Combination of Off-Line and On-Line Signature Verification Systems Based on SVM and DST

Nassim Abbas and Youcef Chibani
Speech Communication and Signal Processing Laboratory,
Faculty of Electronics and Computer Science
University of Science and Technology Houari Boumediene (USTHB),
32, El Alia, Bab Ezzouar, 16111, Algiers, Algeria

nabbas@usthb.dz, ychibani@usthb.dz

Abstract—**The objective of this work is to present a signature verification system based on combination of off-line and on-line systems for managing conflict provided by the Support Vector Machine (SVM) classifiers. This system is basically divided into three parts: i) off-line verification stage, ii) on-line verification stage and iii) combination module using Dempster-Shafer theory (DST). 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. Combination is performed using Dempster-Shafer (DS) rule followed by the likelihood ratio based decision making. Experiments are conducted on the well know NISDCC signature collection using false rejection and false acceptance criteria. The obtained results show that the proposed combination framework using DST yields the best verification accuracy compared to the sum rule even when individual off-line and on-line classifications provide conflicting results.**

Keywords-Off-line signature verification; On-line signature verification; Support Vector Machines; Dempster-Shafer theory; belief assignments; conflict.

I. INTRODUCTION

Biometrics is one of the most widely used approaches for person identification and authentication. 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 the legal and social acceptance by many peoples. Hence, an intense research field has been devoted to develop various robust verification systems [2], [3] according the acquisition mode of the signature. Thus, two acquisition modes are used for capturing the signature: off-line mode and on-line mode. 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 decade [3]. Indeed, the handwritten signature remains important for many government/legal/financial transactions such as office automation, validation of cheques, credit cards, historical documents, etc [4]. Usually, the on-line HSVS provides more reliable comparatively to the off-line HSVS since features are more discriminative between users and are harder to imitate [5].

In order to enhance the performances of both handwritten signature verification systems, we propose a combination method based on DST for managing the conflict generated from the two sources (off-line and on-line systems). The DST has already been used for combining various biometric modalities. For instance, Arif and Vincent [6] proposed a fusion methodology for two biometric applications. Nakanishi et al. proposed a parameter combination in Dynamic Time Warping (DTW) domain [7] for on-line signature verification. Mottl et al. proposed a combination algorithm of on-line and off-line kernels [8] for signature verification using SVM. Recently, combination of off-line image and dynamic information which are obtained from the same signature [9] has been proposed that exploit global and local information.

In this paper, we propose to associate off-line and on-line signatures in order to improve the performance of single-source biometric systems and ensure greater security. Thus, the combination is performed through a biometric decision combination framework using Dempster-Shafer Theory (DST) [9], [11]. The combination framework allows managing significantly the conflict generated between the outputs of SVM classifiers. The performance of the proposed combination framework is evaluated comparatively to the sum rule used in the probabilistic theory.

The paper is organized as follows. We give in section 2 a review of DS rule based on DST. In section 3, we present

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the description of the proposed verification system. Experiments conducted on the NISDCC signature collection 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 DS Combination Rule

In this section, we introduce successively the fundamental concepts and notations involved in the DST based combination algorithm. Generally, the signature verification is formulated as a two-class problem where classes are associated to *genuine* and *impostor*, respectively. Hence, the combination of the off-line and on-line signatures, corresponding to two information sources, are performed through the DST. Hence, we denote S^1 and S^2 two information sources, respectively, while θ_{gen} and θ_{imp} are classes corresponding to genuine and impostor signatures, respectively.
For two-class problem, a reference domain also called the frame of discernment is defined as a finite set of exhaustive and mutually exclusive hypotheses.

In the probabilistic theory, the frame of discernment, namely Θ, is composed of two elements as: $\Theta = \{\theta_{gen}, \theta_{imp}\}$, and a mapping function $m \in [0,1]$ is associated for each class, which defines the corresponding mass verifying $m(\theta_{gen}) + m(\theta_{imp}) = 1$. When combining two sources of information, the sum rule [12] seems effective for non-conflicting responses. To address the limitations of the sum rule, a theoretical framework for evidential reasoning with imperfect data has been proposed by Dempster [9] then developed by Shafer [11]. Example of such approaches is the DS rule.

