Applied Soft Computing xxx (2015) xxx–xxx

Contents lists available at ScienceDirect

Applied Soft Computing

journal homepage: www.elsevier.com/locate/asoc

Robust soft-biometrics prediction from off-line handwriting analysis

Nesrine Bouadjenek*, Hassiba Nemmour, Youcef Chibani

LISIC. Lab, Faculty of Electronics and Computer Sciences, University of Sciences and Technology Houari Boumediene (USTHB), Algiers, Algeria

A R T I C L E I N F O

Article history:
Received 14 June 2015
Received in revised form 26 August 2015
Accepted 11 October 2015
Available online xxx

Keywords:
Handwriting recognition
Soft-biometrics
Fuzzy MIN-MAX combination
GLBP
SVM

A B S T R A C T

Currently, writer's soft-biometrics prediction is gaining an important role in various domains related to forensics and anonymous writing identification. The purpose of this work is to develop a robust prediction of the writer's gender, age range and handedness. First, three prediction systems using SVM classifier and different features, that are pixel density, pixel distribution and gradient local binary patterns, are proposed. Since each system performs differently to the others, a combination method that aggregates a robust prediction from individual systems, is proposed. This combination uses Fuzzy MIN and MAX rules to combine membership degrees derived from predictor outputs according to their performances, which are modeled by Fuzzy measures. Experiments are conducted on two Arabic and English public handwriting datasets. The comparison of individual predictors with the state of the art highlights the relevance of proposed features. Besides, the proposed Fuzzy MIN-MAX combination comfortably outperforms individual systems and classical combination rules. Relatively to Sugeno's Fuzzy Integral, it has similar computational complexity while performing better in most cases.

1. Introduction

Handwriting recognition plays essential roles in various life domains such as mail sorting and bank checks verification. With the new technologies it is increasingly sought in more specific applications including information retrieval in historical documents and soft-biometrics prediction. Soft-biometrics is all what our senses perceive to differentiate us from each others, such as the age range, eye color, gender and ethnicity. These constitute key demographic attributes, which help to classify the human being into categories. During the last years, soft-biometrics traits were systematically predicted from face images [1,2]. Currently, there is a significant number of organizations that already employ handwriting analysis for personality profiling [3,4]. In fact, either for forensic identification of anonymous writing author, or the attribution of historical handwritten documents, soft-biometrics can be extremely useful. Furthermore, various studies tried to explain how the gender can control the human behavior. Specifically, the gender impact has been proved in Parkinson disease [5], motor learning [6], dichotic listening [7] as well as in crimes and violence [8]. Therefore, researchers in handwriting recognition were faced to a straightforward question, that is: Can the gender and other soft-biometrics influence the handwriting? In [9], authors investigated the relationship between sex hormones and the handwriting style. Their findings showed that prenatal sex hormones can affect the women handwriting. In some earlier psychological investigations, differences between men's and women's handwriting were examined [10,11]. Besides, in [12], experts were asked to predict the writer's gender from handwritten sentences. Experiments reported prediction accuracy about 68%. Also, in [13–15], age impact over the handwriting performance was investigated while in [16,17], authors tried to highlight the relationship between handedness and language dominance.

In handwritten document analysis field, automatic soft-biometrics prediction constitutes a new research subject. The literature reports only few studies, which addressed gender, handedness, age range and nationality prediction. The first work was developed in 2001 by Cha et al. [18]. Thereafter some other works were reported in [19–22].

A prediction system is composed of two main steps, that are feature generation and classification. In each step, efficient methods are required to achieve satisfactory performance. The key idea for developing a handwriting recognition system, is the choice of feature generation and classification schemes. Regarding the recognition step, a large number of classifiers that are based on different concepts such as singular value decomposition, principle component analysis, statistical modeling, as well as support vector methods are widely used for handwriting recognition [23]. In previous works on soft-biometrics prediction, various robust classifiers such as neural networks, SVM and Random Forests were employed while the feature generation was based on conventional direction, curvature and edge features. Note that SVM are considered as the best choice in most of recognition tasks where they commonly outperform other learning machines, namely, neural networks and HMM [24,25]. In fact, SVM are based on structural risk minimization, which answers two main problems of the statistical learning theory that are overfitting and controlling the classification complexity [26]. In addition, their training formulation is perfectly adequate to handle data with very large size without requiring dimensionality reduction. Furthermore, gender prediction results reported in [27] reveal that one SVM classifier could outperform the combination of multiple systems if they employ weak descriptors. Therefore, a straightforward way to achieve an efficient prediction is to associate robust data features to SVM.

This work is focused on the use of effective topological and gradient features, which are more suitable for handwriting characterization. Considered topological features are pixel density and pixel distribution, which gave satisfactory performance in handwritten signature verification [28]. As gradient feature the so called Gradient Local Binary Patterns (GLBP) is used. This descriptor was recently introduced for human detection in order to improve the histogram of oriented gradients. Three SVM predictors based respectively, on pixel density, pixel distribution and GLBP, are developed. Subsequently, a Fuzzy MIN-MAX combination algorithm

* Corresponding author. Tel.: +213 551544573.
E-mail addresses: nbouadjenek@usthb.dz (N. Bouadjenek), hnemmour@usthb.dz (H. Nemmour), ychibani@usthb.dz (Y. Chibani).

http://dx.doi.org/10.1016/j.asoc.2015.10.021
1568-4946/

is proposed to aggregate a robust prediction. Experimental analysis is carried out on public Arabic and English handwriting datasets.

The rest of this paper is as follows: Section 2 gives a brief description about the related work. Section 3 presents an overview of the proposed methods utilized to develop the prediction system. Section 4 states the problem of classifier combination in soft-biometrics. Section 5 introduces the proposed Fuzzy MIN-MAX combination algorithm. Section 6 details experimental results along with the experimental setup and computational complexity evaluation. Discussions regarding performance of the proposed combination algorithm and its comparison with the state of the art methodologies is placed in Section 7. The main conclusions are given in Section 8.

2. Related work

The first work on writer's soft-biometrics prediction was published by Cha et al. [18]. The aim was to classify the US population into various sub-categories such as white/male/age group 15–24 and white/female/age group 45–64. Experiments were conducted on CEDAR letter database, which contains 3000 handwritten document images written by 1000 subjects representative of the US population. A corpus of 200 samples was collected by considering six properties in defining categories that are: gender, handedness, age range, ethnicity, highest level of education and the place of schooling. Classical features such as pen pressure, writing movement, and stroke formation, were used with artificial neural networks. Experiments reveal a performance of 70.2% and 59.5% for gender and handedness prediction, respectively. Next, boosting techniques were employed to achieve higher performance where accuracies reached 77.5%, 86.6% and 74.4% for gender, age and handedness classification [29]. Thereafter, a research group on computer vision and artificial intelligence at Bern University developed the IAM handwriting dataset, which is developed for writer identification as well as gender and handedness prediction [30]. Authors utilized a set of 29 on-line and off-line features associated to SVM and Gaussian Mixture Models (GMM) [19,20]. On-line features cover several writing aspects such as the speed and acceleration, writing direction, normalized x and y coordinates, the vicinity curliness and the deviation of the straight line. Off-line features are based on conventional structural traits such as ascenders, descenders and the number of points above or below the corpus line. The handedness prediction using GMM classifier is achieved with an overall precision about 84.66%. The best gender prediction accuracy that is 67.57% was obtained by combining GMM trained separately over on-line and off-line features by using the average rule. In [27], similar gender prediction experiments were conducted by using more effective off-line descriptors, that are Local Binary Patterns (LBP) and Histogram of Oriented Gradients (HOG). SVM classifiers were used to perform the prediction task. HOG features provided the best prediction accuracy that is about 74%.

