# Gender Classification from Multispectral Periocular Images

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## Abstract

*Gender classification from multispectral periocular and iris images is a new topic on soft-biometric research. The feature extracted from RGB images and Near Infrared Images shows complementary information independent of the spectrum of the images. This paper shows that we can fusion these information improving the accuracy of gender classification. Most gender classification methods reported in the literature has used images from face databases and all the features for classification purposes. Experimental results suggest: (a) Features extracted in different scales can perform better than using only one feature in a single scale; (b) The periocular images performed better than iris images on VIS and NIR; c) The fusion of features on different spectral images NIR and VIS allows improve the accuracy; (c) The feature selection applied to NIR and VIS allows select relevant features and d) Our accuracy 90% is competitive with the state of the art.*

## 1. Introduction

Commercial iris recognition systems operate predominately in the Near-Infrared Range (NIR) of the electromagnetic spectrum. Due to the biological diversity of the composition of the iris, different portions of the electromagnetic spectrum may better represent physical characteristics of the epigenetic iris pattern. The absorption, and reflection vary within biological iris composition classes. This paper using images on Visible Spectrum (400nm-700nm) and the Near IR (700nm - 1000nm). The melanin content and the cellular composition in the iris determine what wavelength of light is reflected back, thus giving the appearance of a brown, blue, or green colored iris. Through the use of multispectral imagery (NIR and VIS), the peak reflection (due mostly to the melanin) and other varying reflection phenotypical iris traits can be conveyed.

Soft-biometrics using iris information is a new area that is used to estimate demographic information such as gender, ethnicity, age, and emotions. In a biometric recognition administration system, gender information may lead to searching only one half of a database. If the gender is determined before searching for a match to an enrolled iris code, then the average search time may be halved. In instances where the person is not recognized, it may be useful to know the gender and other information about a person who attempts to gain entry to a restricted zone. Another possible use arises in social settings, where it may be useful to screen entry to an area based on gender, while not recording the identity. Currently, gender classification is also important for banking operation from cellular phones to validate purchases and transfer money. Even in 2016 , the International Conference on Image Processing (ICIP) presented results for mobile ocular biometrics on the VISOB dataset. This collection contains a larger number of individuals, over 500, acquired with smartphones of three different brands and three illumination conditions [21].

Most of the papers in the literature for gender classification used images from face databases or cropped the periocular area from faces [15, 25, 24]. Alonzo-Fernandez et al. [2] report a survey with the most commonly used techniques based on periocular images and databases. They provide a comprehensive framework covering different perspectives, from existing databases to algorithms for the detection of the periocular region, and features for recognition. Databases that were utilized include face and iris databases (because the periocular area appears in such data), as well as newer databases that specifically capture the periocular area [2]. Although initial studies have made use of annotated data, the detection and segmentation of the periocular region has become a research target in itself. Very few databases have been designed specifically for periocular research, with iris databases being the ones that are mostly used for this purpose. A general tendency is for facial databases to exhibit a better accuracy. These are the most commonly used databases, thus each new work builds on previous research, resulting in additional improvements.

Castrillon et al. [8] proposed a system that works with periocular images. This area is extracted after normalizing the face in terms of scale and rotation. Given the rough

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eye-location annotations, the normalized facial image is obtained automatically after rotating, scaling, and cropping the original images. The best result was obtained using five different feature-extraction methods.

Kumari et al. [16], proposes a novel approach of extracting global features from the periocular region of poor-quality grayscale images for gender classification. In their approach, global gender features are extracted using independent component analysis. All relevant experiments are performed on the periocular region cropped from the FERET face database.

Tapia et al [26] predict gender directly from the same binary iris-code that could be used for recognition. They found that information for gender prediction is distributed across the iris, rather than localized in particular concentric bands. They also found that using selected features representing a subset of the iris region achieves better accuracy than using features representing the whole iris region achieving 89% correct gender prediction using the fusion of the best features of iris-code from the left and the right eyes.

Bobeldyk et al. [5] explored the gender-prediction accuracy associated with four different regions from NIR iris images, namely the extended ocular region, the iris-excluded ocular region, the iris-only region, and the normalized iris-only region. They used a binarized statistical image feature (BSIF) texture operator to extract features from the regions that were previously defined. The ocular region reached a best performance of 85.7%, while the normalized or unwrapped images exhibited the worst performance, with almost a 20% difference in the performance over the ocular region (65%).

