data will be reduced in a few significant coefficients using the zig-zag algorithm [19].

2) Curvelet Transform: The CT based method is well adapted for analyzing local line or curve singularities contained in an image [20]. In this work, we only use the energy of the curvelet coefficient computed from the whole of the signature image. More specifically, to generate a feature vector, the CT is applied on the image via the wrapping technique at different scales and different orientations in order to generate curvelet coefficients. For more details, the interested reader is refreed to [7].

C. Similarity Learning Based OC-SVM Classifier

The OC-SVM is an unsupervised learning algorithm proposed by Schölkopf *et al*. [21], which consists to estimate a function $f_{OC}(x)$ that encloses the most of learning data into a hyper sphere $R_x = \{x \in \mathrm{R}^d, f_{OC}(x) \succ 0\}$ with a minimum volume where d is the size of feature vector [21]. Hence, the decision function $f_{OC}(x)$ is given as [21]:

$$f_{OC}(x) = \sum_{k=1}^{S_v} \alpha_k K(x, x_k) - \rho \tag{1}$$

where S_v is the number of support vectors x_k from the training dataset, α_k are Lagrange multipliers, such that $0 \le \alpha_k \le \frac{1}{\upsilon m}$, m is the cardinal of training dataset, υ is the percentage of data considered as outliers, ρ defines the distance of the hyper sphere from the origin, and $K(.,.)$ defines the OC-SVM kernel that allows projecting data from the original space to the feature space.

1) Writer-Independent Verification Scheme: As part of this work, the writer-independent verification scheme of each OC-SVM classifier is proposed by incorporating an intelligent learning technique according to the following steps.

a) Learning Phase: In this step the classifier is only trained with samples belonging to the genuine class of signatures in order to generate the corresponding OC-SVM model. This one will be served for computing an optimal decision threshold, which is determined by using the criterion of equal error rate (EER) during an intermediate step, called *validation phase*.

b) Verification Phase: This step consists to assess the robustness of the classifier using the generated model and the selected optimal threshold during the validation phase for a decision making.

2) Generating Vectors of (Dis) Similarity Measures: The main idea behind the proposed verification scheme employed for designing the individual HSV systems, is based on the use of dissimilarity representation presented in [17], while using a set of prototype genuine signatures (called *representation set*

$\Re$) for generating a unique OC-SVM model. Hence, a distance metric $h(.,.)$ is used for generating the vectors of (dis) similarity measures $\mathrm{H}(x,\Re)=[h(x,p_1),h(x,p_2),\ldots,h(x,p_n)]$ between the feature vector x representing a given signature and the elements $p_i \in \Re$. Thus, the obtained vectors through this operation will be considered as the inputs of OC- SVM classifiers.

It should be noted that the key point of this work is to propose an intelligent learning technique, where training data for each OC-SVM classifier will be established from only the generated vectors of similarity measures between the feature vectors associated to genuine signatures, which are selected for learning.

Let N_{wr} be the number of writers for the learning phase and N_s be the number of genuine signatures per writer selected during this step. The number of vectors of similarity measures generated during learning is denoted N_{sim} and will be computed according the following formula:

$$N_{sim} = \frac{N_s \times (N_s - 1)}{2} \times N_{wr} \tag{2}$$

Moreover, the testing and validation data will be represented by the vectors of (dis) similarity measures which are generated between the feature vector representing the input signature and those associated to reference signatures. Thus, for each signature image belonging to the testing or validation dataset, the vectors of (dis) similarity measures will be then sent to the input of OC-SVM classifier with a number equals to those of reference signatures.