Furthermore, Al-Maadeed et al., [21] employed a K-Nearest Neighbors algorithm for handedness detection from off-line handwriting. A set of direction, curvature, tortuosity and edge-based features was used. The experimental dataset was collected at Qatar University by asking 1017 writers to reproduce two texts in both English and Arabic languages [31]. Then, the same features were used for gender, age range and nationality prediction in [22]. As a prediction method, Random Forest and Kernel Discriminant Analysis were used. Each classifier was trained using individual features and subsequently, various feature combinations were tested. The main conclusion that can be inferred from the experimental findings is that the feature combination that gives the best prediction accuracy is not the same for all soft-biometrics traits. For instance, an accuracy of 74% was collected for gender prediction by using probability density function of the chain code as a single feature, while for age range, the best accuracy reaches 62.5% by combining direction, curvature and tortuosity features. Also, weak prediction scores that are less than 50% were obtained for the nationality classification. Not long after that, using this dataset and another set of

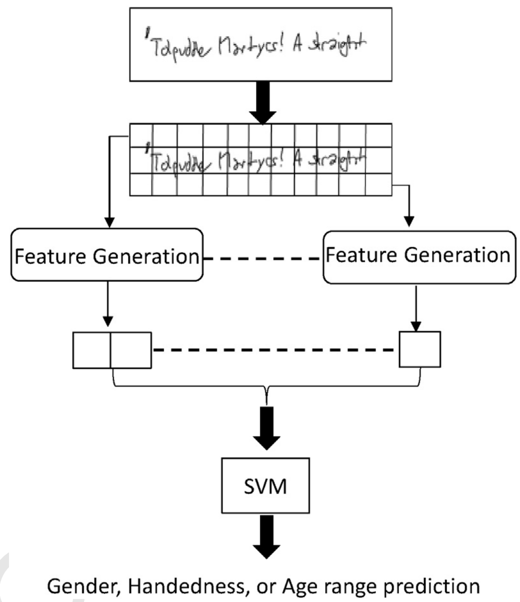


Fig. 1. Proposed system for soft-biometrics classification.

Arabic and French handwritten text, Siddiqi et al. [32] investigated gender classification using curvature, fractal and textural features. The classification was based on neural networks and SVM classifiers. Experiments showed that feature combination at the input of each classifier does not bring a significant improvement compared to individual features. Moreover, similar results are obtained by achieving either text-dependent or text-independent prediction. Unfortunately, in both works, datasets are not publically available to perform comparison.

The inspection of all previous works reveals that predicting writer's soft-biometrics is a very complicated task, since the classification scores are commonly around 70%. Such results let soft-biometrics prediction an open research area where a lot of work could be done in both feature extraction and classification.

3. Proposed systems for soft-biometrics classification

Soft-biometrics classification systems are designed to automatically classify writers into specific categories such as "man" or "woman" in the case of gender prediction, "left hand" or "right hand" for handedness prediction and various age ranges, in the case of age prediction. Similarly to all handwriting recognition systems, two main steps, that are feature generation and classification, are required. As shown in Fig. 1, features are locally extracted by applying grid over text images. Then, the feature vector of the full text image is obtained by concatenating all cells features.

3.1. Feature sets

3.1.1. Topological features

Two grid-based features, namely, pixel density and pixel distribution are used to highlight topological properties of handwritten data. The density is what we call apparent pressure, since it describes the width of the strokes. This feature is obtained by considering the ratio between the number of pixels that belong to the text and the cell's size. As reported in [28,27], within a given cell, the distribution is based on four measures that are: The heights of the left and the right parts of the stroke (designated by A and C in Fig. 2), and the widths of the upper and lower parts of the stroke (designated by B and D in Fig. 2).

Please cite this article in press as: N. Bouadjenek, et al., Robust soft-biometrics prediction from off-line handwriting analysis, Appl. Soft Comput. J. (2015), http://dx.doi.org/10.1016/j.asoc.2015.10.021

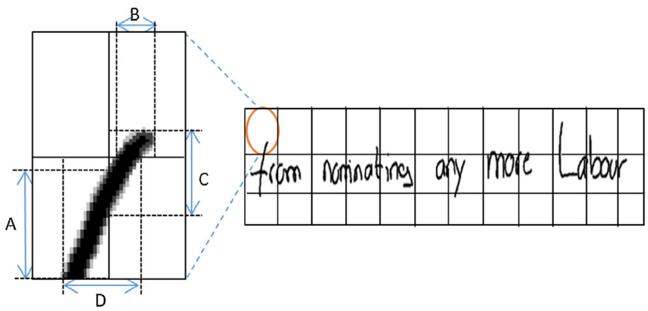


Fig. 2. Pixel distribution within a cell.

3.1.2. Gradient Local Binary Patterns

Gradient Local Binary Patterns (GLBP), was recently introduced for human detection [33]. Its principle idea consists of exploiting uniform Local Binary Patterns (LBP) to compute the histogram of oriented gradients. Presently, we investigate its efficiency for handwritten text characterization. Recall that LBP are used to perform statistical and structural analysis of textural patterns [34]. They describe the gray level distribution by comparing the gray level value of a pixel with neighboring gray levels. Then, LBP takes 1 if the central pixel has a lower gray level, otherwise it takes 0. For P neighbors situated on a circle of radius R, the LBP code is computed as follows:

$$LBP_{P,R}(x, y) = \sum_{p=0}^{P} S(g_p - g_c)2^p \tag{1}$$

with

$$S(l) = \begin{cases} 1, & l \geq 0 \\ 0, & l < 0 \end{cases} \tag{2}$$

g_c is the gray value of the central pixel and g_p is the gray value of the pth neighbor.

So, for a given cell, a GLBP matrix is established as explained in Algorithm 1. Note that uniform patterns correspond to LBP codes that contain two transitions from 1 to 0 (or 0 to 1). The size of the GLBP matrix is defined by all possible angle and width values. Precisely, there are eight possible Freeman directions or angle values while the number of "1" in the uniform patterns can vary from 1 to 7. This yield 7×8 GLBP matrix in which, gradient values are accumulated. Finally, the L2 normalization is used to derive the cell GLBP histogram.

Algorithm 1. GLBP calculation for a given cell

For each pixel:

1. Compute the LBP code,
2. Compute the width and angle values if the LBP code corresponds to a uniform pattern such that (Fig. 3):
   - The width value corresponds to the number of "1" in the LBP code,
   - The angle value corresponds to the Freeman direction of the middle pixel within the "1" area in the LBP code.
3. Compute the gradient on the 1 to 0 (or 0 to 1) transitions in the LBP code.
4. Width and angle values define the position within the GLBP matrix, which is filled by accumulating gradient values.

3.2. SVM classifier

The classification step is based on Support Vector Machines (SVM) which are binary classifiers, that seek the optimal separating hyperplane between two classes [35]. Specifically, let $(k_n, c_n) \epsilon R^M \times \{\pm 1\}$ a set of training samples so that M corresponds to data dimension $\{n = 1, \ldots, N_c\}$, N_c is the number of samples per a class c. SVM training selects the function f, which maximizes the margin between the two classes by minimizing an upper bound on the generalization error [26]. Then, data are classified according to:

$$f(k) = sign\left(\sum_{i=1}^{SV} \beta_i q_i K(k_i, k) + b\right) \tag{3}$$

where b is the bias, q_i the class label, β_i the Lagrange multipliers and SV is the number of support vectors.

Several SVM kernels are used in literature [26] but the radial basis function is the most popular for pattern recognition. This kernel is described as follows:

$$K(k_i, k) = \exp\left(-\frac{1}{2\sigma^2}\|k_i - k\|^2\right) \tag{4}$$

where σ is the user-defined parameter.

4. Classifier combination for soft-biometrics prediction

The prediction performance mainly depends on the feature extraction that helps the SVM to distinguish between writers. In fact, different features yield different aspects of characterization, which brings high level of diversity between classifiers [28]. Consequently, the prediction accuracy can be improved through the combination of such predictors. Recall that classifier combination was introduced for soft-biometrics prediction in [20], by using classical MAX, MIN and Average rules. Experiments were conducted for gender prediction by combining Gaussian mixture models. The prediction accuracy was improved to 67.57%. However, the results reported in [27] on the same dataset showed that this combination is beaten by single SVM classifier associated to more efficient features. From these outcomes, we note that the effectiveness of the combination paradigm comes primarily from the efficiency and the diversity of combined classifiers. Secondly, the use of robust combination algorithms could be useful to achieve more satisfactory performance. In this respect, Fuzzy operator based method outperforms conventional combination rules [36,37]. Presently, the aim is to aggregate more accurate prediction by combining decisions of different SVM predictors. A new Fuzzy MIN-MAX combination algorithm is proposed. The main reason for which Fuzzy logic operators are used is that they allow modeling a priori knowledge about individual predictors performance through Fuzzy measure operators. This combination algorithm is described in the following section.