Aginako et al [1] explore the extraction of local descriptors previous to classification. In this sense, starting from a common iris segmentation information, different normalization procedures are considered, analyzing the use of both iris and periocular patterns. A collection of local descriptors is computed on those patterns, evaluating their performance by means of different classification paradigms. A summary of some relevant works is presented in Table 1.

The scope of this paper is to analyze and to understand which features can be extracted from periocular images using NIR and VIS spectrum. Also is important to us understand if the fusion of the information inside of NIR, VIS or NIR+VIS may improve the accuracy of gender classification.

The remainder of the paper is organized as follows. In Section 2, we review the method used to extract information regarding periocular images. In Section 3 and 4, we provide details about the feature selection method and experiments. Section 5 describe the dataset used in our experiments. Sections 6, we present the conclusions.

Table 1. Summary of gender classification using eyes. I represents: Iris Images, P represents: Periocular Images, CP represent: Cellphones Images.

| Paper | I/P | Source | $N^o$ Subjects | Type | Acc. % |
|---|---|---|---|---|---|
| V .Thomas et al. [28] | I | Iris | N/A | NIR | 75,00 |
| S. Lagree et al. [17] | I | Iris | 300 | NIR | 62,17 |
| A. Bansal et al. [4] | I | Iris | 200 | NIR | 83,60 |
| J. Tapia et al. [27] | I | Iris | 1,500 | NIR | 91.00 |
| M. Fairhurst et al. [11] | I | Iris | 200 | NIR | 89,74 |
| J. Tapia et al. [26] | I | Iris | 1,500 | NIR | 89,00 |
| D. Bobeldyk et al. [5] | I/P | Iris | 1,083 | NIR | 85,70 |
| J. Merkow et al. [18] | P | Faces | 936 | VIS | 80,00 |
| C. Chen et al. [9] | P | Faces | 1,003 | NIR/Thermal | 93,59 |
| Castrillon-Santana et al. [8] | P | Faces | 1,500 | VIS | 92,46 |
| Rattani et al. [22] | P | Iris | 550 | VIS/ CP | 91,60 |
| **This paper**. | P | Iris | 120/120 | NIR/VIS | **90,00** |

# 2. Feature extraction

Feature extraction is a relevant process and several techniques and algorithm has been used to predict gender. For this research we extracted features from Intensity, Texture and Shape.

## 2.1. Intensity images

Regarding to the intensity, we used the pixel raw values normalized between 0 and 1. The images acquired under NIR wavelength have a single channel, while the visible spectrum iris images contain three channels of information. The CROSS-EYED database [3] used a custom developed sensor that can capture simultaneously the NIR and RGB image. Therefore the conditions and distance of capture are very challenger. See Figure 1.

## 2.2. Uniform Local binary patterns (ULBP)

The texture feature is extracted from ULBPs as a grayscale texture operator that characterizes the spatial structure of the local image texture [19]. Given a central pixel in the image, a binary pattern number is computed by comparing its value with those of its neighbors. In [14] the authors show the relevance of uniform patterns increasing the accuracy of the texture method using the (8, 1) neighborhood and showing the statistically robustness of the patterns [25, 23]. The original operator used a 3x3 windows size that contains nine values. We computed the LBP features from the pixel intensities in a neighborhood.

$$LBP_{P,R}(x,y) = \bigcup_{(x',y')\in N(x,y)} h(I(x,y), I(x',y')) \quad (1)$$

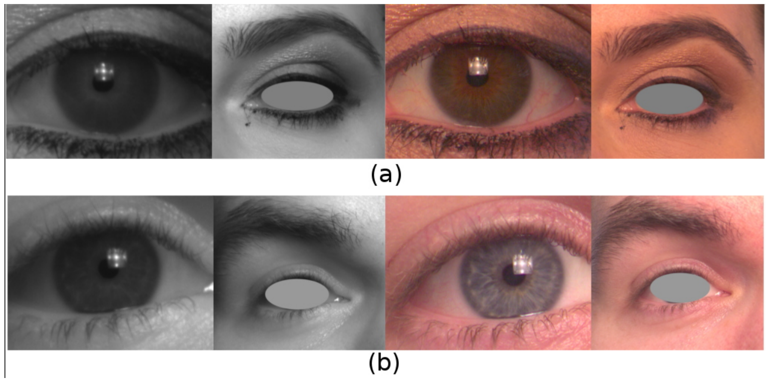


Figure 1. Examples of Cross-Eyed 2016 database. Figure a) Shown an Iris and Periocular female images with iris covered from NIR and VIS spectrum with make-up evidence. Figure b) Shown an Iris and Periocular male images with iris covered from NIR and VIS spectrum without make-up evidence.

where $N(x, y)$ is the vicinity around $(x, y)$, $\cup$ is the concatenation operator, $P$ is the number of neighbors, and $R$ is the radius of the neighborhood.