The main concept of the DST is to distribute unitary mass of certainty over all the sub-sets of Θ instead of making this distribution over the elementary hypothesis only. Therefore, the belief functions, also known as the basic belief assignment (bba), are computed on the power set defined as $2^\Theta = \{\emptyset, \theta_{gen}, \theta_{imp}, \theta_{gen} \cup \theta_{imp}\}$, such that $m(.): 2^\Theta \longrightarrow [0,1]$ and $m(\theta_{gen}) + m(\theta_{imp}) + m(\theta_{gen} \cup \theta_{imp}) = 1$. In this way, the belief in the occurrence of one of two hypotheses that cannot be distinguished by a given sensor will be attributed to the compound set (the compound hypotheses, or sub-sets, represent the evidential type of imperfection or ignorance, i.e. probabilistic uncertainty and imprecision) with these two hypotheses and no belief will be affected to them independently. In the evidential framework, the combined bba m_{DS} obtained from $m_1(.)$ and $m_2(.)$ by means of Dempster-Shafer combination rule [11] is defined by:

$$m_{DS}(A) = \begin{cases} 0 & \text{if } A = \emptyset \\ \frac{1}{1-K_c} \sum_{\substack{X,Y \in 2^\Theta \\ X \cap Y = A}} m_1(X) m_2(Y) & \text{otherwise} \end{cases} \quad (1.a)$$

where K_c is defined as:

$$K_c = \sum_{\substack{X,Y \in 2^\Theta \\ X \cap Y = \emptyset}} m_1(X) m_2(Y) \quad (1.b)$$

$m_1(.)$ and $m_2(.)$ represent the corresponding basic belief assignments provided by two information sources S^1 and S^2, respectively. K_c ($\in [0,1]$) defines the mass assigned to the empty set, after combination, in the absence of normalization by $(1 - K_c)$, and it is often interpreted as a conflict measure between the different sources. The larger K_c is, the more the sources are conflicting and the less sense has their combination. Finally, the combination based on DS rule does not exist when K_c equals 1. In this case, the sources are totally contradictory, and it is no longer possible to combine them.

III. Description of the System

The proposed combination handwritten signature verification system is presented in figure 1, which is composed of an off-line verification system, an on-line verification system and a combination module. s_1 and s_2 define the off-line and on-line handwritten signatures provided by two sources of information S^1 and S^2, respectively. Both verification systems are generally composed of three modules: pre-processing, feature generation and classification.

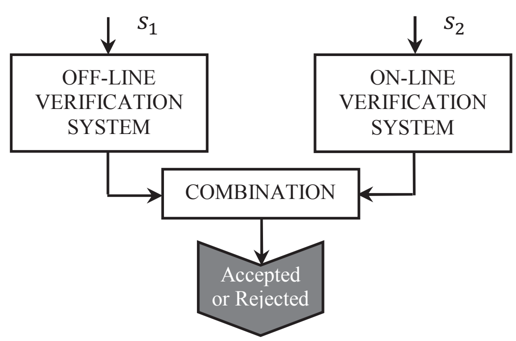


Figure 1. Structure Of The Verification System

A. Pre-processing

According the acquisition mode, each handwritten signature is pre-processed for facilitating the feature generation. Hence, the pre-processing of the off-line signature consists to eliminate the useless information around the binarized image without unifying its size. While, the on-line signature, no specific pre-processing is required.

B. Feature Generation

Features are generated according the acquisition mode, which are based on the uniform grid for off-line signature and dynamic characteristics for on-line signature, respectively.

1) Off-Line Signature: Features are generated using the Uniform Grid (UG) [13], which consists to create $n \times m$ rectangular regions for sampling. Each region has the same size and shape. Parameters n and m define the number of the lines (vertical regions) and columns (horizontal regions) of the grid, respectively. Hence, the feature associated to each region is defined as the ratio of the number of pixels belonging to the signature and the total number of pixels of the region. Therefore, the different values are finally stored in a vector x_1 of dimension $n \times m$, which characterizes the off-line signature image.

2) On-Line Signature: For the on-line signature verification stage, features are generated using only the dynamic features. Each on-line signature is represented by a vector x_2 composed of 11 features: signature total duration, average velocity, vertical average velocity, horizontal average velocity, maximal velocity, average acceleration, maximal acceleration, variance of pressure, mean of azimuth angle, variance of azimuth angle, and mean of elevation angle.

C. Classification Based On SVMs

1) Review of SVMs: The classification based on Support Vector Machines (SVMs) has been used widely in many pattern recognition applications as the handwritten signature verification [8], [14]. The SVM is a learning method introduced by Vapnik et al. [15], which tries to find an optimal hyperplane for separating two classes. Its concept is based on the maximization of the distance of two points belonging each one to a class. Therefore, the misclassification error of data both in the training set and test set is minimized.

