Robust Periocular Recognition by Fusing Local to Holistic Sparse Representations

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ABSTRACT

Sparse representations have been advocated as a relevant advance in biometrics research. In this paper we propose a new algorithm for fusion at the data level of sparse representations, each one obtained from image patches. The main novelties are two-fold: 1) a dictionary fusion scheme is formalised, using the ℓ^1-minimization with the gradient projection method; 2) the proposed representation and classification method does not require the non-overlapping condition of image patches from where individual dictionaries are obtained.

In the experiments, we focused in the recognition of periocular images and obtained independent dictionaries for the *eye*, *eyebrow* and *skin* regions, that were subsequently fused. Results obtained in the publicly available UBIRIS.v2 data set show consistent improvements in the recognition effectiveness when compared to state-of-the-art related representation and classification techniques.

Categories and Subject Descriptors

C.2.0 [**Security and Protection**]; I.5.1 [**Pattern Recognition**]; I.2.10 [**Vision and Scene Understanding**]

General Terms

Biometrics, Sparse Representations

1. INTRODUCTION

Biometrics attempts to recognize human beings according to their physical characteristics or behavioural traits [6]. In the past, various traits were used for biometric recognition, being the *iris* and the *face* among the most popular (e.g., [13], [15], [7] and [9]). Recently, the concept of *periocular recognition* arisen [11] as a trait that profits from the advantages of both the iris and face, being particularly suitable for the recognition under visible wavelength light and uncontrolled acquisition conditions (e.g., [10] and [17]).

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Figure 1: Examples of periocular images of a single subject, containing the *corneal*, *eyebrows* and *skin* regions, with varying gazes.

Wright *et al.* [18] proposed the concept of *sparse representation* for *classification* (SRC) purposes, which attains high effectiveness when a sufficient number of training images is available and images are moderately aligned. Subsequently, Pillai *et al.* [12] proposed a SRC model for the iris trait, recognizing different sectors of the iris separately and combining results at the score level, according to a confidence estimate from each sector.

In this paper, we propose a periocular recognition model based on sparse representations of image patches, that are fused into a single representation, and does not require the non-overlapping condition of image patches.

The proposed model differs from the work of Wright *et. al.* [18] recognition model in the sense that it is able to combine overlapping patches. Also, it is different from the work of Pillai *et al.* [12], as we do not recognize each image patch separately. Also, Pillai *et al.* [12] used a Bayesian fusion framework with combination of different regions as quality measure. Our implementation considers an ℓ^1-norm minimization problem solved by a fast algorithm based on gradient projection methods (GP) [5, 8, 16] which allows us to efficiently obtain sparse solutions of our models. In the experiments we used a set of periocular images from the UBIRIS.v2 data set [14], acquired in visible wavelengths from 4 to 8 meters away of the subjects, in uncontrolled acquisition conditions and varying gazes, poses and amounts of occlusions. Examples of images used are shown in Figure 1. The obtained results allowed us to observe consistent increases in performance when compared to the classical SRC model and to the state-of-the-art approaches due to Wright *et. al.* [18] and Pillai *et al.* [12]. Also, it should be stressed that such increases in performance were obtained without a significant overload in the computational burden of the recognition process.

The remainder of this paper is organized as follows. Section 2 summarizes the existing methods in the scope of the proposed paper. Section 3 introduces the proposed representation and classification model. Section 4 describes the experimental validation procedure that was carried out, with respect to state-of-the-art techniques. Finally, Section 5 concludes the paper.

2. RELATED METHODS

Here we summarize the work of Wright *et al.* [18] (SRC model) and Pillai *et al.* [12] (Fusion model), which are among the most relevant algorithms proposed in this scope.