5. Sugeno's Fuzzy Integral

In the past years, robust combination rules were developed based on the concept of Fuzzy MIN and Fuzzy MAX operators. Among them, Sugeno's Fuzzy Integral (SFI), provided outstanding success in several applications such as digit recognition, land cover change detection, as well as for combining document object locators [38–40]. This method combines objective evidences generated from classifier outputs according to the expectations estimated through Fuzzy measures. Expectations bring complementary information about the classifier relevance. Furthermore, in [41] Lu and Ito showed that combined MIN-MAX rules can achieve a robust modular classifier combination. Inspired from all these research works, we propose a Fuzzy MIN-MAX combination algorithm, in which expectations are expressed in terms of Fuzzy measures. Before describing the proposed combination algorithm, some basic Fuzzy operators are briefly reviewed.

5.1. Fuzzy operators

- Fuzzy sets: Fuzzy sets and Fuzzy operators were basically defined by Zadeh [42]. A Fuzzy set A is a subset of the universe of discourse

Please cite this article in press as: N. Bouadjenek, et al., Robust soft-biometrics prediction from off-line handwriting analysis, Appl. Soft Comput. J. (2015), http://dx.doi.org/10.1016/j.asoc.2015.10.021

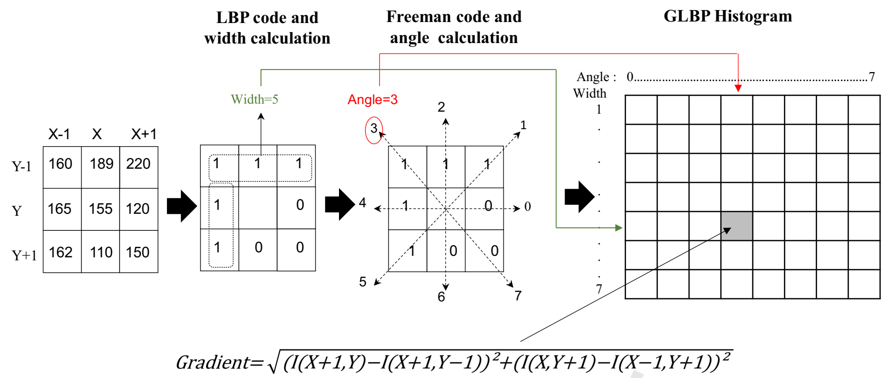


Fig. 3. GLBP calculation for a given pixel.

χ (presently, classes space), that admits partial memberships. So, we note $h_A(v)$, the membership degree with which, a sample v belongs to the class A.

- Union: The union of two Fuzzy sets A and B, termed $A \vee B$ corresponds to the Fuzzy OR operator that is achieved by the MAX rule.

$$A \vee B = MAX(A, B) \quad (5)$$

- Intersection: The intersection of two Fuzzy sets A and B, termed $A \wedge B$ is the Fuzzy AND expressed in terms of MIN rule.

$$A \wedge B = MIN(A, B) \quad (6)$$

- Fuzzy measures: A set function is called Fuzzy measure if it verifies the following properties [38]:
  - $g(\Phi) = 0$
  - $g(Z) = 1$
  - $g(Z_i) \leq g(Z_j)$ if $Z_i \subset Z_j$

Specifically, $Z = \{Z_i\}_{i=1:N}$ constitutes the set of classifiers (SVM) while $g(Z_i)$ designate their performances. According to the nature of Fuzzy measures, Sugeno showed that the Fuzzy measure for the union of two classifiers does not correspond to the sum of individual Fuzzy measures [38]. As a solution, he proposed the λ-Fuzzy measure that expresses the degree of interaction between two classifiers Z_i and Z_j as:

$$g(Z_i \cup Z_j) = g(Z_i) + g(Z_j) + \lambda g(Z_i) g(Z_j) \quad (7)$$

λ is the unique non zero root of a $N-1$ degree equation that belongs in the interval $[-1, \ldots, +\infty[$. It is computed by using the following equation:

$$\lambda + 1 = \prod_{i=1}^{N} (1 + \lambda g(Z_i^{\pm})) \quad (8)$$

The λ-Fuzzy measure is required in Sugeno's Fuzzy Integral calculation [38,43]. Presently, this concept is used to reinforce the proposed Fuzzy MIN-MAX combination.

5.2. Fuzzy MIN-MAX algorithm

The aim is to aggregate a robust decision by combining various SVM trained using different data features. The role of Fuzzy measures is to strengthen membership degrees derived from each classifier. Note that Eq. (7) provides both the weight of a single predictor as well as the weight of a subset of predictors. However, there is no rule, which can be followed to attribute $g(Z_i)$ values. In fact, they can be subjectively assigned by an expert, or computed from training data [39]. In this paper, $g(Z_i)$ of SVM predictor in negative and positive classes are derived from the training accuracy. Let (t_i^+, t_i^-) the training accuracy of the SVM Z_i in the two classes. These accuracies are handled through a weighted soft-max function, such that:

$$g(Z_i^{\pm}) = \alpha \frac{1 + \exp(t_i^{\pm})}{\sum_{i=1}^{N} [1 + \exp(t_i^{\pm})]} \quad (9)$$

where N is the number of trained SVM.

The weight α scales in the range]0.1, 1] to control the importance assigned to the Fuzzy measure. It is experimentally tuned so that, it allows the best training accuracy.

In a first step, SVM outputs are transformed into membership degrees in positive and negative classes, by adapting the membership model proposed in [44]. Fuzzy measures are adapted according to the evidences derived from each SVM decision. The evidence value scales in the range [0, 1] to express the membership degree of the considered sample to a given class of interest. Precisely, the output of each SVM Z_i, is transformed into membership degrees $h^+(Z_i)$ and $h^-(Z_i)$ in both positive and negative classes. Recall that theoretical outputs are defined by values that are at least greater than 1 for the positive class and at max equals −1 for the negative class. Therefore, a sample is considered to entirely belong to one of the classes if the absolute value of the SVM response is larger than 1. In this case its membership degree for the respective class equals 1 and that of the other class is 0. On the other hand, if the SVM output is inside the separating margin $]-1, +1[$, the decision is confused and the sample can belong to each class according to complementary membership degrees as shown in Algorithm 2.

Algorithm 2. Fuzzy class membership model

If $Z_i \geq 1$ then $\begin{cases} h_+(Z_i) = Z_i / MaxVal \\ h_-(Z_i) = 0 \end{cases}$
Else
{
If $Z_i \leq -1$ then $\begin{cases} h_+(Z_i) = 0 \\ h_-(Z_i) = Z_i / MaxVal \end{cases}$
Else
$\begin{cases} h_+(Z_i) = (1 + Z_i)/2 \\ h_-(Z_i) = (1 - Z_i)/2 \end{cases}$
}

Then, membership degrees are associated to their respective Fuzzy measure in order to incorporate a priori knowledge about the classifier performance. This yields new class memberships $U(Z_i^+)$ or $U(Z_i^-)$ obtained using the Fuzzy disjunction the MAX operator. Subsequently, the Fuzzy MIN-MAX combination is applied to aggregate the final decision. Algorithm 3 describes the details of this combination scheme.