3) Decision Rule in OC-SVM Framework: Generally, the decision making in OC-SVM classifier framework is performed through a function, denoted here f_{OC}, which takes positive values in some region of the representation space and negative values somewhere else. The value of this one for a given vector of (dis) similarity measures is defined by equation (1). In other words, if we note θ_{gen} and θ_{imp} as the classes associated respectively to genuine and impostor, then the decision rule is given as follows:

$$x \in \begin{cases} \theta_{gen} & \text{if } f_{OC}(x) \succ 0 \\ \theta_{imp} & \text{otherwise} \end{cases} \tag{3}$$

In this work, the decision on learning data will be performed according to (3). In contrast, the majority voting rule is applied to validation and testing data as follows:

$$x \in \begin{cases} \theta_{gen} & \text{if } N_{gen} \geq N_{imp} \\ \theta_{imp} & \text{otherwise} \end{cases} \tag{4}$$

where N_{gen} and N_{imp} are the number of the responses, i.e. $f_{OC_j}(x)$ generated in relation to the reference signatures associated to the sample x such that $0 \leq j \leq N_{scores}$, provided by the $i-\mathrm{th}$ OC-SVM classifier under constraints $f_{OC_j}(x) \geq t_{opt}$ and $f_{OC_j}(x) \prec t_{opt}$, respectively. The index i stands here for the information source corresponding to the used descriptor, N_{scores} is the number of vectors of (dis) similarity measures generated for each signature of testing or validation, t_{opt} is the optimal threshold associated with $i-\mathrm{th}$ OC-SVM classifier and determined during the validation phase.

D. Combining Individual HSV Systems in DSmT Framework

The proposed combination module consists of three steps: i) transform the OC-SVM outputs into belief assignments using an estimation technique, ii) combine masses through a DSmT based combination rule and iii) implementing a new decision criterion for accepting or rejecting a signature.

1) Estimation of Masses: We propose in this paper an inspired version of Appriou's model, which is initially defined for two classes [22], for estimating the mass function within DSmT framework. Thus, the estimation of masses is performed into two steps: i) mapping the uncalibrated outputs provided by each OC-SVM classifier to posterior probabilities, ii) estimation of masses of the two simple classes and their classes representing the ignorance and paradox, respectively.

a) Calibration of the OC-SVM Outputs: Each OC-SVM classifier provides an uncalibrated output that allows representing the distance between the data to classify and the hyperplane of separating. However this one can be converted to posterior probability measure. Hence, we first exploit the logarithmic function in order to redistribute the decision outputs on large range. The reassigned OC-SVM output using logarithmic function is given as follows [23]:

$$g_i(x) = -\log\left[\sum_{j=1}^{Sv_i} \alpha_j K(x, x_j)\right] + \log(\rho_i) \tag{5}$$

where Sv_i and ρ_i are the number of support vectors and the distance of the hyper sphere from the origin for each $i-\mathrm{th}$ OC-SVM which is trained with samples of the genuine class θ_{gen} provided by the source of information S_i, $i = 1,2$ (i.e. the $i-\mathrm{th}$ descriptor), respectively. However, this logarithmic function will only concern the chosen responses by a selection rule in order to find a single response among the N_{scores} responses for each tested signature. Hence, the selection rule is defined according the following criterion:

$$g_i^*(x) = \max\left\{f_{OC_j}(x), 0 \leq j \leq q\right\} \tag{6}$$

$g_i^*(x)$ is the output of $i-\text{th}$ OC-SVM classifier selected from N_{scores} responses and q is the number of majority responses, representing the scores of similarity measures issued from the same classifier, with respect to an optimal decision threshold. Then, we use a sigmoid transformation for mapping the reassigned OC-SVM outputs, obtained by applying Equation (5), to probabilities in the range of $[0,1]$ as follows [23]:

$$P_i(\theta_i)=\frac{1}{1+\exp(-g_i(x))} \tag{7}$$

where θ_i defines the class of features issued from the first descriptor $(i=1)$ and the second descriptor $(i=2)$, respectively.

b) Assignment of the Masses within DSmT Framework: In this paper, the frame of discernment, namely Θ, is composed of two distinct elements as: $\Theta=\{\theta_1,\theta_2\}$. Thus, we consider the outputs issued from information sources S_1 (First classifier) and S_2 (Second classifier) using features of *target* class θ_1 and *complementary* class θ_2, respectively. Hence, the set of focal elements F generated within DSmT framework for each source is given as: $F=\{\theta_1,\theta_2,\theta_1\cup\theta_2,\theta_1\cap\theta_2\}$. Then, we assign a mass to each element in F using an inspired version of Appriou's model defined as follows [23]:

$$m_i(\theta_i)=\frac{(1-\beta)P_i(\theta_i/x)}{P_i(\theta_i/x)(1+\varepsilon)} \tag{8}$$

$$m_i(\overline{\theta_i})=\frac{(1-\beta)}{P_i(\theta_i/x)(1+\varepsilon)} \tag{9}$$

$$m_i(\theta_i\cup\overline{\theta_i})=\frac{\varepsilon}{(1+\varepsilon)} \tag{10}$$

$$m_i(\theta_i\cap\overline{\theta_i})=\frac{\beta}{(1+\varepsilon)} \tag{11}$$

where $\varepsilon\geq 0$ is a tuning parameter, and β is the sum of false accepted rates (FAR) made by both sources of information (i.e. OC-SVM classifiers) during the validation phase. Furthermore, $\beta/(1+\varepsilon)$ is used to quantify the belief for conflicting region, and $\varepsilon/(1+\varepsilon)$ is used to quantify the belief that the pattern x belong to the subset of ignorance $\theta_i\cup\overline{\theta_i}, i=1,2$. Therefore, the value of ε is fixed here to 0.001.

2) Combination of Masses: In order to manage the conflict generated from the two information sources S_1 and S_2 (i.e. both OC-SVM classifiers), the belief assignments ($m_i(.), i=1,2$) are combined as follows:

$$m_c=m_1\underset{F}{\oplus}m_2 \tag{12}$$

where m_c is the combined mass calculated for any element in F and $\oplus$ defines the combination operator of fifth version of Proportional Conflict Redistribution (PCR5) rule [18] (see Section II).

3) Decision Criterion: To take a decision whether the signature is accepted or rejected, we propose here a new decision criterion which consists to determine an optimal decision threshold expressed in terms of mass according the following steps:

- Perform a combination between the two belief assignments $m_1(.)$ and $m_2(.)$ computed according to equations (8), (9), (10) and (11), in DSmT framework and associated to the posterior probabilities of the two decision thresholds determined for both information sources S_1 and S_2 through using the EER criterion during the validation phase.
- Compute the threshold t_1 according the following formula:

$$t_1=\min\{m_c(\theta_1),m_c(\theta_2)\}$$

  where $m_c(\theta_1)$ and $m_c(\theta_2)$ are the combined masses of θ_1 and θ_2 using PCR5 rule, respectively.
- Perform a second combination between the two belief assignments $m_1(.)$ and $m_2(.)$ computed according to equations (8), (9), (10) and (11), in DSmT framework and associated to the posterior probabilities of both learning and validation responses resulting from the corresponding OC-SVM classifiers.
- Compute the threshold t_2 according the following formula:

$$t_2=\min\{\min(m_{learn}(\theta_1)),\min(m_{learn}(\theta_2))\}$$

  where $m_{learn}(\theta_1)$ and $m_{learn}(\theta_2)$ are the combined masses of θ_1 and θ_2 using PCR5 rule for a given learning sample, respectively.
- Determine the optimal decision threshold t_{opt}^{new} expressed in terms of mass through computing the mean between t_1 and t_2, i.e:

$$t_{opt}^{new}=\frac{t_1+t_2}{2} \tag{13}$$

Once the threshold has reached a predetermined value, a decision rule is applied to the combined masses generated from belief assignments associated to posterior probabilities corresponding to test data. Each test sample is accepted or rejected according to the following rule:

$$\text{Decision}=\begin{cases}\textit{Accepted} & \text{if } \min\{m_{test}(\theta_1),m_{test}(\theta_2)\}\geq t_{opt}^{new}\\ \text{Rejected} & \text{otherwise}\end{cases} \tag{14}$$

where $m_{test}(\theta_1)$ and $m_{test}(\theta_2)$ are the combined masses of θ_1 and θ_2 using PCR5 rule for a given test sample, respectively.

IV. DATASET AND EXPERIMENTAL PROTOCOL USED FOR VALIDATION

A. Dataset

The Center of Excellence for Document Analysis and Recognition (CEDAR) signature dataset [24] is used for evaluating the verification performance of the proposed combined writer-independent off-line HSV system in DSmT framework. The CEDAR dataset consists of 55 signature users, each one provided 24 genuine and 24 forgery samples, respectively.