Basically, SVMs have been defined for separating linearly two classes. When data are non linearly separable, a kernel function K is used. Thus, all mathematical functions, which satisfy Mercer's conditions, are eligible to be a SVM-kernel [15]. Examples of such kernels are sigmoid kernel, polynomial kernel, and Radial Basis Function (RBF) kernel. Then, the decision function $f: \mathbb{R}^p \rightarrow \{-1, +1\}$, is expressed in terms of kernel expansion as:

$$f(x) = \sum_{k=1}^{Sv} \alpha_k y_k K(x, x_k) + b \tag{2}$$

where α_k are Lagrange multipliers, Sv is the number of support vectors x_k which are training data, such that $0 \leq \alpha_k \leq C$, C is a user-defined parameter that controls the tradeoff between the machine complexity and the number of nonseparable points [16], the bias b is a scalar computed by using any support vector.
Finally, test data are classified according to:

$$x \in \begin{cases} class\ (+1) & \text{if } f(x) > 0 \\ class\ (-1) & \text{otherwise} \end{cases} \tag{3}$$

2) Decision Rule: The direct use of SVMs does not allow defining a decision threshold to assign a signature to genuine or forgery classes. Therefore, outputs of SVM are transformed to objective evidences, which express the membership degree (MD) of a signature to both classes (genuine or forgery). In practice, the MD has no standard form. However, the only constraint is that it must be limited in the range of $[0, 1]$ whereas SVMs produce a single output. In this paper, we use a fuzzy model which has been proposed in [17] to assign MD for SVM output in both genuine and impostor classes. Let $f(x_d)$ be the output of a SVM obtained for an off-line $(d = 1)$ or on-line $(d = 2)$ signature to be classified. The respective membership degrees $h_d(\theta_i), i = \{gen, imp\}$ associated to genuine and impostor classes are defined according to membership models given in [17]. We select the optimal values $\left(h_d^{opt}, d = 1\right)$ of j-th off-line signature by searching the optimal size $\left[n_{opt} \times m_{opt}\right]$ of the grid for which the error rate in the test phase is minimal. In the same way, we select also the optimal values $\left(h_d^{opt}, d = 2\right)$ of j-th on-line signature for which the error rate in the test phase is minimal. Hence, a decision rule is performed about whether the signature is genuine or forgery as follows:

$$\begin{array}{l} \textbf{if } \dfrac{h_d(\theta_{gen})}{h_d(\theta_{imp})} \geq t \textbf{ then } s_d \in \theta_{gen} \\ \textbf{else } s_d \in \theta_{imp} \\ \textbf{end if} \end{array}$$

where t defines a decision threshold.

D. Classification Based On DST

The proposed combination is conducted into three steps: i) transformation of the normalized SVM outputs into belief assignments using estimation technique based on the dissonant model of Appriou, ii) combination of masses through a combination rule and iii) decision rule.

1) Estimation of Masses: Let the power set of hypotheses $2^\Theta = \{\emptyset, \theta_{gen}, \theta_{imp}, \theta_{gen} \cup \theta_{imp}\}$. In this paper, the mass functions are estimated using a dissonant model of Appriou, which is defined for two classes [18] as:

$$m_{id}(\emptyset) = 0 \tag{4.a}$$

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

$$m_{id}(\overline{\theta_i}) = \frac{1-\beta_{id}}{1+h_d^{opt}(\theta_i)} \quad (4.c)$$

$$m_{id}(\theta_i \cup \overline{\theta_i}) = \beta_{id} \quad (4.d)$$

where $i = \{gen, imp\}$, $h_d^{opt}(\theta_i)$ is the membership degree of j-th 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 Half Total Error Rate defined as [19]:

$$HTER_d = \frac{FRR_d + FAR_d}{2} \quad (5)$$

where FRR_d and FAR_d correspond to False Reject Rate and False Accepted Rate, respectively.

In the case of probabilistic framework, the mass assigned to the total ignorance $m_{id}(\theta_i \cup \overline{\theta_i})$ is assumed to be null. Therefore, the masses of simple classes $m_{id}(\theta_i)$ and $m_{id}(\overline{\theta_i})$ are adjusted by adding the half of the mass $m_{id}(\theta_i \cup \overline{\theta_i})$ to the masses given by equation (4.b) and (4.c), respectively.