A. Sparse Representation for Classification (SRC) Model

Having a set of labeled training samples (n_i samples from the ith subject), they are arranged as columns of a matrix $A_i = [\mathbf{v}_{i,1}, \ldots, \mathbf{v}_{i,n_i}] \in \mathbb{R}^{m \times n_i}$. The dictionary results from the concatenation of all samples of all classes:

$$\begin{aligned}\mathbf{A} &= [\mathbf{A}_1, \ldots, \mathbf{A}_k] \\ &= [\mathbf{v}_{1,1}, \cdots, \mathbf{v}_{1,n_1} | \ldots | \mathbf{v}_{k,1}, \cdots, \mathbf{v}_{k,n_k}].\end{aligned}$$

Next, the key insight is that any probe $\mathbf{y}$ can be expressed as a linear combination of elements of $\mathbf{A}$. As the data acquisition process often induces noisy samples, it turns out to be impractical to express the test sample exactly as a sparse superposition of the training samples. In this case, for any test sample $\mathbf{y} \in \mathbb{R}^m$ the system to solve is given by the following ℓ^1-minimization problem:

$$(\ell^1_s): \quad \hat{\mathbf{x}}_1 = \arg\min \|\mathbf{x}\|_1 \quad \text{subj. to } \|\mathbf{A}\mathbf{x} - \mathbf{y}\|_2 \leq \epsilon, \tag{1}$$

where $\|\mathbf{x}\|_1 = \sum |x_i|$. This way, it is expected to get a sparse solution [4, 1, 3, 2] of the system

$$\mathbf{y} = \mathbf{A}\mathbf{x} + \mathbf{z}.$$

where $\mathbf{z} \in \mathbb{R}^m$ is the noise term with a bounded energy constraint $\|\mathbf{z}\|_2 \leq \epsilon$, and the solution is expected to be similar to

$$\mathbf{x}_0 = [0, \cdots, 0| \ldots |x_{i,1}, \cdots, x_{i,n_i}| \ldots |0, \cdots, 0]^T.$$

Classification is based on the observation that high values of the coefficients in the solution $\mathbf{x}_0$ are mainly associated with the columns of $\mathbf{A}$ of a single class, corresponding to the identity of the probe. A residual score per class is obtained, $\mathbb{1}_i : \mathbb{R}^n \to \mathbb{R}^n$, defined by $\hat{\mathbf{x}} \to \mathbb{1}_i(\hat{\mathbf{x}})$. The probe $\mathbf{y}$ is then reconstructed by $\hat{\mathbf{y}}_i = \mathbf{A}\mathbb{1}_i(\hat{\mathbf{x}})$ and the minimal reconstruction error deemed to correspond to the identity of the probe:

$$r_i(\mathbf{y}) = \|\mathbf{y} - \hat{\mathbf{y}}_i\|_2,$$

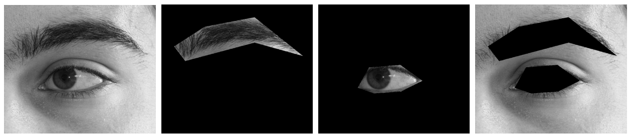
between $\mathbf{y}$ and $\hat{\mathbf{y}}_i$, that is we find,

$$\text{id}(\mathbf{y}) = \arg\min_i r_i(\mathbf{y}).$$

Further, a sparsity concentration index (SCI) is used to accept/reject the response given by the minimal reconstruction error [18]. The SCI of a coefficient vector $\hat{\mathbf{x}} \in \mathbb{R}^n$ corresponds to:

$$SCI(\hat{\mathbf{x}}) = \frac{\frac{k \max_i \|\mathbb{1}_i(\hat{\mathbf{x}})\|_1}{\|\hat{\mathbf{x}}\|_1} - 1}{k - 1} \in [0, 1], \tag{2}$$

where $\mathbb{1}_i$ is a indicator function that set the values of all coefficients to 0, except those associated to the ith class. Having a sparse solution $\hat{\mathbf{x}}$, if $SCI(\hat{\mathbf{x}}) \approx 1$, the probe is considered to be acceptably represented by samples from a single class. Otherwise, if $SCI(\hat{\mathbf{x}}) \approx 0$ the sparse coefficients spread evenly across all classes and a reliable identity for that probe cannot be given.