B. Experimental Protocol

In this work, we took the 2640 preprocessed signature images spread over 55 writers (i.e. 48 images for each one), and then we assigned them to two datasets, whose the first one will only contain 600 genuine signatures of the first 25 writers (i.e. 24 images for each one), that will be used for both learning and validation of the OC-SVM models and the second will contain the 1440 signatures of the remaining 30 writers (i.e. 48 images for each one) for the testing phase whose 5 genuine signatures serve as the references for each writer. The 24 genuine signature images per writer selected for the first dataset have been partitioned into three subsets whose the first one will contain 5 signatures to be used for the learning phase, the second one will include 5 other signatures that will be considered as signature references and used for generating test scores and the last one will contain the remaining 14 signatures to be served for both validation phase and computing the optimal thresholds. For each individual classifier, a decision optimal threshold is established during the validation phase according the EER criterion which corresponds to operating point resulting from the intersection between both FAR and FRR curves. By reason of the adapted protocol where the signature images associated to the validation phase are genuine, the generation of the forged signatures for each writer represents the genuine signatures of the other writers, known as fictitious signatures.

V. EXPERIMENTAL RESULTS

The following sections present details of the experiments and are followed by the discussion of obtained results. Furthermore, we choose to evaluate the performance of each individual OC-SVM classifier using only five signatures per writer during the learning phase.

A. Validation of Individual OC-SVM Models

In order to train and validate both individual OC-SVM models, the choice of the optimal hyper parameters, namely the percentage of outliers ν and RBF kernel parameter γ, for each OC-SVM model is performed according to the maximization criterion of the number of support vectors Sv representing the learning data: higher the number of support vectors is, the better the information is representative for each class. Table I shows the optimal parameters of both individual OC-SVM models associated to DCT and CT based descriptors using validation data, respectively. We notice that not only there is an increased ranges of variation of ν and γ but also the number of support vectors that allows a better representation of genuine class of signatures.

TABLE I. OPTIMAL PARAMETERS OF INDIVIDUAL OC-SVM MODELS DURING VALIDATION PHASE

Parameter of the OC-SVM Model	**Descriptor**	
	DCT	***CT***
ν	9.50	0.20
γ	8.02	65.1
Sv	238	220

B. Parameters in Relation with both Descriptors During the Validation Phase

In what follows, we shall describe how the optimal number of DCT coefficients, optimal decomposition level of CT and the corresponding decision thresholds for each OC-SVM classifiers are determined during the validation phase, respectively.

1) Selecting the Optimal Number of DCT Coefficients and the Corresponding Decision Threshold: In order to set the optimal number of the significant DCT coefficients, we have studied the influence of the number of DCT coefficients on the different error rates computed from the validation samples. Indeed, we have chosen to set in the DCT based feature vector the number of significant coefficients to 24 in accordance with best global error rate AER (23.2857%) obtained for this value. Thus, this optimal number of coefficients will be retained for the next experiments. Fig. 2 shows the FRR and FAR computed for different values of the decision threshold, which allows determining the optimal threshold ($\cong$ - 0.06071) for the OC-SVM classifier associated to DCT based descriptor during the validation phase. Hence, the same optimal value of threshold will be used for evaluating the performance of the OC-SVM classifier associated to DCT based descriptor during the testing phase.

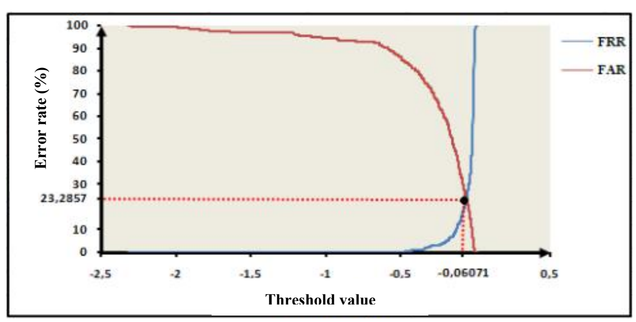

Fig. 2. Error rates of the OC-SVM classifier associated to DCT based descriptor using different values of the decision threshold during validation phase.