Please cite this article in press as: N. Bouadjenek, et al., Robust soft-biometrics prediction from off-line handwriting analysis, Appl. Soft Comput. J. (2015), http://dx.doi.org/10.1016/j.asoc.2015.10.021

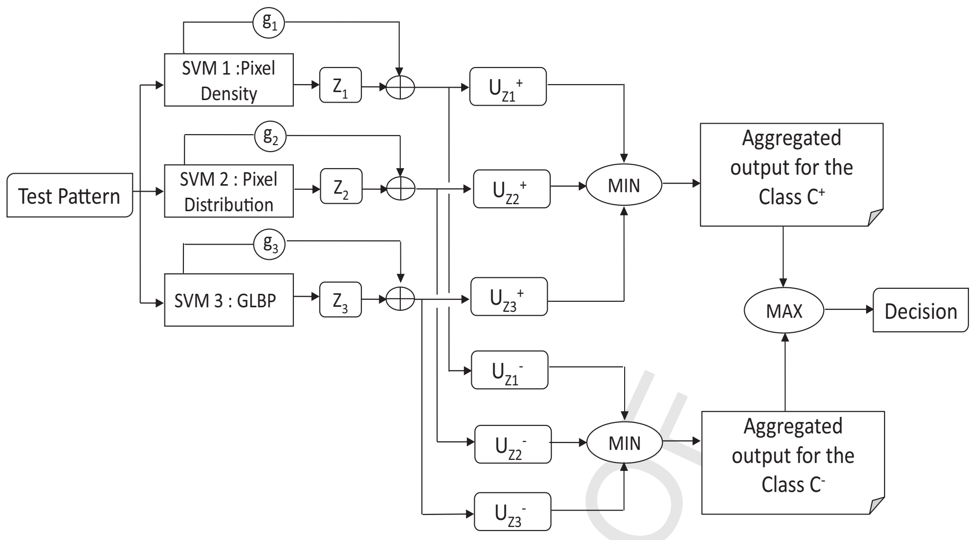


Fig. 4. Flowchart of the Fuzzy MIN-MAX combination.

Algorithm 3. Fuzzy MIN-MAX combination

For each test pattern do:

1. Calculate prediction decisions in the two classes as follows:
   - Generate predictor outputs Z_i, $i = 1, \ldots, N$ (N: number of predictors or SVM)
   - Transform each output into membership degrees in positive and negative classes $h^+(Z_i)$, $h^-(Z_i)$, according to Algorithm 2.
   - The decision in each class is such as:
     $U_{Z_i^+} = MAX(h^+(Z_i), G^+(Z_i))$
     $U_{Z_i^-} = MAX(h^-(Z_i), G^-(Z_i))$
2. Evaluate aggregated decisions in positive and negative classes as:
   $C^+ = MIN(U_{Z_i^+})_{i=1:N}$
   $C^- = MIN(U_{Z_i^-})_{i=1:N}$
3. Assign the test pattern to the class with the highest decision:
   $Decision = MAX(C^+, C^-)$

Using the same membership degrees and Fuzzy measures, Sugeno Fuzzy Integral (SFI) is computed as:

$$SFI^{\pm} = \underset{i=1,\ldots,N}{MAX}\left[MIN(h^{\pm}(Z_i), G^{\pm}(Z_i))\right] \tag{10}$$

$G^{\pm}(Z_i)$ are new values of Fuzzy measures, that are adapted according to an ascendant ranking of membership degrees by using Eq. (7). Thereby, the FI rule selects the best association between the membership degrees and Fuzzy measures. This means that the SVM giving the best agreement between the evidence and the Fuzzy measure, is selected. Thanks to this principle, the agreement of most efficient individual SVM is taken as the FI value. However, when the combined systems have approximately similar performances, it seems possible to develop a more precise decision by considering all systems. This idea is carried out by Fuzzy MIN-MAX combination, which aggregates a decision from all evidences. From an analytical point of view, this idea can achieve higher prediction values in both classes. For instance, Table 1 reports the calculation steps of both combination rules, for a randomly selected sample of the gender prediction task. This sample belongs to the Woman writing class that is labeled as class +. SVM outputs are: $Z_1 = 0.2771$, $Z_2 = 0.3232$ and $Z_3 = -0.7609$, while Fuzzy measures are normalized with $\alpha = 0.45$. As can be seen, although the two rules, give correct predictions, the proposed approach provides higher values, which favorites a better prediction.

Note that, *MaxVal* corresponds to the maximal value of all SVM outputs. In this work, three prediction systems are combined to improve soft-biometrics prediction. The flowchart of this combination is presented in Fig. 4.

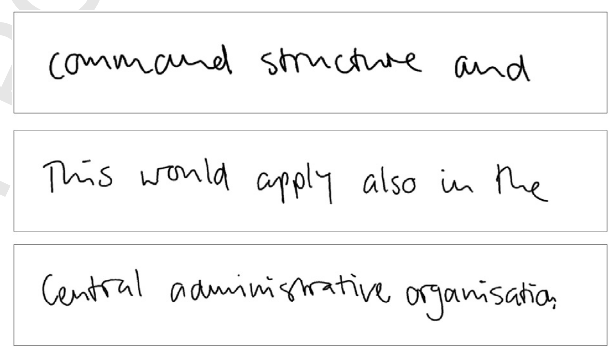


Fig. 5. Samples from IAM dataset.

6. Experimental results

Proposed methods are evaluated on corpuses extracted from two public datasets, collected in a multi-script unconstrained writing environment. These datasets, namely, IAM and KHATT contain handwritten sentences, in English and Arabic languages, respectively. Note that in a first step, experiments were separately performed on each dataset. Then, corpuses were blended in order to try language-independent prediction.

6.1. Datasets

6.1.1. IAM dataset

IAM On-line handwriting database was developed by a research group on computer vision and artificial intelligence at Bern University. [1] It contains forms of unconstrained English handwritten text acquired on a whiteboard. Specifically, more than 200 writers contributed with eight texts that are averagely composed of seven lines, in the dataset collection. Each line is indexed according to the writer's gender, age and handedness. To perform soft-biometrics prediction, the number of collected patterns depends on the subcategory availability within the dataset. Fig. 5 shows some samples from this dataset.

[1] http://www.iam.unibe.ch/fki.

Please cite this article in press as: N. Bouadjenek, et al., Robust soft-biometrics prediction from off-line handwriting analysis, Appl. Soft Comput. J. (2015), http://dx.doi.org/10.1016/j.asoc.2015.10.021

Table 1
SFI and Fuzzy MIN-MAX calculation steps for a given sample.

Class	λ	$g(Z_i)$	$h(Z_i)$	$G(Z_i)$	SFI		Fuzzy MIN-MAX	
					$SFI^{+/-}$	C^+/C^-	U_{Z_i}	C^+/C^-
+	−0.9997	0.8091 0.9636 0.9636	0.6616 0.6386 0.1196	0.2825 0.4642 0.6156	0.2825 0.4642 0.1196	0.4642	0.6616 0.6386 0.6156	0.6156
−	−0.9996	0.7545 0.8455 0.9909	0.8804 0.3614 0.3384	0.2978 0.4748 0.6158	0.2978 0.3614 0.3384	0.3614	0.8804 0.4748 0.6158	0.4748

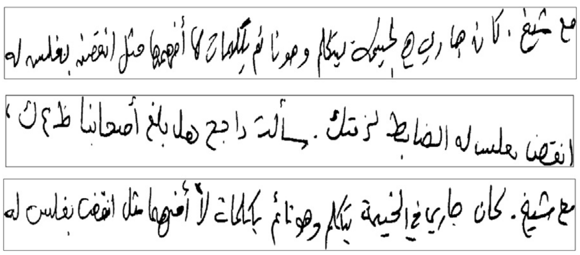


Fig. 6. Samples from KHATT dataset.

Presently, a first corpus was selected according to the protocol introduced in [19,20], which constitute the first work on automatic gender and handedness prediction using IAM dataset. So, the IAM-1 corpus is constituted by considering one sample from each writer. For gender prediction 75 samples per class were randomly selected and partitioned into 40 training samples, 10 validation samples and 25 testing samples. For handedness prediction, there are 20 samples for each class. Among them, 15 samples were used in the training stage while 5 samples were used to test the prediction performance. In a second step, a larger dataset (IAM-2) was collected to allow a deeper investigation on gender and age classification. Specifically, there are 165 samples per class, for gender prediction. On the other hand, 84 samples were collected for the two main age ranges that are 25–34 years and 35–56 years. As for most of classification and data mining tasks [45] as well as the soft-biometrics state of the art [22], 2/3 of samples were used for the training step while the remaining 1/3 were used for testing the system.

6.1.2. KHATT dataset

Recently, Mahmoud et al., [46,47] published a new Arabic dataset, namely, KHATT (KFUPM Handwritten Arabic TexT) for writer identification. [2] About 1000 writers from several Arabic countries participated by one handwritten form segmented into several line images. This dataset was collected by considering gender, age range, handedness and nationality categories but up to now it was not employed for soft-biometrics classification. Fig. 6 shows some examples from this dataset.