(a) (b) (c) (d)

Figure 2: Periocular regions defined from a given image. (a) Original image. (b) Eyebrow region. (c) Eye region. (d) The surrounding skin region.

B. Fusion Model

The recognition model proposed by Pillai *et al.*[12] obtains separate sparse representation from disjoint regions of an image and combines the results considering a *quality* index from each region. Let L be the number of classes with labels $\mathbf{C} = \{c_i\}_{i=1}^{L}$. Any vector $\mathbf{y}$ is divided into sectors, each one described by the SRC algorithm. SCI values are obtained over each sector, allowing to reject those with quality bellow a threshold. Let $\{d\}_i$ represent the class labels of the retained sectors, and $\mathbb{P}(d_i|c)$ be the probability that the i-th sector returns a label d_i when the true class is c:

$$\mathbb{P}(d_i|c) = \begin{cases} \frac{t_1^{SCI(d_i)}}{t_1^{SCI(d_i)} + (L-1)t_2^{SCI(d_i)}} & \text{if } d_i = c, \\ \frac{t_2^{SCI(d_i)}}{t_1^{SCI(d_i)} + (L-1)t_2^{SCI(d_i)}} & \text{if } d_i \neq c, \end{cases}$$

being t_1 and t_2 constants such that $0 > t_1 > t_2 > 1$. According to a maximum a posteriori (MAP) estimate of the class label, the response corresponds to the class having the highest accumulated SCI:

$$\tilde{c} = arg \max_{c \in \mathbf{C}} \frac{\sum_{j=1}^{L} SCI(d_j)\delta(d_j = c)}{\sum_{j=1}^{L} SCI(d_j)}.$$

3. PROPOSED METHOD

As above stated, the proposed method was developed in the context of periocular recognition, even though it can be easily extended to other biometric traits. In the case of the periocular region, it has varying levels of contrast, and suffers from heavy heterogeneity in terms of average local intensities, due to the morphologic properties that induce shadows, and uneven illumination (some examples are given in Figure 1).

The rationale is as follows: instead of recognizing the entire periocular region, we combine the information given by regions that can be easily detected by standard object detection algorithms: the eye, eyebrow and the (remaining) skin. As in the general SRC model, a $w \times h$ grayscale periocular image is concatenated into a column vector $\mathbf{v} \in \mathbb{R}^{wh}$. Given n_i training samples of the ith class, each sample is divided into three sub-sets (as shown in Figure 2). Formally, let $\mathbf{v}_{i,n_i,1}$, $\mathbf{v}_{i,n_i,2}$ and $\mathbf{v}_{i,n_i,3}$ be vectors such that:

- $\mathbf{v}_{i,n_i,1}$ has non-zero values in the regions corresponding to the eye.
- $\mathbf{v}_{i,n_i,2}$ has non-zero values in the regions corresponding to the eyebrow.
- $\mathbf{v}_{i,n_i,3}$ has non-zero values in the regions corresponding to the skin.

Vectors $\mathbf{v}_{i,n_i,j}$ have the same dimension, i.e., $v_. \in \mathbb{R}^m$. Let $\mathbf{z_0} \in \mathbb{R}^m$ be a vector with all values equal to 0. Three matrices $\bar{\mathbf{A}}_{i,s}$ $(s = 1, 2, 3)$ are defined as follows:

$$\bar{\mathbf{A}}_{i,1} = \begin{pmatrix} \mathbf{v}_{i,1,1} & \cdots & \mathbf{v}_{i,r,1} & \cdots & \mathbf{v}_{i,n_i,1} \\ \mathbf{z}_0 & \cdots & \mathbf{z}_0 & \cdots & \mathbf{z}_0 \\ \mathbf{z}_0 & \cdots & \mathbf{z}_0 & \cdots & \mathbf{z}_0 \\ \mathbf{z}_0 & \cdots & \mathbf{z}_0 & \cdots & \mathbf{z}_0 \end{pmatrix}$$