2) Selecting the Optimal Decomposition Level of CT and the Corresponding Decision Threshold: In following, we try to investigate the use of CT based descriptor in order to train the second individual OC-SVM classifier. The determination of the optimal decomposition level j_{opt} has been established by varying the decomposition level between 4 and 7, where the value 7 defines here the maximal decomposition level due to the size of the normalization of signature images associated to the CT, which has been fixed to $[1024\times1024]$ using CEDAR dataset. Fig. 3 shows the FRR and FAR computed for different values of the decision threshold, which allows determining the optimal threshold for the OC-SVM classifier associated to CT based descriptor during the validation phase for an optimal decomposition level j_{opt} equal to 4.

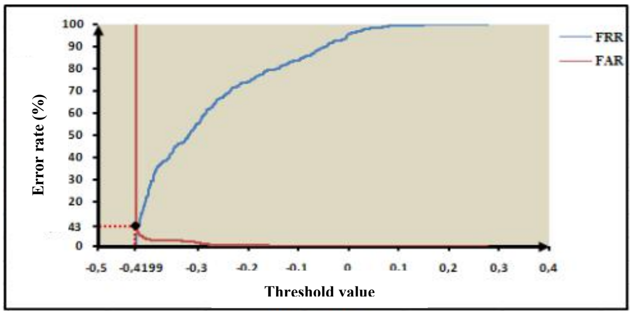

Fig. 3. Error rates of the OC-SVM classifier associated to CT based descriptor using different values of the decision threshold during validation phase.

According to the above figure, we notice that the optimal decision threshold of the OC-SVM classifier associated to CT based descriptor during the validation phase corresponds to -0.4199 for which the AER is minimal with a value of 7.7143%. Hence, the same optimal value of threshold will be used for evaluating the performance of the OC-SVM classifier associated to CT based descriptor during the testing phase.

C. *Performance Evaluation and Discussion*

The effectiveness of the proposed writer-independent HSV system based on DSmT is demonstrated experimentally by computing the verification performance of the two individual writer-independent off-line HSV systems, which will be tested on testing signatures of the CEDAR dataset. In these experiments, we compare the performance of the proposed DSm theory-based combination algorithm with learning-based individual OC-SVM classifiers, statistical match score combination algorithms, and DS theory-based combination algorithm. Table II shows the FRR, FAR and AER based verification error rates computed for the corresponding optimal values of decision threshold of both individual OC-SVM classifiers and the proposed combination frameworks with Max, Sum, Min, Dempster-Shafer (DS) and PCR5 rules. Here OC-SVM classifier 1 represents the individual writer-independent off-line HSV system using OC-SVM classifier associated to DCT based descriptor that yields an AER of 37.2868% corresponding to the optimal value of threshold $t=-$ 0.060712; while OC-SVM classifier 2 represents the individual writer-independent off-line HSV system using OC-SVM classifier associated to CT based descriptor that yields an AER of 4.2636% corresponding to the optimal value of threshold $t=-$ 0.41988. The Max and Sum based combination algorithms decrease the AER of OC-SVM classifier 1 to 32.3256% and 27.5969% for the corresponding optimal values of threshold $t=-$ 0.06071 and $t=-$ 0.48059, respectively. While Min based combination algorithm provides a similar result, which is obtained when using the OC-SVM classifier 2 (i.e. an AER of 4.2636%) with the same corresponding optimal value of threshold $t=-$ 0.41988. Indeed, the Max, Sum and Min based combination algorithms failed to improve the verification performance of the proposed combination system since it couldn't handle managing correctly the conflict generated from the two individual writer-independent off-line HSV systems. Hence, the proposed statistical match score combination algorithms are not appropriate to solve our problem for writer-independent off-line HSV.

