Understanding Critical Factors in Appearance-Based Gender Categorization

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Abstract. Gender categorization, based on the analysis of facial appearance, can be useful in a large set of applications. In this paper we investigate the gender classification problem from a non-conventional perspective. In particular, the analysis will aim to determine the factors critically affecting the accuracy of available technologies, better explaining differences between face-based identification and gender categorization.

A novel challenging protocol is proposed, exploiting the dimensions of the Face Recognition Grand Challenge version 2.0 database (FRGC2.0). This protocol is evaluated against several classification algorithms and different kind of features, such as Gabor and LBP. The results obtained show that gender classification can be made independent from other appearance-based factors such as the skin color, facial expression, and illumination condition.

1 Introduction

It can be rather difficult to reliably categorize the gender of an unknown individual from its exterior appearance. Humans can perform this task pretty well on the basis of a number of independent features, not limited to the facial appearance. The tone of the voice, the gait, the hair style and dressing are all factors which strongly affect our judgement of gender. Yet, in some cases, gender categorization can be difficult for humans as well. For these reasons, gender categorization, posed as a binary classification problem from a number of face samples, is a very challenging task, but with a strong application potential [1,2]. A successful gender classification system can boost a large number of applications, such as search engines, surveillance systems, and interfaces, and it may help to better tailor public services to the user's needs. In the last two decades, the computer vision community has proposed several approaches to face-based gender classification. Starting from the seminal work of Golomb, Lawrence, and Sejnowski [3], key contributions are due to Cottrell and Metcalfe [4] – who proposed a multi-layer neural network approach – and Brunelli and Poggio [5], who detailed in the early 90s a system based on HyperBF networks. More recently, Moghaddam et al. [6] proposed a methodology based on Support Vector Machines (SVM). Mäkinen and Raisamo [7] surveyed several methodologies based on Multilayer Neural Network, SVM and Discrete AdaBoost. Lapedriza and

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colleagues [8] investigated the usage of boosting classifiers, like AdaBoost and JointBoosting. Shobeirinejad and Gao [9] presented a technique in which a histogram intersection is used as a measure of similarity for classification.

Most of the contributions listed above agree on a generic processing scheme composed of a preliminary feature extraction step, followed by a classification algorithm. This scheme proved to be effective in face recognition and the extension to gender classification has been quite straightforward and equally effective. In fact, these two steps are semantically very different: feature extraction has to do with image signals which are considered relevant for the problem (for instance the skin color could be extremely relevant for race detection) whilst classification has to do with the optimal partition of the feature space, possibly taking into account existing constraints.

In this paper we investigate gender categorization by means of an extended empirical analysis on the Face Recognition Grand Challenge version 2.0 (FRGC2.0) dataset [10]. To this extent, a **first contribution** concerns the proposal of a challenging experimental protocol for gender categorization. Inspired by the above feature extraction-classification dichotomy and from the experiments detailed in [10], a procedure is described based on exploiting the dimensions embedded in the data collected in FRGC2.0 – i.e. identity, facial expression, skin color, and environmental conditions. The proposed protocol is for general purpose, and it can be easily extended to other datasets and to different features and classifiers.

A **second, and more relevant contribution**, concerns the application of the proposed protocol to a significant set of features and classifiers, proving that gender classification should be treated as a very different problem from face classification. In our experiments 1-Nearest-Neighbour [11], Aggregation Pheromone density based pattern Classification (APC) [12], and Support Vector Machines [13] are used as classifiers. Feature extraction is based on Gabor features – see, e.g., [14] –, Local Binary Patterns (LBP) [15] and raw pixel values with histogram equalization.

Notably external factors critically affecting the accuracy of face recognition like race, expressions and environmental conditions, are almost <u>irrelevant</u> for gender categorization. This fact is in agreement with the human ability to judge a person's gender from the facial appearance only. We also report interesting insights related to the feature extraction step. Particularly, Gabor features turn to be an effective choice in uncontrolled environment, while, in the case of controlled environment raw pixel values perform equally well.

The paper is structured as follows. In Section 2 we introduce the notation used and we give a brief description of the FRGC2.0 dataset. We also briefly introduce both the classification algorithms and the feature extraction methods herewith employed. In Section 3 we describe our experimental setup, detailing the experimental protocol. Section 4 shows the results of the experimental protocol applied to a selected set of features and classifiers. Finally, in Section 5 conclusions are drawn.

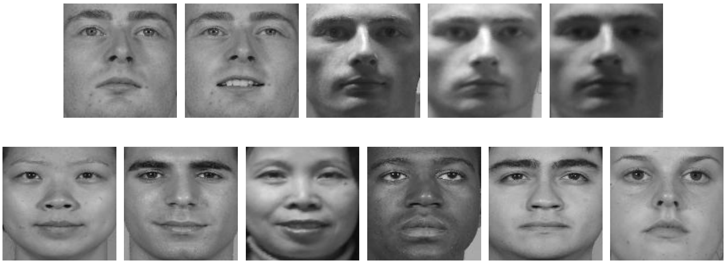

Fig. 1. Images samples from the FRGC2.0 database. Neutral, smiling and different light conditions images from the same person are depicted in the first row. In the second row, they are depicted images related to the different races, namely Asian, Asian Middle Eastern, Asian Southern, Black or African American, Hispanic, and White.

2 Data, Algorithms, and Features

2.1 The FRGC2.0 Dataset

The proposed computational analysis of gender categorization is based on processing 2D face images comprised in the Face Recognition Grand Challenge dataset, version 2.0. The dataset is composed of more than 50,000 images (see Figure 1), divided into a training and a validation set [10], denoted as Γ and Σ, respectively.