### 2.3. Histogram of gradients

The shape features are extracted from the HOG [12] using three different scales: 3 x 3, 5 x 5, and 10 x 10. Vertical and horizontal edge maps were computed using the masks $[-1, 0, 1]$ and $[-1, 0, 1]^T$. Consider $v$ and $h$ to be the vertical and horizontal edge values at any pixel, respectively, which were obtained by the convolution of the edge mask with the original image, respectively. The edge map is found using $\theta = tan^{-1}\left(\frac{v}{h}\right)$, and the edge magnitude is given by $m = \sqrt{v^2 + h^2}$. The edge map is discretized at $18^\circ$ intervals. Each pixel adds its magnitude $m$ to the bin that corresponds to its edge directions $\theta$. For $N$ image windows, an image is represented by $20 \times N$ real values.

## 3. Feature selection

Feature selection is a process in which features from a dataset are selected with the characteristics such as face, fingerprint, iris, hand, voice, gait, and signature. Biometric systems are based on the premise that many of the physical or behavioral attributes of humans can be uniquely associated with an individual of improving classification accuracy and decreasing computational complexity. It is closely related to feature extraction, a process in which feature vectors are created from the original dataset through manipulations of the data space, and can be considered to be a superset of the feature selection techniques.

Feature selection can be classified into three main groups: Filters, Wrappers, and Embedded [13]. Feature selection is also a broad field in continuous evolution, since selection of the most relevant and non-redundant features is not solved for complex problems such as in iris classification. Eliminating relevant or non-redundant features would result in poor behavior of the classifier. We present a strategy to select the most important features (relevant non-redundant) using methods based on Conditional Mutual Information [7, 13, 20, 29]. Since relevant features are often unknown a priori, irrelevant and redundant features may be introduced to represent the domain.

Mutual information ($MI$) is defined as a measure of how much information is jointly contained in two variables, or the degree to which knowledge of one variable determines the other variable. It forms the basis of information-theoretic feature selection, as it provides a function for calculating the relevance of a variable with respect to the target class (male or female). The $MI$, between two variables, $x$ and $y$, is defined based on their joint probabilistic distribution $p(x, y)$ and the respective marginal probabilities $p(x)$ and $p(y)$ as:

$$MI(x, y) = \int\int p(x, y) log \frac{p(x, y)}{p(x)p(y)} dxdy \qquad (2)$$

We consider $MI$ base for discrete (categorical) feature variables, the integral operation reduces to summation. In this case, computing $MI$ is straightforward, because both joint and marginal probability tables can be estimated by tallying the samples of categorical variables in the data.

One of the main concerns in gender classification using iris images has relationship with the influence of the make-up or mascara over the eyes. Therefore we used the feature selection methods as a tool to see the localization of the features on the NIR/VIS on iris/periocular images.

## 4. Experiments

In this paper we presents results for seven different experiments divided in three branches: The first branch is the experiment with iris NIR and VIS. The second branch is the experiment with periocular images with NIR and VIS image. The third branch is the feature selection based on $MI$.

In the Experiment 1, we used images with **VIS Iris Images** for the Left and the Right eyes. Experiment 2, we used images with **NIR Iris Images** for the Left and the Right eyes. Experiment 3, we used images with the **fusion of VIS +NIR Iris Images** for the Left and the Right eyes. Experiment 4, we used images with **VIS Periocular Images** for the Left and the Right eyes with iris area covered. Experiment 5, we used images with **NIR Periocular Images** for the Left and the Right eyes also with the iris area covered. Experiment 6, we used images with the **fusion of VIS +NIR periocular images** for the Left and the Right eyes. Finally, on Experiment 7 we used a feature selection method to analyze the best features to classify gender. See details of images in Figure1.

In order to extract features, we used three traditional techniques: Intensity (Pixels value), Texture (Local Binary Patterns) and Shape (Histogram of Oriented Gradients). We used a Uniform Local Binary Pattern (ULBP) with different radii from radius 1 up to 8 using RGB images (Visual images) and NIR spectrum for the left and right iris images. Also, we used an Histogram of Oriented Gradient (HOG) using different sizes of blocks in order to improve the results (3x3, 5x5, 10x10).