$$\bar{\mathbf{A}}_{i,2} = \begin{pmatrix} \mathbf{z}_0 & \cdots & \mathbf{z}_0 & \cdots & \mathbf{z}_0 \\ \mathbf{v}_{i,1,2} & \cdots & \mathbf{v}_{i,r,2} & \cdots & \mathbf{v}_{i,n_2,2} \\ \mathbf{z}_0 & \cdots & \mathbf{z}_0 & \cdots & \mathbf{z}_0 \\ \mathbf{z}_0 & \cdots & \mathbf{z}_0 & \cdots & \mathbf{z}_0 \end{pmatrix}$$

$$\bar{\mathbf{A}}_{i,3} = \begin{pmatrix} \mathbf{z}_0 & \cdots & \mathbf{z}_0 & \cdots & \mathbf{z}_0 \\ \mathbf{z}_0 & \cdots & \mathbf{z}_0 & \cdots & \mathbf{z}_0 \\ \mathbf{v}_{i,1,3} & \cdots & \mathbf{v}_{i,r,3} & \cdots & \mathbf{v}_{i,n_3,3} \\ \mathbf{z}_0 & \cdots & \mathbf{z}_0 & \cdots & \mathbf{z}_0 \end{pmatrix}$$

Each $\bar{\mathbf{A}}_{.,.}$ regards local information of the set of training images. Also, we consider a new matrix that contains information of the complete periocular region, resulting from the concatenation of vectors $\mathbf{v}_{i,1,4}, \ldots, \mathbf{v}_{i,n_i,4}$:

$$\bar{\mathbf{A}}_{i,4} = \begin{pmatrix} \mathbf{z}_0 & \cdots & \mathbf{z}_0 & \cdots & \mathbf{z}_0 \\ \mathbf{z}_0 & \cdots & \mathbf{z}_0 & \cdots & \mathbf{z}_0 \\ \mathbf{z}_0 & \cdots & \mathbf{z}_0 & \cdots & \mathbf{z}_0 \\ \mathbf{v}_{i,1,4} & \cdots & \mathbf{v}_{i,r,4} & \cdots & \mathbf{v}_{i,n_i,4} \end{pmatrix}.$$

Our goal is to combine the local and holistic information in a single representation, by considering the concatenation of the four types of matrices above defined:

$$\mathbf{A}_i = [\bar{\mathbf{A}}_{i,1}|\bar{\mathbf{A}}_{i,2}|\bar{\mathbf{A}}_{i,3}|\bar{\mathbf{A}}_{i,4}] \in \mathbb{R}^{4m \times 4n_i},$$

yielding the final dictionary :

$$\mathbf{A} = [\mathbf{A}_1 \ldots, \mathbf{A}_k] \in \mathbb{R}^{4m \times n}.$$

The following properties of the new dictionary with respect to previous works should be noted:

- In opposition to Wright *et al.* [18], our approach allows to combine sectors from different image samples.
- In opposition to Pillai *et al.* [12], the used sectors do not need to satisfy the non-overlapping condition.
- The obtained performance is not sensitive to accurate estimates of each sector.
- The proposed classification scheme can be implemented without any fusion technique, and by solving a unique system of linear equations.

In our model, a sample $\mathbf{y}$ is represented by the vector $[\mathbf{y}_1|\mathbf{y}_2|\mathbf{y}_3|\mathbf{y}_4]^T$ where $\mathbf{y}_i, i \in \{1, 2, 3\}$, have non-zero components exclusively in an image patch and $\mathbf{y}_4$ regards the complete periocular region. It follows that

$$\mathbf{y}_s^T = \mathbf{A}_s \mathbf{x}_s = \sum_{i=1}^{k} \sum_{j=1}^{n_k} \mathbf{v}_{i,j,s} \alpha_{i,j,s},$$

with $\mathbf{A}_s = [\mathbf{v}_{1,1,s}, \cdots, \mathbf{v}_{1,n_1,s}| \cdots |\mathbf{v}_{k,1,s}, \cdots, \mathbf{v}_{1,n_k,s}]$ and $s = 1, 2, 3$. Moreover, $\mathbf{y}$ satisfies

$$2\mathbf{y} = \sum_{s=1}^{4} \mathbf{y}_s^T = \sum_{i=1}^{k} \sum_{j=1}^{n_k} \sum_{s=1}^{4} \mathbf{v}_{i,j,s} \alpha_{i,j,s},$$