2) Combination of Masses: In order to manage the conflict generated from the two sources (i.e. off-line and on-line SVM classifications), 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:

$$m_1 = m_{\{gen\}1} \oplus m_{\{imp\}1} \quad (6.a)$$

$$m_2 = m_{\{gen\}2} \oplus m_{\{imp\}2} \quad (6.b)$$

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

$$m_c = m_1 \oplus m_2 \quad (7)$$

where $\oplus$ represents the basic sum rule combination (case of probabilistic framework), or DS rule combination (case of DST framework).

3) Decision Rule: A decision for accepting or rejecting a 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 [20] defined as:

$$DSmP_\epsilon(\theta_i) = m_c(\theta_i) + \quad (8)$$

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

where $i = \{gen, imp\}$, $\epsilon \geq 0$ is a tuning parameter, $\mathcal{M}$ is the Shafer's model for Θ, and $C_\mathcal{M}(A_k)$ denotes the DSm cardinal [20] of the set A_k. DSmP allows transforming belief assignment into probability assignment. Therefore, the decision rule is defined as:

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

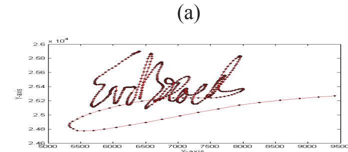
where $s = \{s_1, s_2\}$ is the j-th signature represented by both off-line and on-line modalities and t is the decision threshold.

IV. EXPERIMENTAL RESULTS

A. Data Description and Performance Criteria

The Norwegian Information Security laboratory and Donders Centre for Cognition (NISDCC) signature collection has been used in the ICDAR'09 signature verification competition [21]. This collection contains simultaneously acquired on-line and off-line samples. The off-line dataset is called "NISDCC-offline" and contains only static information while the on-line dataset which is called "NISDCC-online" also contains dynamic information, which refers to the recorded temporal movement of handwriting process. Thus, the acquired on-line signature is available under form of a subsequent sampled trajectory points. Each point is acquired at 200 Hz on tablet and contains five recorded pen-tip coordinates: x-position, y-position, pen pressure, azimuth and elevation angles of the pen. Interested readers are directed to reference [22] for more details on these datasets. Fig 2.a and 2.b show an example of both preprocessed off-line signature and a plotted matching on-line signature for one writer, respectively. For evaluating the performances of the signature verification system, three different kinds of error have been considered: False Accepted Rate (FAR) allows taking into account only skilled forgeries; False Rejected Rate (FRR) allows taking into account only genuine signatures and finally the Half Total Error Rate (HTER) allows taking into account both rates. Thus, Equal Error Rate is a special case of HTER when $FRR = FAR$.

(a)



(b)

Figure 2. Signature Samples of the NISDCC Signature Collection: (a) Off-line Signature and (b) On-line Signature

Signature data are split into training and testing sets for evaluating the performances of the proposed system.

B. SVM model

The SVM model is produced for each individual system according the uniform grid features and dynamic information, respectively. The NISDCC-offline dataset is composed of 1920 images from 12 authentic writers (5 authentic signatures per writer) and 31 forging writers (5 forgeries per authentic signature). For each writer and both datasets, 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) for both SVM classifiers (off-line and on-line) are tuned experimentally, which are fixed as $(C = 9.1, \sigma = 9.4)$ and $(C = 13.1, \sigma = 2.2)$, respectively.

C. Verification Results and Discussion

In order to appreciate the advantage of combining two sources of information through the DS rule, we present in figure 3 three examples of conflict measured between off-line and on-line signatures for writers 3, 7, and 10, respectively. The values K_{c3} ($\in [0.09, 0.37]$), K_{c7} ($\in [0.09, 0.59]$), and K_{c10} ($\in [0.09, 0.88]$) represent the mass assigned to the empty set, after combination.