In this paper we used a Random Forest classifier [6]. It has a good predictive performance, incorporates interaction among predictor variables and returns measures of variable (pixels or feature) importance. Random Forest consists of a number of decision trees. Every node in the decision trees is a condition on a single feature, designed to split the dataset into two so that similar response values end up in the same set. The measure based on which the (locally) optimal condition is chosen is called impurity. For classification, it is typically either Gini impurity (GDI) for regression trees it is variance. Thus when training a tree, it can be computed how much each feature decreases the weighted impurity in a tree. For a forest, the impurity decrease from each feature can be averaged and the features are ranked according to this measure.

The Gini's Diversity Index (GDI):

$$1 - \sum_{i=1} = p^2(i) \tag{3}$$

where, the sum is over the classes $i$ at the node, and $p(i)$ is the observed fraction of classes with class $i$ that reach the node. A node with just one class (a pure node) has Gini index 0; otherwise the Gini index is positive. So the Gini index is a measure of node impurity.

## 5. Database

One of the most challenging problems in gender classification in iris or periocular research is related to databases because they were created focusing on the iris/face identification problem instead gender classification; thus, we can identify many sessions using the same subjects, and many of them do not have the gender information available, or it is a private information. Even more difficult is to capture images from the same person in different spectrum, Near Infrared Images and RGB images.

The CROSS-EYED, [3] - "Reading Cross-spectrum Iris/Periocular Dataset," is a benchmark dataset for the identification competition presented in BTAS 2016. It is composed of two eyes images in both visible (VIS/RGB) and NIR. The images are acquired from a distance of around 1.5 m. The images acquired under NIR wavelength have a single channel, while the visible spectrum iris images contain three channels of information. The images present a realistic indoor environment with a realistic illumination condition, and there are large variations in the ethnicity and eye color as well as realistic and challenging illumination reflections. The database is constructed with 120 subjects. Each subject is composed of two additional folders, one NIR and one VIS. For each subject, there are eight images (960 left and 960 right, 1,920 images per spectrum, **3,840 in total**), as demonstrated by 632 males and 328 females images with 18 females subject with visual evidence of make-up. See Figure 1.

A training portion per spectrum of 504 images dataset was created by selecting 320 males and 184 females images. We used a training set of 53% of the original data to select parameters of each method (Number of Trees). Once parameter selection is finalized, the selected parameterization of the method is trained on the full 53% training data, and a single evaluation is made on the 47% test data.

## 6. Results

In this section we present nine tables with the best results in bold for each experiment described previously in Section 4. All the Tables from 2 to 7 using the following acronyms: ACC: represent the Accuracy. TPR: True Positive Rate and TNR: represent the True Negative Rate. Also we present results using feature selection method (mRMR [20],CMIFS [10] and CMIM [13]) on Tables 8 and 9 in order to show the localization of the best feature on the iris and periocular images. In order to understand the influence of the periocular images we masked the iris area and compare the results of periocular images on NIR and VIS. This mask cover all the iris area, therefore we do not analyze the relevance of sclera on gender classification when used periocular images. See Figure 1.

Tables 2 to 7 show the accuracy using also a True Positive Rate and the Negative Rate. When a dataset is unbalanced, where the number of samples in one class is significantly more than that in the other class - this happens with Cross-Eyed 2016 dataset, the evaluated accuracy of a classifier is not representative of the true performance of the classifier. For the binary classification, problems as gender classification, we used this two metrics (TPR,TNR) which are commonly used to evaluate any binary classifier. For this paper the TNR refers to the accuracy on the class negative (female), and the TPR refers to the accuracy on the class positive (male). We can conclude that the male prediction is more confident, and this is especially based on the high value of the TPR and the low level of TNR due to the imbalance of female and male images. As can be seen, this is an important metric for analyzing the performance of classifiers only looking both separated.

Table 2. Results of Gender Classification using Cross-Eye Database with NIR Spectrum Iris images for the Left and the Right eyes.