Sparse Models	Recognition Rate
Proposed Method	**97.63%**
Proposed Method Without $\mathbf{A}_{i,4}$	97.02%
Wright *et al.*[18] (SRC)	96.88%
Pillai *et al.*fusion [12]	87.56%
Eyebrow Region	61.25%
Eye Region	38.95%
Skin Region	94.79%

Table 1: Summary of the recognition rates observed. Values regard the average from all recognition experiments.

and the solution of the ℓ^1-minimization system (1) has the form

$$\mathbf{x}_0 = [0, \cdots, 0| \ldots |\alpha_{i,1,1}, \cdots, \alpha_{i,n_i,1}, \alpha_{i,1,2}, \cdots, \alpha_{i,n_i,2} \\ \alpha_{i,1,3}, \cdots, \alpha_{i,n_i,3}, \alpha_{i,1,4}, \cdots, \alpha_{i,n_i,4}| \cdots |0, \cdots, 0]^T.$$

In this paper, we use the gradient projection method by considering the LASSO problem [16] for solving the ℓ^1-minimization problem (1) .

4. EXPERIMENTS AND DISCUSSION

Our experiments were conducted in the UBIRIS.v2 database [14]. The periocular regions were manually detected and the ROI down-sampled to 10×9 pixels. Six samples from 80 different subjects were used, captured from different distances (4 to 8 meters), with varying gazes/poses and notable changes in lighting conditions, as shown in Figure 1. One image per class was randomly drawn as probe data and the remaining five samples included in the dictionary. Experiments were repeated, changing the image used as probe (per subject). Hence, six dictionaries with dimension 270×1600 were considered, each one tested in 80 probe samples.

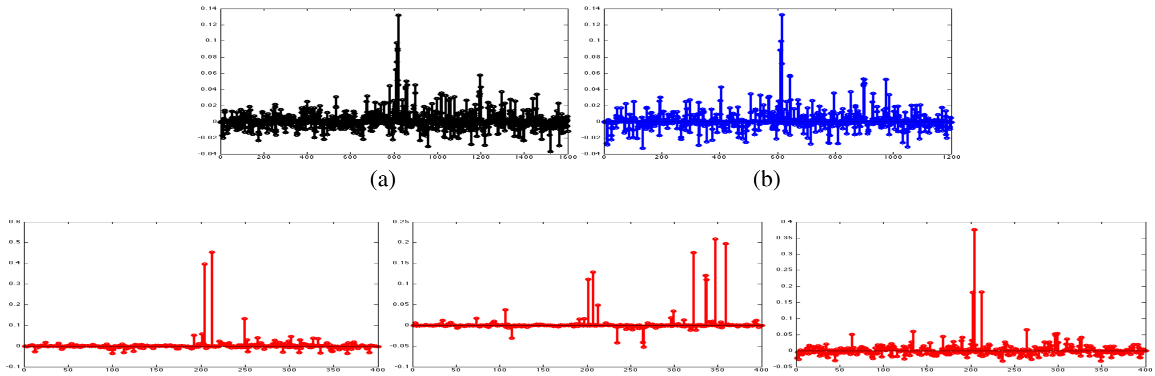
Results are summarized in Table 1 in terms of the recognition rates. For the sparse solutions validated by the sparsity concentration index (SCI) values (2), the corresponding confusion matrix CM was computed. Then, the recognition rates obtained:

$$RR = 1 - \frac{\sum_{i \neq j} CM(i,i)}{\sum_{i,j} CM(i,j)}.$$

The method proposed in this paper got better results than the classical SRC model (96.88% to 97.63%), which was considered an achievement due to the high effectiveness attained by the baseline algorithm. Also, the fusion technique due to Pillai *et* al. got consistently lower recognition rates in our experiments: the fusion at score level of different sparse representations actually decreased the recognition effectiveness, when compared o the original SRC model. This might be due to the non-rigidity of the periocular regions, that induce non-linear local distortions that might be contributing for the decrease in results.

Even if the proposed method does not use the complete periocular region in the sparse representation (second line of results in Table 1), the results were still slightly better than for the other algorithms tested. Even though, we concluded that including overlapping data in the dictionaries ($A_{i,4}$ contains information from $A_{i,1}$, $A_{i,2}$ and $A_{i,3}$), contributes for the improvement of the results (97.02% to 97.63%).

Another interesting analysis is the effectiveness attained by each of the regions in a singular way, i.e., when sparse representations are obtained exclusively from a single region. In this case, we confirmed that the skin area provided the most discriminant information, followed by the eyebrow and the eye region. As illustrated



(a) (b)

(c) (d) (e)

Figure 3: Coefficient vector found using ℓ^1- minimization based on sparse representation approaches. (a) Proposed dictionary fusion model. (b) Wright *et al.* [18] sparse representation based classification. (c), (d) and (e) are sparse solutions obtained using only eyebrow, eye and the surrounding skin region (as shown in Figure 2), respectively.

in Figure 2, the eye region comprises exclusively the ocular globe, which due to its moving nature and to the fact that eyelids often occlude significant portions of the ocular globe, might explain the results obtained.

In Figure 3 we illustrate the sparsity of the solutions found, according to the ℓ^1-minimization system (1). Solutions in our model tend to be sparse (a) and relatively similar to those observed for Wright *et. al.* [18] (b), even though a higher density of non-zero coefficients in the class of interest can be observed in our model (note the number of non-zero coefficients near the peak in our model and Wright *et* al's. Another interesting observation is the high similarity of the coefficients found for the proposed model and when using exclusively the skin area (e). Also, both the coefficients found from the eyebrow and eye regions appear to have some complementarity, which from our viewpoint justifies the outperforming results obtained by the proposed SRC algorithm.

A comparison between the ROC curves of our algorithm (black curve) and of the Wright *et al.* [18]'s (green curve) is given in Figure 4, when varying the SCI value to accept a *match*. Even though both algorithms got identical performance, the proposed algorithm (black line of the Image at left) approximates more to the *optimal performance* point (complement of specificity=0, sensitivity=1). In this case, the minimal distance from the ROC values to the $(0, 1)$ point was of 0.1417, while a value of 0.2021 was observed for the Wright *et al.* [18] algorithm. Again, we considered this slight difference meaningful due to the extremely high effectiveness of the baseline algorithm.

Finally, the statistical correlation between the outputs given by our method and the methods used as comparison terms was assessed. This kind of analysis is of particular interest for further research, pointing about improvements in performance that might obtained, if the fusion of multiple SRC algorithms is considered. The levels of correlation of the responses attained when using exclusively each of the periocular regions considered (skin, eye and eyebrow) were also obtained. Considering that eventual dependences will be linear, the Pearson's sample correlation was used for that purpose. Given a pair of samples, the correlation coefficient is given by:

$$r(X, Y) = \frac{1}{k-1} \sum_{i=1}^{k} \left(\frac{X_i - \bar{X}}{\sigma_X} \right) \left(\frac{Y_i - \bar{Y}}{\sigma_Y} \right),$$