Three corpuses were randomly selected to perform gender, handedness and age range prediction. Precisely, 135 samples per class were collected for both gender and age range applications. Note that age ranges are grouped into two categories that are “16 to 25 years” and “26 to 50 years”. The handedness corpus is composed of 84 samples for both right-hand and left-hand classes. Furthermore, to perform language-independent soft-biometrics prediction, selected KHATT samples were blended with those selected for IAM-1. Unfortunately, since age ranges are not the same in both datasets, this experiment was limited to gender and handedness traits.

6.2. Experimental setup

The model selection is a key experimental issue that is addressed when implementing prediction systems. Presently, for SVM classifier, the kernel function as well as the best values of both regularization and kernel parameters are experimentally tuned. Another aspect that is worth of investigation is the number of grid cells that are used for feature generation. As claimed in [28], the adequate grid size depends on the feature and the database that are used. Therefore, various grid sizes were tried to find the configuration that allows the best training accuracy. Such experiments were performed for each application, since similar behavior has been observed, only the results obtained for gender prediction using the IAM-1 dataset, are presented.

- *Kernel selection*
  Four kernel functions that are linear, quadratic, polynomial and RBF kernel are used. Tests were executed by varying the regularization parameter in the range [0.01: 10: 200]. For the polynomial kernel, the degree values vary from 1 to 3 while the RBF kernel sigma was varied in the range [2: 2: 80]. In each test, the couple giving the best training accuracy was selected. As reported in Table 2, which summarizes the best prediction accuracies, the RBF kernel provides at least a gain of about 2% over all other kernels. This kernel was then employed in the rest of experiments.
- *Impact of the grid size*
  The impact of the grid size over the prediction accuracy was addressed in the training of individual prediction systems, where different grid sizes were considered in the feature generation step. For topological features, the number of cells in horizontal and vertical senses was varied from 1×1 cells (which corresponds to the whole image) to 10×30 cells. For GLBP, which yields a feature vector of 56 components in each cell, the grid size was varied from 1×1 to 4×8 cells. Experiments showed that the number of grid cells has a significant influence over the prediction performance. Fig. 7 plots the most meaningful results obtained using the different features. As can be seen, unlike topological features for which, the accuracy varies from 52% to 72%, for GLBP, several configurations provide the same performance. In addition, topological features need a large number of cells (6×21 cells for pixel density and 6×10 cells for distribution) to achieve a precision of 72%. The best performance of GLBP that is about 76% is obtained using grid of 1×7 cells. In light of these outcomes, it is clear that the grid size has an important impact on the prediction performance.

6.3. Gender prediction results

Table 3 summarizes the results obtained for gender prediction. Note that for IAM-1, IAM-2 and KHATT datasets, GLBP outperforms pixel density and distribution. Surprisingly, for the blended dataset the pixel distribution gives the best performance. In addition, for IAM-1 dataset, which is collected according to the state of the

[2] http://khatt.ideas2serve.net.

Please cite this article in press as: N. Bouadjenek, et al., Robust soft-biometrics prediction from off-line handwriting analysis, Appl. Soft Comput. J. (2015), http://dx.doi.org/10.1016/j.asoc.2015.10.021

Table 2
Gender prediction results obtained using different SVM kernels.

	Linear	Polynomial	Quadratic	RBF
Pixel density	66.00	62.00	62.00	72.00
Pixel distribution	68.00	70.00	70.00	72.00
GLBP	74.00	70.00	70.00	76.00

Table 3
Gender prediction results for individual systems (%).

Dataset	Pixel density	Pixel distribution	GLBP	GMM (On-line + Off-line features) [20]	Human performance [20]
IAM-1	72.00	72.00	**76.00**	67.57	63.88
IAM-2	73.63	70.90	**75.45**	–	–
KHATT	71.11	73.33	**74.44**	–	–
IAM-1 + KHATT	69.29	**72.14**	70.00	–	–

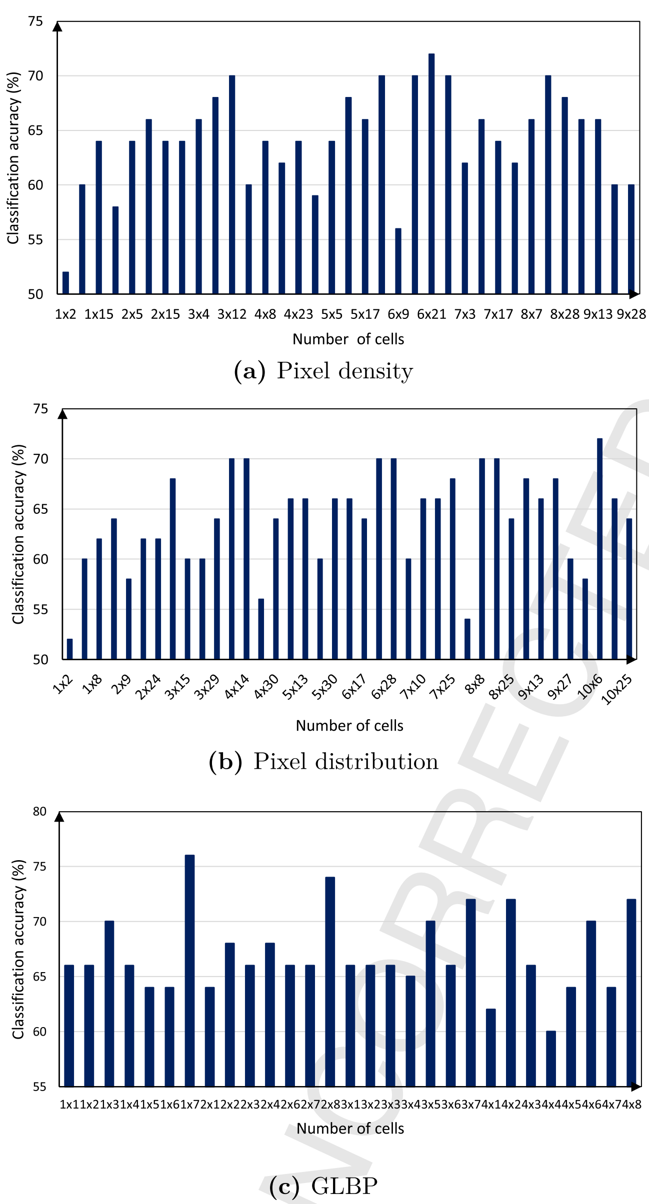


Fig. 7. Grid size influence for the gender prediction.

art, proposed features provide an improvement that exceeds 4%. Also, the global inspection of all classification scores reveals that the gender prediction seems to be language-independent since the classification results are quite similar.

Furthermore, the performance of the Fuzzy MIN-MAX combination is assessed comparatively to Max, Mean, Majority vote and SFI. Except the Majority vote, all combination rules were performed by considering SVM membership degrees in positive and negative classes. Also, both Fuzzy MIN-MAX and SFI, employed the same Fuzzy measures. As reported in Table 4, the proposed algorithm outperforms commonly all other rules. Indeed, for IAM-2, KHATT as well as the blended dataset, it achieves the best accuracies that are 82.73%, 82.22% and 76.43%, respectively. Nevertheless, for IAM-1 it is beaten by the SFI with a difference of 2%. Despite this, compared to individual systems, the proposed combination rule provides an improvement that varies between 4% and 8%.

6.4. *Handedness prediction results*

As for gender prediction, experiments were initially focused on setup parameters. The best results in term of classification accuracy are reported in Table 5. For this task, prediction scores of IAM-1 are high because of the reduced number of data (20 samples for each class). For this reason, the performance reaches 100% with GLBP features. So, comparatively to the state of the art, our individual systems allow at least a gain of 5%. Regarding the other corpuses, the precision varies approximately between 75% and 80%, where the pixel distribution system gives the best results when using KHATT corpus. This outcome could be explained by the fact that the stroke geometry information given by the distribution feature is more suitable for Arabic handwriting characterization. Regarding the combination step, experiments were limited to KHATT and the blended dataset since for IAM-1, individual system based on GLBP provide the optimal performance. Table 6 reports the results obtained for the different combination rules. One surprising result is denoted also for KHATT dataset where the Majority vote outperforms the proposed combination algorithm with more than 1%. Nevertheless, for the blended dataset the best classification accuracy that is 86.36% is obtained using SFI and the proposed Fuzzy MIN-MAX algorithm.