| METHOD | LEFT EYE (%) IRIS NIR | | | RIGHT EYE (%) IRIS NIR | | |
|---|---|---|---|---|---|---|
| | ACC. | TPR | TNR | ACC. | TPR | TNR |
| RAW | 64.69 | 90.71 | 8.33 | 68.20 | 90.38 | 20.14 |
| LBP | | | | | | |
| (8,1) | 75.22 | 80.77 | 63.19 | **81.80** | **84.98** | **75.00** |
| (8,2) | 72.59 | 84.62 | 46.53 | 79.17 | 90.38 | 54.86 |
| (8,3) | 72.59 | 84.62 | 46.53 | 78.73 | 86.86 | 61.11 |
| (8,4) | 75.44 | 85.90 | 52.78 | 80.92 | 89.10 | 63.19 |
| (8,5) | 75.88 | 84.29 | 57.64 | 80.26 | 88.78 | 61.81 |
| (8,6) | 74.56 | 83.33 | 55.56 | 76.75 | 86.86 | 54.86 |
| (8,7) | 72.37 | 85.26 | 44.44 | 74.56 | 85.58 | 50.69 |
| (8,8) | 68.86 | 87.82 | 27.78 | 72.37 | 81.09 | 53.47 |
| [(8,1),(8,8)] | 77.85 | 87.18 | 57.64 | 81.36 | 90.38 | 61.81 |
| HOG | | | | | | |
| 3x3 | 78.51 | 85.29 | 63.89 | 76.97 | 87.82 | 53.47 |
| 5x5 | 76.32 | 84.94 | 57.64 | 80.26 | 90.38 | 58.33 |
| 10x10 | **78.73** | **84.62** | **65.97** | 77.85 | 87,82 | 56.25 |
| [5x5 10x10] | 77.85 | 84.62 | 63.19 | 78.73 | 88.78 | 56.94 |

Table 3. Results of Gender Classification using Cross-Eye Database with VIS Spectrum iris images for the Left and the Right eyes.

| METHOD | LEFT EYE (%) IRIS VIS | | | RIGHT EYE (%) IRIS VIS | | |
|---|---|---|---|---|---|---|
| | ACC. | TPR | TNR | ACC. | TPR | TNR |
| RAW | 68.42 | 100.00 | 0.00 | 71.05 | 100.00 | 8.33 |
| LBP | | | | | | |
| (8,1) | 74.78 | 82.69 | 57.64 | 75.22 | 80.77 | 63.19 |
| (8,2) | **77.63** | **83.65** | **64.58** | 78.73 | 84.94 | 65.28 |
| (8,3) | 75.88 | 87.82 | 50.00 | 78.29 | 83.97 | 65.97 |
| (8,4) | 67.54 | 85.58 | 28.47 | 75.88 | 77.56 | 72.22 |
| (8,5) | 69.74 | 79.17 | 49.31 | 80.70 | 83.01 | 75.69 |
| (8,6) | 68.20 | 80.13 | 42.36 | 82.46 | 91.03 | 63.89 |
| (8,7) | 70.83 | 78.21 | 54.86 | 79.17 | 87.18 | 61.81 |
| (8,8) | 69.74 | 75.96 | 56.64 | 77.63 | 89.42 | 52.08 |
| [(8,1),(8,8)] | 76.97 | 85.90 | 57.64 | **84.87** | **92.95** | **67.36** |
| HOG | | | | | | |
| 3x3 | 72.37 | 78.85 | 58.33 | 73.46 | 81.09 | 56.94 |
| 5x5 | 71.49 | 80.77 | 51.39 | 77.63 | 84.29 | 63.19 |
| 10x10 | 71.71 | 78.21 | 57.64 | 76.10 | 83.33 | 60.42 |
| [5x5 10x10] | 73.25 | 79.49 | 59.72 | 75.22 | 82.37 | 59.72 |

The results also show that the accuracy of gender classification from Iris images is lower than Periocular images. The NIR and VIS results are very similar using iris images. See Table 2 and 3. The fusion of NIR + VIS images using iris images did not improve the results of each one alone, even the results are competitive with the state of the art without using the iris recognition approach (Segmentation, Normalization, Encoding). See Table 4.

Table 4. Results of Gender Classification using Cross-Eye Database with the fusion of NIR + VIS Iris Images for the Left and the Right eyes.

| METHOD | LEFT EYE (%) IRIS VIS+NIR | | | RIGHT EYE (%) IRIS VIS+NIR | | |
|---|---|---|---|---|---|---|
| | Acc | TPR | TNR | Acc | TPR | TNR |
| HOG 3x3 | 76.75 | 84.29 | 60.42 | 73.68 | 83.88 | 52.78 |
| HOG 5x5 | 77.41 | 86.22 | 58.33 | **78.51** | **86.86** | **60.42** |
| HOG 10x10 | 77.63 | 83.65 | 64.58 | 77.41 | 86.86 | 56.94 |
| HOG [5x5 10x10] | **78.07** | **83.97** | **65.28** | 78.51 | 87.82 | 58.33 |

Regarding to periocular images, this approach achieved the best results using NIR and VIS and also with NIR + VIS fusion. See Tables 5 and 6.