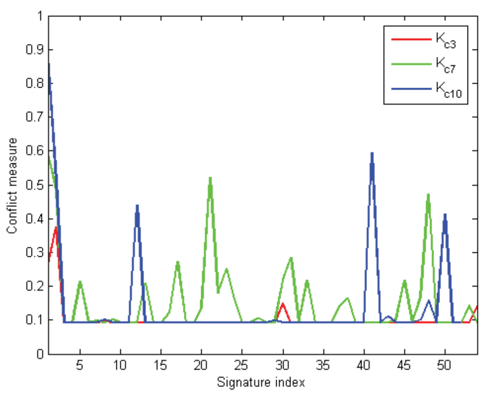
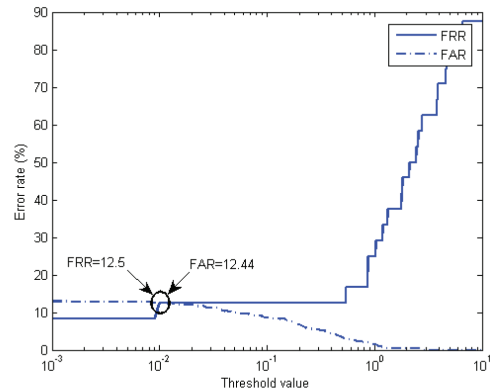


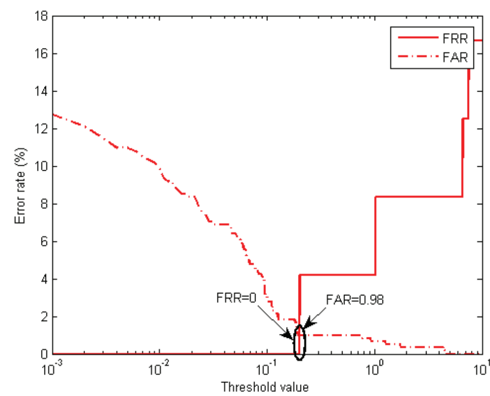
Figure 3. Conflict between Off-Line and On-Line Signatures for the Writers 3, 7, and 10, respectively

We can see that the two sources of information are very conflicting. Hence, the task of the proposed combination module is to manage the conflicts generated from both sources ($K_{cw}, w = 1, 2, \ldots, 12$) for each signature using the combination algorithms. For that, we compute the verification errors of both SVM classifiers and the proposed combination frameworks with sum rule and DS rule. Fig 4.a and 4.b show the FRR and FAR computed for different values of decision threshold using the SVM classifier on both off-line and on-line data sets, respectively.

For better comparison, figure 5 shows the HTER computed for different values of decision threshold from the SVM classifiers and combination algorithms (sum rule and DS rule). Therefore, results corresponding to the optimal values of threshold are determined for each algorithm.



(a)



(b)

Figure 4. Performance Evaluation in SVM Framework: (a) Off-line signature verification, (b) On-line signature verification

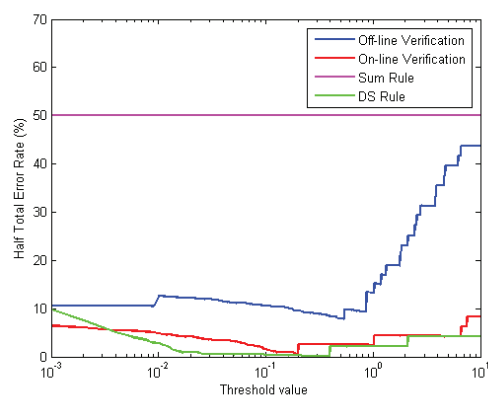


Figure 5. HTER Curves of Off-line, On-line and Combined Systems for Signature Verification

The off-line verification system based on SVM classifier yields a HTER of 12.47% corresponding to the optimal value of threshold $t = 0.012$ while the on-line verification system based on SVM classifier yields a HTER of 0.49%

with an optimal value of threshold $t = 0.195$. The proposed combination framework with DS combination rule reduces the HTER to 0.16% (for an optimal value of the threshold $t = 0.218$) corresponding to an improvement greater than 0.30%. While basic sum rule combination decreases the HTER to 50%. This is because the estimation model of masses which assigns the same confidence to the combined sources in probabilistic framework. Hence, the sum rule couldn't handle managing correctly the conflict generated from the two sources.

V. CONCLUSION AND FUTURE WORK

We proposed and presented a new system for the signature verification by associating static image and dynamic information in order to improve simultaneously the performance of off-line and on-line verification systems to ensure a greater security. The combination framework is performed through the DS rule using the estimation technique based on the dissonant model of Appriou. Experimental results show that the proposed combination framework with DS rule yields the best verification accuracy compared to the sum rule even when the individual off-line and on-line classifications provide conflicting outputs.

In continuation to the present work, the next objectives consist to explore the combination of off-line and on-line verification systems based on Dezert-Smarandache theory framework in order to attempt to reduce the HTER.

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