6.5. *Age prediction results*

In this experiment, two different age ranges were considered in IAM-2 and KHATT corpuses, the reason for which we could not blend the two datasets. Age prediction results are presented in Table 7 while those obtained for the combination step are reported in Table 8. Unlike all previous results, pixel density outperforms other features with a gain of 1.79% with IAM-2 and 4.45% for the KHATT corpus. Furthermore, when combining these systems, the classification scores are improved to more than 75% with Majority vote, SFI and the proposed Fuzzy MIN-MAX algorithm. This latter has significantly higher performance.

Please cite this article in press as: N. Bouadjenek, et al., Robust soft-biometrics prediction from off-line handwriting analysis, Appl. Soft Comput. J. (2015), http://dx.doi.org/10.1016/j.asoc.2015.10.021

Table 4
Combination results for gender prediction (%).

Dataset	Max	Mean	Majority vote	SFI	Fuzzy MIN-MAX
IAM-1	80.00	82.00	78.00	**84.00**	82.00
IAM-2	75.45	72.73	80.00	80.00	**82.73**
KHATT	73.33	73.33	80.00	81.11	**82.22**
IAM-1 + KHATT	61.42	67.86	75.00	75.71	**76.43**

Table 5
Handedness prediction results for individual systems (%).

Dataset	Pixel density	Pixel distribution	GLBP	GMM (On-line features) [19]	Human performance [19]
IAM-1	90.00	90.00	**100.00**	84.66	62.00
KHATT	76.78	**80.36**	78.57	–	–
IAM-1 + KHATT	75.76	**78.79**	**78.79**	–	–

Table 6
Combination results for handedness prediction (%).

Dataset	Max	Mean	Majority vote	SFI	Fuzzy MIN-MAX
KHATT	78.57	78.57	**85.71**	82.14	83.93
IAM-1 + KHATT	75.76	75.76	81.82	**86.36**	**86.36**

Table 7
Age range prediction results for individual systems (%).

Dataset	Pixel density	Pixel distribution	GLBP
IAM-2	**73.21**	71.42	69.64
KHATT	**76.67**	72.22	70.00

Table 9
2×2 contingency table.

Number of examples misclassified by A and B	Number of examples misclassified by A but not by B
Number of examples misclassified by B but not by A	Number of examples misclassified by neither A nor B

6.6. Statistical and computation complexity comparison

In a final evaluation step, the difference between combination schemes, was evaluated according to a pairwise statistical significance test based on the contingency table. To compare two algorithms A and B, this table is composed of four values, as shown in Table 9 [48].

From this table, McNemar's test that is based on χ^2 can inform whether an algorithm is better than the other. Specifically, a p-value is computed with a confidence of 5%. If the p-value is less than 0.05, the difference between the algorithms is significant. Otherwise the two algorithms are statistically considered with close performances. Presently, this evaluation was used by considering the largest corpus for each application. Table 10 presents p-values obtained for pairwise comparisons of the Fuzzy MIN-MAX with the other combination rules. Note that the main drawback for p-values calculation, is the number of test samples which, is not sufficient to correctly perform statistical significance tests. As example, for age prediction there are only, 28 and 45 test samples per class for IAM and KHATT corpuses, respectively. For this reason, the statistical test of Fuzzy MIN-MAX and the Majority vote is not significant (p-values more than 0.05), although the Fuzzy MIN-MAX gives the best classification scores. Moreover, as SFI and Fuzzy MIN-MAX have close precisions, the results show that they are statistically not different.

Table 10
p-values obtained for pairwise comparison of the Fuzzy MIN-MAX with other combination rules.

	Gender	Handedness	Age
Max	0.0003	0.0327	0.0029
Mean	0.0001	0.0327	0.0346
Majority Vote	0.0054	0.2900	0.2862
SFI	0.2260	0.6100	0.1796

Furthermore, except the Majority vote that considers directly SVM outputs, all combination rules share the use of membership degrees. However, both Fuzzy MIN-MAX and SFI are computationally much more expensive than the others because of the use of Fuzzy measures. In fact, similar calculation steps are involved by these methods but with different positions of MIN and MAX operators. For each test sample, once membership degrees in the two classes computed, operations that are required to aggregate the class decision for SFI or Fuzzy MIN-MAX can be summarized as follows. For each class, membership degrees are ranked in the ascending sense. Accordingly, Fuzzy measures of the second and third ranks are adapted using the λ-Fuzzy measure, which needs two multiplications and one sum. Then, the association between the membership degree and the Fuzzy measure is obtained by applying three Fuzzy MAX operators (or MIN in the case of SFI) while the class decision is expressed by the MIN operator (or the MAX for SFI). In total, these steps require approximately ($2 \times$ (4 scalar products + 2 sums + 7 logical comparisons)). Finally, the Fuzzy MAX operator is applied between class decisions to give the prediction result. Table 11 reports the number of floating point operations (flops) required for the prediction of one randomly selected test sample. A look at this table indicates that predictions based on the SFI and the Fuzzy MIN-MAX involve the same number of flops. As expected Max and Mean rules utilize much less

Table 8
Combination results for age range prediction (%).

Dataset	Max	Mean	Majority vote	SFI	Fuzzy MIN-MAX
IAM-2	69.64	69.64	75.00	75.00	**78.57**
KHATT	68.89	76.67	78.89	80.00	**81.11**

Please cite this article in press as: N. Bouadjenek, et al., Robust soft-biometrics prediction from off-line handwriting analysis, Appl. Soft Comput. J. (2015), http://dx.doi.org/10.1016/j.asoc.2015.10.021

Table 11
Number of flops involved for predicting one test sample.

Combination rule	Number of flops
Max	9
Mean	21
SFI	79
Fuzzy MIN-MAX	79

flops since they employ only membership degrees to infer the class prediction.

7. Discussion and comparison with the state of the art

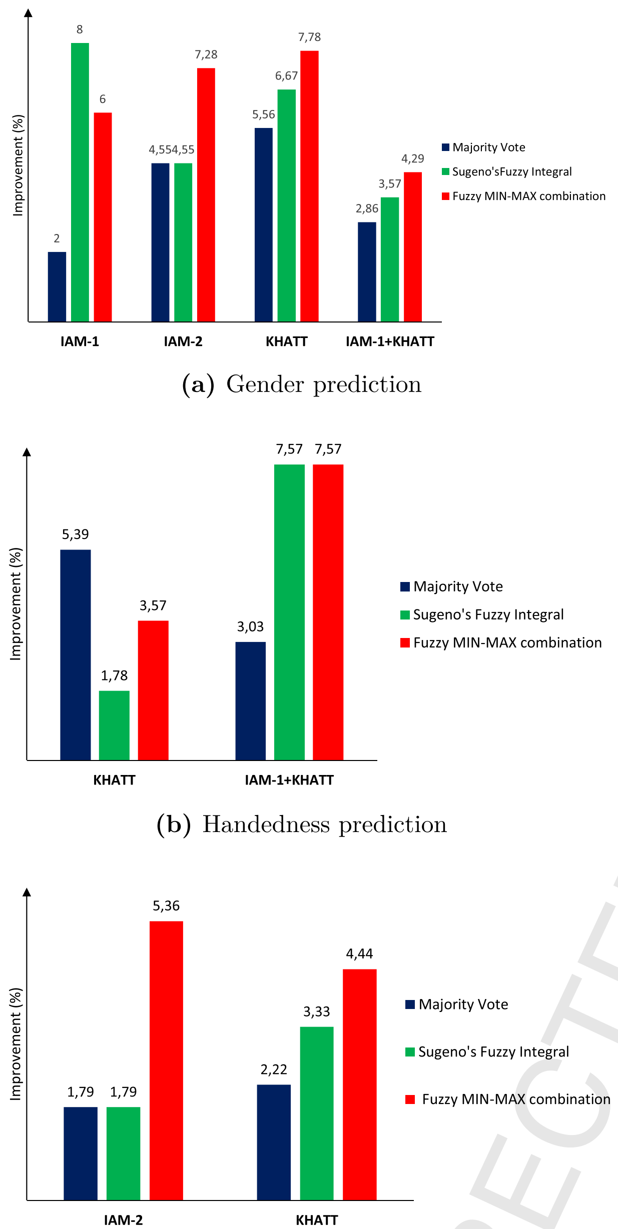
The purpose of this work is to develop a combination paradigm to achieve robust gender, handedness and age range prediction from handwriting analysis. Recall that there are only few research works, which deal with this topic. From the results reported in Table 12, all previous works were carried out using private datasets, which does not favorite a fair quantitative comparison. Nevertheless, through methods observation, one can easily deduce the superiority of the proposed prediction systems. This is due to the incorporation of new topological and gradient features that allow local characterization of handwritten text. In addition, the Fuzzy MIN-MAX combination provides significant improvement compared to individual systems.