Table 5. Results of Gender Classification using Cross-Eye Database with NIR Spectrum Periocular images for the Left and the Right eyes.

| METHOD | LEFT EYE(%) PERIOCULAR NIR | | | RIGHT EYE (%) PERIOCULAR NIR | | |
|---|---|---|---|---|---|---|
| | ACC. | TPR | TNR | Acc | TPR | TNR |
| RAW | 68.86 | 100.00 | 1.39 | 70.18 | 100.00 | 5.56 |
| LBP | | | | | | |
| (8,1) | 72.37 | 83.33 | 48.61 | 67.54 | 97.44 | 2.78 |
| (8,2) | 69.96 | 88.78 | 29.17 | 79.82 | 95.51 | 45.83 |
| (8,3) | 72.59 | 92.31 | 29.86 | 80.26 | 93.59 | 51.39 |
| (8,4) | 75.88 | 94.87 | 34.72 | 80.70 | 92.95 | 54.17 |
| (8,5) | 73.03 | 94.87 | 25.69 | 80.26 | 93.59 | 51.39 |
| (8,6) | 71.71 | 94.55 | 22.22 | 75.66 | 97.44 | 28.47 |
| (8,7) | 71.05 | 93.59 | 22.22 | 81.80 | 96.79 | 49.31 |
| (8,8) | 71.71 | 93.27 | 25.00 | 82.89 | 94.23 | 58.33 |
| [(8,1),(8,8)] | 74.56 | 96.79 | 26.39 | 79.82 | 100.00 | 36.11 |
| HOG | | | | | | |
| 3x3 | 69.74 | 77.24 | 10.20 | 76.75 | 78.85 | 72.22 |
| 5x5 | 81.14 | 88.14 | 65.97 | 84.21 | 87.50 | 77.08 |
| 10x10 | 82.24 | 92.31 | 60.42 | **85.31** | **88.74** | **75.69** |
| [5x5 10x10] | **83.77** | **91.67** | **66.67** | 84.21 | 89.74 | 72.22 |

Table 6. Results of Gender Classification using Cross-Eye Database with VIS Spectrum Periocular images for the Left and the Right eyes.

| METHOD | LEFT EYE (%) PERIOCULAR VIS | | | RIGHT EYE (%) PERIOCULAR VIS | | |
|---|---|---|---|---|---|---|
| | ACC. | TPR | TNR | ACC | TPR | TNR |
| RAW | 75.44 | 99.04 | 24.31 | 73.68 | 94.55 | 28.47 |
| LBP | | | | | | |
| (8,1) | 69.74 | 90.38 | 25.00 | 67.76 | 90.71 | 18.06 |
| (8,2) | 67.32 | 98.40 | 0.00 | 65.13 | 92.63 | 5.56 |
| (8,3) | 67.54 | 96.79 | 4.17 | 69.30 | 94.55 | 14.58 |
| (8,4) | 75.88 | 93.27 | 38.19 | 70.39 | 98.08 | 10.42 |
| (8,5) | 76.54 | 95.51 | 35.42 | 77.19 | 96.47 | 35.42 |
| (8,6) | 74.12 | 95.51 | 27.78 | 76.97 | 98.40 | 30.56 |
| (8,7) | 70.83 | 92.95 | 22.92 | 73.68 | 95.51 | 26.39 |
| (8,8) | 69.96 | 91.67 | 22.92 | 75.00 | 95.83 | 29.86 |
| [(8,1),(8,8)] | 75.66 | 95.19 | 33.33 | 72.15 | 99.36 | 13.19 |
| HOG | | | | | | |
| 3x3 | 69.52 | 89.74 | 25.69 | 75.22 | 87.82 | 47.92 |
| 5x5 | 76.97 | 83.97 | 61.81 | 82.24 | 88.78 | 68.06 |
| 10x10 | **78.07** | **86.54** | **59.72** | **83.11** | **84.94** | **79.17** |
| [5x5 10x10] | 76.54 | 86.22 | 55.56 | 82.02 | 83.65 | 78.47 |

The fusion of two spectrum in NIR and VIS with iris and periocular images increase the dimension of the data

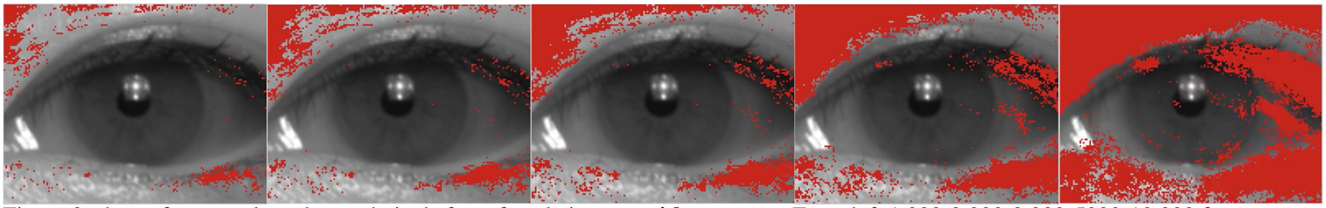

Figure 2. shows feature selected on red pixels from female images **with mascara**. From left 1,000-2,000-3,000-5000-10,000 features.