where X_i, Y_i denote the systems outputs, $\bar{X}$, $\bar{Y}$ are the sample means and σ_X, σ_Y the standard deviations. As it can be observed from the results in Table 2, the proposed method and the SRC [18] model are strongly correlated, which is expected due to the high recognition rates both achieve. Also, it should be noted the strong correlation between the outputs given by the model of Wright *et. al.* [18] and the model obtained when using exclusively the skin region. This is also easily explained, as the skin region comprises the large majority of the periocular region. Also, using the proposed method on a singular region corresponds to the classical SRC algorithm. The correlation values between the proposed method and the responses when using exclusively one kind of regions (eyebrow, eye and skin) confirmed the role of each region in the responses of our method, as the values given in Table 1 and Figure 3 point. Also, it is particularly interesting to observe the negative (and small) correlation values between the responses obtained when using the eye and the eyebrow, pointing for a complementarity that might contribute for the outperforming results of the method proposed in this paper.

5. CONCLUSIONS AND FURTHER WORK

This paper focused in the recognition of periocular images and proposed an algorithm based on the sparse representation for classification (SRC) model. The main singularity is to fuse at the data level representations from easily detectable areas in the periocular region (skin, eye and eyebrows), and obtain a unique sparse representation subsequently. Also, in contrast to previous works, the proposed algorithm does not require that image patches used in sparse representations are disjoint, augmenting the robustness to inaccuracies in the algorithm that detects ROIs. Using highly challenging images of the UBIRIS.v2 dataset, we compared the performance of the proposed model against state-of-the-art SRC algorithms, and observed slight but consistent improvements, which was regarded as an achievement, considering the high effectiveness of baseline algorithms.

Our current efforts are concentrated in formalising the conditions required for maximize performance, in fusing local/holistic image patches for SRC algorithms. This should enable extend the proposed classification algorithm for other regions than the periocular.

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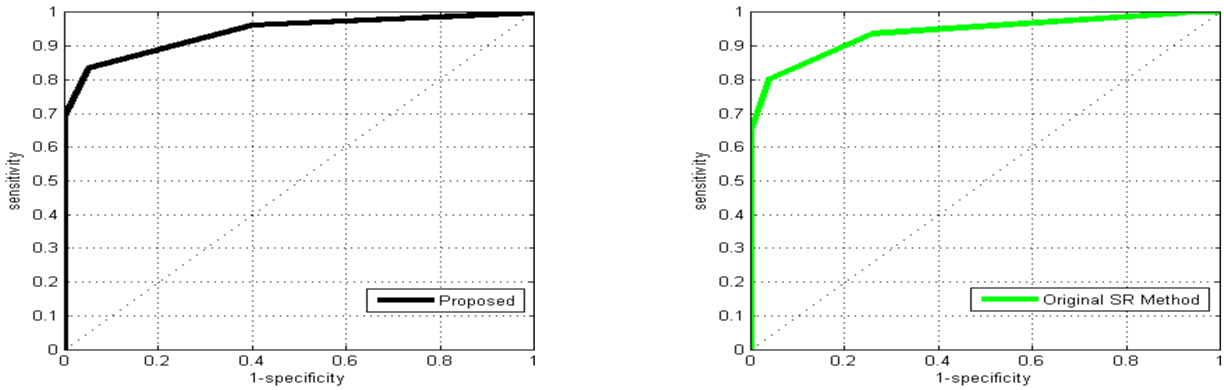

(a) (b)

Figure 4: Comparison between the ROC curves of the proposed recognition model (a), and according to the model proposed by Wright *et al.* [18](b).

	Proposed	SRC [18]	Fusion [12]	Eyebrow	Eye	Skin
Proposed	1	0.7423	0.3744	0.2024	0.3822	0.7827
SRC [18]	-	1	0.3649	0.1100	0.1972	0.6604
Fusion [12]	-	-	1	0.4288	0.4516	0.3733
Eyebrow	-	-	-	1	-0.1166	0.2223
Eye	-	-	-	–	1	0.2808
Skin	-	-	-	-	-	1

Table 2: Pearson's sample correlation coefficients between the responses given by the recognition algorithms evaluated in this paper.

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