- From all experiments, the main remark respective to soft-biometrics prediction is that it is a language-independent task, since quite similar scores were obtained for Arabic and English corpuses. Unlike, IAM dataset in which, handwritten text is composed of detached characters. Arabic writing is semi-cursive, where a single word can be composed of several connected-components. Also, Arabic language has its specific diacritical marking such as dumma ('), hamza (ء), or chadda (ω). Despite all these different properties, results of the blended corpus are typically in the same range as those of separated corpuses.
- Another particularity of this work consists in performing feature generation by segmenting images into a uniform grid where features are calculated on each cell. This provides a local description of the image content. Experimental results highlighted the relationship between the gird size and the reliability of the feature characterization. Prediction accuracies obtained with individual systems, vary between 69% and 80%. The inspection along all datasets, reveals that the three SVM predictors provide satisfactory performance but there is no descriptor that allows the best discriminative power for SVM. According to the theory, such differences can promote the accuracy improvement of a combination framework that contains not necessarily excellent classifiers, that disagree as much as possible on difficult cases [28].
- Results of the proposed combination show a consistency on both IAM and KHATT databases as far as accuracy is concerned. It significantly achieves higher performance than the state of the art. The first reason behind the development of the Fuzzy MIN-MAX algorithm is to employ the Fuzzy measures that assess the SVM relevance with respect to each sample. Moreover, since the combined prediction systems have close performances, the MIN rule considers the agreement between all SVM memberships weighted by their Fuzzy measures. In contrast, the SFI selects the best SVM response. Due to this conceptual difference the Fuzzy MIN-MAX achieved higher prediction accuracies in most cases. However, the statistical significance test showed no important differences between these two methods since *p*-values were larger than 0.05. This outcome is due to the small size of the datasets, which prevents performing a thorough statistical comparison. In fact, for the largest experimental corpus a difference of 2% corresponds to only 6 misclassifications. Nevertheless, the aim of the combination algorithm is to correct misclassifications by exploiting at best complementary information between individual systems. In this respect, Fig. 8 shows the improvement brought by the Majority vote, the SFI and the proposed Fuzzy

Table 12
State of the art results.

Soft biometrics	Reference	Dataset	# Training data	# Test data	Features	Classifier	Classification rate (%)
Gender	[12]	English + Urdu	30		Human performance		67.84
	[22]	QUWI	–	–	Direction + Curvature + Turtuosity + Chain code	Kernel discriminant analysis	73.7
	[32]	QUWI Arabic	300	100	Slant + Curvature + LBP	Neural Network	71.00
	[32]	QUWI English	300	100	Slant + Curvature	SVM	70.00
	[32]	MSHD French	42	42	Slant + Curvature	SVM	68.25
	[32]	MSHD Arabic	42	42	LBP	SVM	74.20
	[20]	IAM-1	80	50	Off-line + On-line	GMM	67.57
	[20]	IAM-1	24		Human performance		63.88
	Proposed	IAM-1	80	50		Fuzzy Min-Max	82.00
		IAM-2	220	110		Fuzzy Min-Max	82.73
		KHATT	180	90		Fuzzy Min-Max	82.22
		IAM-1 + KHATT	280	140		Fuzzy Min-Max	76.43
Handedness	[21]	QUWI	–	–	Direction + Curvature + Turtuosity + Chain code	KNN	70.00
	[19]	IAM-1	30	10	Off-line + On-line	GMM	86.64
	[19]	IAM-1	20		Human performance		62.00
	Proposed	IAM-1	30	10	GLBP	SVM	100.00
		KHATT	112	56		Fuzzy Min-Max	83.93
		IAM-1 + KHATT	142	66		Fuzzy Min-Max	86.36
Age	[22]	QUWI	–	–	Direction + Curvature + Turtuosity	Random Forest	62.40
	Proposed	IAM-2	112	56		Fuzzy Min-Max	78.57
		KHATT	180	90		Fuzzy Min-Max	81.11

Please cite this article in press as: N. Bouadjenek, et al., Robust soft-biometrics prediction from off-line handwriting analysis, Appl. Soft Comput. J. (2015), http://dx.doi.org/10.1016/j.asoc.2015.10.021



(a) Gender prediction

(b) Handedness prediction

(c) Age prediction

Fig. 8. Improvement allowed by classifier combination rules.

MIN-MAX combination compared to the best individual system for all applications. Specifically, the Fuzzy MIN-MAX improvement is at least about 3%.

8. Conclusion

This paper proposed a Fuzzy MIN-MAX combination algorithm, as a strategy to improve the writer's soft-biometrics prediction. First, three SVM predictors associated to different data features were developed to perform writer's gender, handedness and age range prediction. Thereafter, SVM responses are combined to improve the prediction accuracy. Comprehensive experiments using two English and Arabic handwritten text datasets, demonstrated that the proposed combination algorithm can considerably improve the prediction accuracy. Also, what we could observe is that the comparison to various combination rules as well as the state of the art, confirmed the effectiveness of this approach. Based on the results reported in this work, we believe that efficiency of the Fuzzy MIN-MAX combination can be demonstrated better when using larger datasets. It is important to note that the combination process, handles SVM outputs provided with relevance information. This property allows the use of any kind of data features and makes it reproducible to any other pattern recognition task. To improve again our results, we intend in a future work, to investigate more robust features such as Histogram of Templates as well as new classifiers such as Artificial Immune Recognition Systems (AIRS).