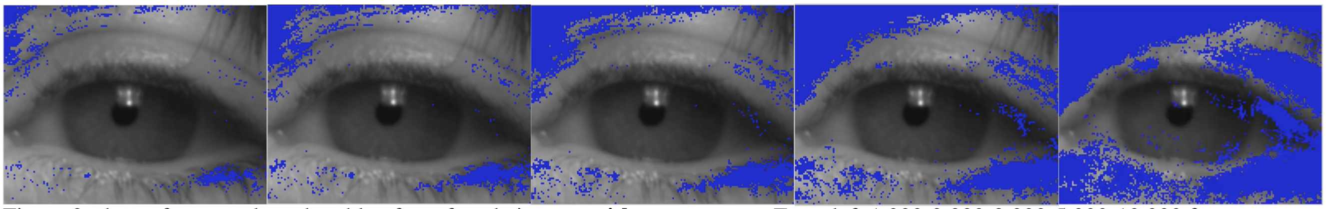

Figure 3. shows feature selected on blue from female images **without mascara**. From left 1,000-2,000-3,000-5,000-10,000 features.

although the results show improvements, we have a lot of redundancy in the fusion. See Table 7. Therefore the feature selection can increase the accuracy even more. See Tables 8 and 9.

Table 7. Results of Gender Classification using Cross-Eye Database with the fusion of NIR+ VIS Periocular images for the Left and the Right eyes.

| METHOD | LEFT EYE (%) PERIOCULAR VIS+NIR | | | RIGHT EYE (%) PERIOCULAR VIS + NIR | | |
|---|---|---|---|---|---|---|
| | ACC. | TPR | TNR | Acc | TPR | TNR |
| HOG 3x3 | 71.05 | 92.31 | 25.00 | 77.85 | 89.74 | 52.08 |
| HOG 5x5 | 77.41 | 87.82 | 54.86 | 81.14 | 91.67 | 58.33 |
| HOG 10x10 | 80.04 | 90.71 | 56.94 | **87.06** | **91.48** | **81.94** |
| HOG [5x5 10x10] | **80.26** | **87.50** | **64.58** | 85.31 | 90.06 | 75.00 |

Table 8. Results of Gender Classification using Cross-Eye Database with HOG 5x5 from Periocular Left and the Right eyes. N FEAT: represents the number of the best features. N TREES: The number of the trees for Random Forest Classifier.

| HOG 5x5 | | | | | | |
|---|---|---|---|---|---|---|
| FEAT. | LEFT EYE (%) | | | RIGHT EYE (%) | | |
| | ACC. | N FEAT. | N TREES | ACC. | N FEAT. | N TREES |
| VISUAL SPECTRUM | | | | | | |
| CMIFS | 82.24 | 20 | 150 | 86.62 | 50 | 100 |
| mRMR | 85.53 | 20 | 200 | 87.28 | 20 | 150 |
| CMIM | 87.28 | 10 | 200 | **87.94** | **20** | **200** |
| NEAR INFRARED SPECTRUM | | | | | | |
| CMIFS | 85.53 | 80 | 175 | 85.75 | 30 | 75 |
| mRMR | **88.60** | **40** | **175** | 84.87 | 30 | 50 |
| CMIM | 85.31 | 120 | 175 | 85.75 | 100 | 100 |

The best results using feature selection were reached with HOG 3x3 and 5x5 with less of 50% of features for each case. See Table 8 and 9. The feature selection methods using all the features (with an without make-up) to computing the mutual information, the relevance and redundancy of each feature. However if we continue increasing the number of relevant features the accuracy lower drastically because we add higher redundancy information thus we may confused the classifier. The results also show that with a