TABLE II. EXPERIMENTAL RESULTS OF PROPOSED ALGORITHMS

Algorithm	Optimal Threshold	Verification Error Rates (%)		
		FRR	***FAR***	***AER***
Classifier 1 (DCT)	- 0.060712	28.7719	44.0278	37.2868
Classifier 2 (CT)	- 0.419880	9.6491	0.0000	4.2636
Max rule	- 0.060710	17.5439	44.0278	32.3256
Sum rule	- 0.480590	6.8421	44.0278	27.5969
Min rule	- 0.419880	9.6491	0.0000	4.2636
DS rule	0 .334200	0.0000	6.3158	2.7907
PCR5 rule	0.267100	0.0000	6.1404	2.7132

In the following, DS theory (DST) and DSmT are based on different approaches for modelling respectively the notion of ignorance and paradox which seem to be an excellent choice for managing the conflicting outputs provided by both individual writer-independent off-line HSV systems, where statistical match score algorithms of combination fail to improve the performance attained through using OC-SVM learning algorithm associated to CT based descriptor. In this vein, we consider only the DS and PCR5 combination algorithms which are the more appropriate combination rules developed within DST and DSmT frameworks, respectively. For each combination rule, a decision making has been performed about whether the signature is genuine or forgery by using a decision threshold expressed in terms of mass according to (13), which will be applied on the combined masses (see equation (14)). In order to appreciate the advantage of combining two sources of information through both DS and PCR5 combination rules, we present in Fig. 4 the conflict measured during testing phase between the two OC-SVM classifiers associated to DCT and CT-based descriptors. By analyzing the different values of conflict, we first notice that the minimal value of conflict for all testing genuine and forged signatures is respectively the same and equals to 0.4999. Moreover, this representation is very attractive because of the constant value of the conflict ($K_c=0.4999$) for all testing forged signatures due to the values of the posterior probabilities related to DCT based descriptor, which are negligible compared to those provided through using the CT based descriptor. Furthermore, the proposed combination module (see Fig. 4) is even more interesting in terms of discriminating values of conflict of the forged and genuine signatures, which allows defining an optimal threshold for the decision making. We can see that the two sources of information are very conflicting since the value of conflict for any testing signature is greater than or equal to 0.4999. Hence, the task of the proposed combination module is to manage the conflicts generated from both individual writer-independent off-line HSV systems for each testing signature.

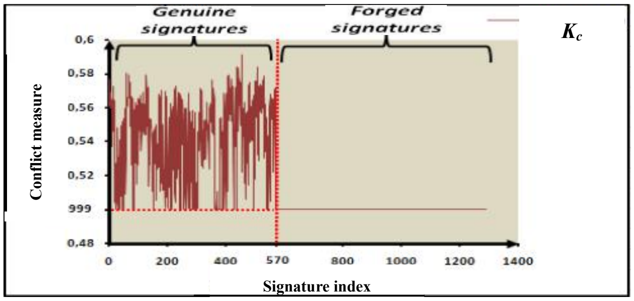

Fig. 4. Conflict between both OC-SVM classifiers using DCT and CT-based descriptors for testing signatures.

The proposed combination scheme using the DS combination algorithm yields an AER of 2.7907% corresponding to the optimal value of threshold $t = 0.3342$; while PCR5 combination algorithm yields the best AER of 2.7132% corresponding to the optimal value of threshold $t = 0.2671$. Indeed, the use of DS rule in the combination module allows efficiently redistributing the beliefs through a simple normalization by $(1\text{-}K_c)$ in the combination process of masses and combining the normalized outputs of both individual writer-independent off-line HSV systems which are not highly conflicting. However, when outputs are highly conflicting, they do not provide reliable decision. Further, an improvement of 0.0775% in the verification performance is obtained through using PCR5 combination algorithm. This is due to the efficient redistribution of the partial conflicting mass only to the elements involved in the partial conflict.

VI. CONCLUSION

This paper proposed and presented an effective combination scheme of two writer-independent off-line HSV systems in a general belief function framework. The OC-SVM classifiers associated respectively to DCT and CT features can be incorporated as an intelligent learning technique using only genuine signatures. The combination framework is performed through belief function theories using the estimation technique based on an inspired version of Appriou's model, DST and DSmT based combination algorithms. A new decision criterion has been implemented in DST and DSmT frameworks for a decision making whether the signature is accepted or rejected. Experimental results show that the proposed combination scheme with PCR5 rule yields the best verification accuracy compared to the statistical match score combination algorithms and DS theory-based combination algorithm even when the individual writer-independent off-line HSV systems provide conflicting outputs.

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