References

[1] Y. Andreu, P. García-Sevilla, R.A. Mollineda, Face gender classification: a statistical study when neutral and distorted faces are combined for training and testing purposes, Image Vision Comput. 32 (1) (2014) 27–36.
[2] D. Huang, H. Ding, C. Wang, Y. Wang, G. Zhang, L. Chen, Local circular patterns for multi-modal facial gender and ethnicity classification, Image Vision Comput. 32 (12) (2014) 1181–1193.
[3] R.N. King, Illusory correlations in graphological inference, J. Exp. Psychol. Appl. 6 (4) (2000) 336–348.
[4] V. Shackleton, S. Newell, European management selection methods: a comparison of five countries, Int. J. Select. Assess. 2 (2) (1994) 91–102.
[5] L.M. Shulman, Gender differences in Parkinson's disease, Gend. Med. 4 (1) (2007) 8–18.
[6] S. Dorfberger, E. Adi-Japha, A. Karni, Sex differences in motor performance and motor learning in children and adolescents: an increasing male advantage in motor learning and consolidation phase gains, Behav. Brain Res. 198 (1) (2009) 165–171.
[7] D. Voyer, Sex differences in dichotic listening, Brain Cogn. J. 76 (2011) 245–255.
[8] S. Bennett, D.P. Farrington, L.R. Huesmann, Explaining gender differences in crime and violence: the importance of social cognitive skills, Aggress. Violent Behav. 10 (3) (2005) 263–288.
[9] J.R. Beech, I.C. Mackintosh, Do differences in sex hormones affect handwriting style? Evidence from digit ratio and sex role identity as determinants of the sex of handwriting? Pers. Individ. Dif. 39 (2005) 459–468.
[10] J. Hartley, Sex differences in handwriting: a comment on spear, Br. Educ. Res. J. 17 (2) (1991) 141–145.
[11] W. Hayes, Identifying sex from handwriting, Percept. Mot. Skills 83 (3 (Pt 1)) (1996) 791–800.
[12] S. Hamid, K.M. Loewenthal, Inferring gender from handwriting in Urdu and English, J. Soc. Psychol. 136 (6) (1996) 778–782.
[13] F.I. Dixon, R.A.D. Kurzman, Handwriting performance in younger and older adults: age, familiarity, and practice effects, Psychol. Aging 8 (5) (1993) 360–370.
[14] L.N. van Drempt, A. McCluskey, A review of factors that influence adult handwriting performance, Aust. Occup. Ther. J. 58 (5) (2011) 321–328.
[15] D.K. Burger, Australian norms for handwriting speed in healthy adults aged 60–99 years, Aust. Occup. Ther. J. 58 (5) (2011) 355–363.
[16] A.A.-M. Alkahtani, The influence of right or left handedness on the ability to simulate handwritten signatures and some elements of signatures: a study of Arabic writers, Sci. Justice 53 (2) (2013) 159–165.
[17] S. Knecht, B. Dräger, M. Deppe, L. Bobe, H. Lohmann, A. Flöel, E.-B. Ringelstein, H. Henningsen, Handedness and hemispheric language dominance in healthy humans, Brain 123 (12) (2000) 2512–2518.
[18] S.H. Cha, S.N. Srihari, A priori algorithm for sub-category classification analysis of handwriting, in: International Conference on Document Analysis and Recognition, Seattle, USA, 2001, pp. 1022–1025.
[19] M. Liwicki, A. Schlapbach, P. Loretan, H. Bunke, Automatic detection of gender and handedness from on-line handwriting, in: Conference of the International Graphonomics Society, Melbourne, Australia, 2007, pp. 179–183.
[20] M. Liwicki, A. Schlapbach, H. Bunke, Automatic gender detection using on-line and off-line information, Pattern Anal. Appl. 14 (2011) 87–92.
[21] S. Al-Maadeed, F. Ferjani, S. Elloumi, A. Hassaine, Automatic handedness detection from off-line handwriting, in: GCC Conference and Exhibition (GCC), 2013 7th IEEE, Doha, Qatar, 2013, pp. 119–124.
[22] S. Al-Maadeed, A. Hassaine, Automatic prediction of age, gender, and nationality in offline handwriting, EURASIP J. Image Video Process. Q4
[23] B. Savas, L. Eldén, Handwritten digit classification using higher order singular value decomposition, Pattern Recogn. 40 (3) (2007) 993–1003.
[24] E.J.R. Justino, F. Bortolozzi, R. Sabourin, A comparison of SVM and HMM classifiers in the off-line signature verification, Pattern Recogn. Lett. 26 (9) (2005) 1377–1385.
[25] E. Frias-Martinez, A. Sanchez, J. Velez, Support vector machines versus multi-layer perceptrons for efficient off-line signature recognition, Eng. Appl. Artif. Intell. 19 (6) (2006) 693–704.
[26] C.J.C. Burges, A tutorial on support vector machines for pattern recognition, Data Min. Knowl. Discov. 2 (2) (1998) 121–167.
[27] N. Bouadjenek, H. Nemmour, Y. Chibani, Local descriptors to improve off-line handwriting-based gender prediction, in: 6th International Conference of Soft Computing and Pattern Recognition (SoCPaR), Tunisia, 2014, pp. 43–47.

Please cite this article in press as: N. Bouadjenek, et al., Robust soft-biometrics prediction from off-line handwriting analysis, Appl. Soft Comput. J. (2015), http://dx.doi.org/10.1016/j.asoc.2015.10.021

[28] D. Bertolini, L. Oliveira, E. Justino, R. Sabourin, Reducing forgeries in writer-independent off-line signature verification through ensemble of classifiers, Pattern Recogn. 43 (1) (2010) 387–396.

[29] K.R. Bandi, S.N. Srihari, Writer demographic classification using bagging and boosting, in: Proceedings of International Graphonomics Society Conference, Salerno, Italy, 2005, pp. 133–137.

[30] M. Liwicki, H. Bunke, Iam-ondb – an on-line English sentence database acquired from handwritten text on a whiteboard, in: Proceedings. Eighth International Conference on Document Analysis and Recognition, vol. 2, Seoul, South Korea, 2005, pp. 956–961.

[31] S. Al-Maadeed, W. Ayouby, A. Hassaine, J. Aljaam, QUWI: an Arabic and English handwriting dataset for offline writer identification, in: International Conference on Frontiers in Handwriting Recognition (ICFHR), Bari, Italy, 2012, pp. 746–751.

[32] I. Siddiqi, C. Djeddi, A. Raza, L. Souici-meslati, Automatic analysis of handwriting for gender classification, Pattern Anal. Appl. (2014) 1–13.

[33] N. Jiang, J. Xu, W. Yu, S. Goto, Gradient local binary patterns for human detection, in: IEEE International Symposium on Circuits and Systems (ISCAS), 2013, Beijing, China, 2013, pp. 978–981.

[34] T. Ojala, M. Pietikäinen, D. Harwood, A comparative study of texture measures with classification based on featured distributions, Pattern Recogn. 29 (1) (1996) 51–59.

[35] V.N. Vapnik, The Nature of Statistical Learning Theory, Springer-Verlag New York, Inc., New York, NY, USA, 1995.

[36] A. Quteishat, C.P. Lim, A modified fuzzy min-max neural network with rule extraction and its application to fault detection and classification, Appl. Soft Comput. 8 (2) (2008) 985–995.

[37] M. Seera, C.P. Lim, C.K. Loo, H. Singh, A modified fuzzy min-max neural network for data clustering and its application to power quality monitoring, Appl. Soft Comput. 28 (2015) 19–29.

[38] S.-B. Cho, J. Kim, Combining multiple neural networks by fuzzy integral for robust classification, IEEE Trans. Syst. Man Cybern. 25 (2) (1995) 380–384.

[39] H. Nemmour, Y. Chibani, Neural network combination by fuzzy integral for robust change detection in remotely sensed imagery, EURASIP J. Appl. Signal Process. 2005 (2005) 2187–2195.

[40] J. Soh, Computational method for document object locator combination, Image and Vision Computing, Proceedings from the 15th International Conference on Vision Interface 22 (12) (2004) 1015–1029.

[41] B.-L. Lu, M. Ito, Task decomposition and module combination based on class relations: a modular neural network for pattern classification, IEEE Trans. Neural Netw. 10 (5) (1999) 1244–1256.

[42] L. Zadeh, Fuzzy sets, Inform. Control 8 (3) (1965) 338–353.

[43] P. Melin, A. Mancilla, M. Lopez, O. Mendoza, A hybrid modular neural network architecture with fuzzy Sugeno integration for time series forecasting, Appl. Soft Comput. 7 (4) (2007) 1217–1226, soft Computing for Time Series Prediction.

[44] H. Nemmour, Y. Chibani, Multiple support vector machines for land cover change detection: an application for mapping urban extensions, ISPRS J. Photogramm. Remote Sens. 61 (2) (2006) 125–133.

[45] T.Y. Lin, Y. Xie, A. Wasilewska, C.-J. Liau, Data Mining: Foundations and Practice, vol. 118, Springer, Berlin, Heidelberg, 2008.

[46] S.A. Mahmoud, I. Ahmad, M. Alshayeb, W.G. Al-Khatib, M.T. Parvez, G.A. Fink, V. Margner, H.E. Abed, Khatt: Arabic offline handwritten text database, in: Proceedings of the International Conference on Frontiers in Handwriting Recognition, IEEE Computer Society, Seattle, USA, 2012, pp. 449–454.

[47] S.A. Mahmoud, I. Ahmad, W.G. Al-Khatib, M. Alshayeb, M.T. Parvez, V. Märgner, G.A. Fink, KHATT: an open Arabic offline handwritten text database, Pattern Recogn. 47 (3) (2014) 1096–1112.

[48] Y. Kessentini, T. Burger, T. Paquet, A Dempster-Shafer theory based combination of handwriting recognition systems with multiple rejection strategies, Pattern Recogn. 48 (2) (2015) 534–544.

Please cite this article in press as: N. Bouadjenek, et al., Robust soft-biometrics prediction from off-line handwriting analysis, Appl. Soft Comput. J. (2015), http://dx.doi.org/10.1016/j.asoc.2015.10.021