Table 9. Results of Gender Classification using Cross-Eye Database with HOG 10x10 from Periocular Left and the Right eyes. N FEAT: represents the number of the best features. N TREES: The number of the trees for Random Forest Classifier

| HOG 10x10 | | | | | | |
|---|---|---|---|---|---|---|
| FEAT. | PERIOCULAR LEFT(%) | | | PERIOCULAR RIGHT (%) | | |
| | ACC. | N FEAT. | N TREES | ACC. | N FEAT. | N TREES |
| VISUAL SPECTRUM | | | | | | |
| CMIFS | 84.87 | 250 | 600 | 88.82 | 275 | 700 |
| mRMR | 84.87 | 50 | 700 | 89.04 | 425 | 700 |
| CMIM | **86.40** | **25** | **400** | **89.25** | **300** | **400** |
| NEAR INFRARED SPECTRUM | | | | | | |
| CMIFS | 87.72 | 200 | 800 | 89.47 | 175 | 600 |
| mRMR | **89.69** | **50** | **900** | 89.47 | 400 | 400 |
| CMIM | 89.47 | 50 | 800 | **89.69** | **400** | **400** |

lower number of relevant features, we can reach a higher performance on gender classification in both classes using the features around the iris and surrounding areas on periocular images. See Figure 2 and 3.

Also we analyze the relative influence of make-up on the images due to the number of females subjects with mascara. The features or pixels that belongs to make-up only are selected if we use a higher number of features, more than the half. Therefore this represent a suboptimal condition with features with high redundancy. Thus, we can classify gender using only the more relevant features of iris or periocular images. The best performance was reached with a lower number of features and did not select the features that belong to the make-up. See Figure 4 and 5.

## 7. Conclusion

Gender classification from periocular images is a challenging topic, this is an ongoing research. To understand all previous works on gender-from-periocular studies, we find the best feature-extraction techniques to represent the information of eyes. Experimental results suggest: (a) Features extracted in different scales can perform better than using only one feature in a single scale; (b) The periocular images

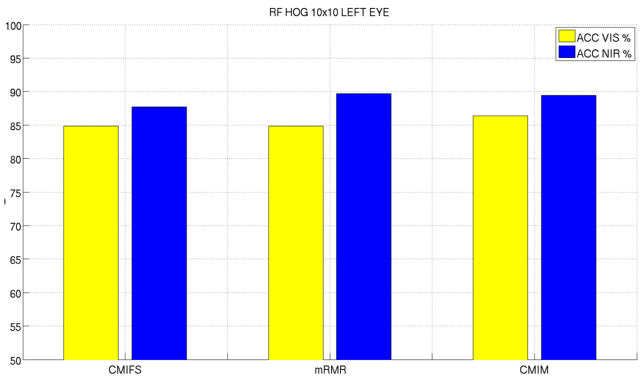


Figure 4. Comparison of the best results considering NIR (blue) versus VIS (yellow) spectrums for the left eye using HOG 10x10 with CMIFS, mRMR and CMIM. The Y axis shows the accuracy in percent and X axis shows the three feature selected methods.

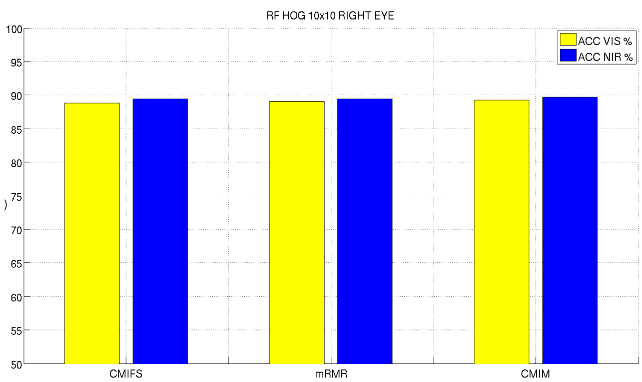


Figure 5. Comparison of the best results considering NIR (blue) versus VIS (yellow) spectrums for the right eye using HOG 10x10 with CMIFS, mRMR and CMIM. The Y axis shows the accuracy in percent and X axis shows the three feature selected methods.

performed better than iris images on VIS and NIR; c) The fusion of features on different spectral images NIR and VIS allows improve the accuracy but increase the dimension of the data therefore higher redundancy; (c) The feature selection applied to NIR and VIS allows select relevant features and improvement the results d) The features selected from iris or periocular images only included the make-up on high dimensional problem. The make-up may be considered data with redundancy information. Our accuracy 90% is competitive with the state of the art. The results show promise towards using periocular region for classify gender and also add complementary information to recognition system when the data is not sufficient for iris recognition. A bigger dataset with a high number of females with and without make-up must be developed to establish a general conclusion.


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