As both Γ and Σ include all subjects (males and females) involved in the images collections, the FRGC2.0 training set can be regarded as a set $\Gamma = \{\underline{\gamma}_1, \ldots, \underline{\gamma}_n\}$, with $n = 291$ (the total amount of involved subjects), in which each $\underline{\gamma}_j$ denotes the pool of images related to the subject j. Each image $\gamma_{jk} \subset \underline{\gamma}_j$ is characterized by a tuple of three elements $< C, E, R >$, where:

- $C = \{c2l, c3l, u\}$ denotes the types of control, i.e., controlled images with two or three studio lights ($c2l$ and $c3l$, respectively), and uncontrolled images (denoted as u).
- $E = \{BlankStare, Happiness\}$ denotes the facial expressions in the dataset images, i.e., neutral and smiling, respectively.
- $R = \{A, AME, AS, BAA, H, U, W\}$ denotes the race of the subject, where, following the categorization of FRGC2.0, A stands for "Asian", AME for "Asian Middle Eastern", AS for "Asian-Southern", BAA for "Black or African American", H for "Hispanic", while U stands for "Unknown", and, finally, W denotes "White" race.

The same categorization can be applied to the test set $\Sigma = \{\underline{\sigma}_1, \ldots, \underline{\sigma}_n\}$, with n =466.

2.2 Algorithms

In this paper, gender categorization is modeled as a binary pattern classification problem. In binary classification, a set of patterns is given, i.e., input vectors

$X = \{\underline{x}_1, \ldots \underline{x}_k\}$ with $\underline{x}_i \in \mathbb{R}^n$, and a corresponding set of labels, i.e., output values $Y \in \{0, 1\}$ – in this case, male and female. The labels as generated by some unknown function $f : \mathbb{R}^n \to \{0, 1\}$ applied to the patterns, i.e., $f(\underline{x}_i) = y_i$ for $i \in \{1, \ldots, k\}$ and $y_i \in \{0, 1\}$. The task of a binary classifier c is to extrapolate f given X and Y, i.e., to construct c from X and Y so that when given some $\underline{x}^\star \in X$, $c(\underline{x}^\star)$ will equal $f(\underline{x}^\star)$; such task can be achieved *training an inductive model* of c.

In the following, the classifiers applied for gender categorization analysis are briefly reviewed.

- **1-nearest-neighbor** (1-NN): this classifier yields the label of the training instance which is closer to the given test instance, whereby closeness is evaluated using some proximity measure, e.g. Euclidean distance; we use the method described in [11] to store the training instances for fast look-up.
- **Aggregation Pheromone density based pattern Classification** (APC): this is a pattern classification algorithm modeled on the ants colony behavior and distributed adaptive organization in nature. Each data pattern is considered as an ant, and the training patterns (ants) form several groups or colonies depending on the number of classes present in the data set. Each colony releases a quantity of pheromones proportional to the population of ants. A new test pattern (ant) will move along the direction where the average aggregation pheromone density (at the location of the new ant) is higher and eventually it will join that colony [12].
- **Support Vector Machines** (SVM): this is a supervised learning algorithm used for both classification and regression tasks. Roughly speaking, the basic training principle of SVMs is finding an optimal linear hyperplane such that the expected classification error for (unseen) test patterns is minimized [13].

2.3 Features

Different input vectors X are extracted from Γ and Σ either as raw pixel values, Gabor or LBP features. In order to avoid registration errors, all images are first aligned according to the positions of the eyes.

The most elementary features used are the raw pixel values (denoted as PV), extracted from the image matrix (re-scaled to 64x64 pixels) and aligned in a mono-dimensional vector. To compensate for illumination changes, histogram equalization is first applied.

Gabor features are extracted by applying a standard bank of Gabor kernels with 5 scales and 8 orientation. For each image, a feature vector of 2560 elements is extracted by sampling the filters outputs on the 64 nodes of a uniform 8×8 grid. All processing is based on the Feature Extraction Library (FELib) [16].

A modified version of the original Local Binary Pattern operator (LBP) has been also applied. The LBP operator is denoted as $LBP_{P,R}$, where P is the number of sampling points on a circle of radius R. An interesting extension of LBP takes into account the bitwise transitions of the obtained binary pattern [15]. In order to obtain a good trade-off between description performance and feature

Table 1. Synopsis of training, validation and test sets. The table is structured as follows. The first column shows the name of set (in the case of test sets, we report groups only), and it is followed by three columns. The first column ("#") reports the total amount of images in the set, while the remaining two ("F" and "M") report the percentage of the images in the set, labeled as female and male, respectively.

	#	**F**	**M**
Γ_t	1027	42.65%	57.35%
Σ_v	1292	43.19%	56.61%
Σ_a	1262	45.01%	54.99%
Σ_b	1958	50.56%	49.45%
Σ_c	1958	50.56%	49.45%

vector length, the $LBP^{u2}_{8,2}$ operator has been used [17]. Each image is divided into a a uniform 7 × 7 grid and the $LBP^{u2}_{8,2}$ is applied to each resulting sub-window. The histograms are computed within each window independently and concatenated. The resulting histogram has size m x n where m is the number of windows (49 in this case) and n is the length of a single $LBP^{u2}_{8,2}$ histogram (10 in this case). Therefore, the total histogram is composed of 490 buckets.

3 Experimental Setup

In order to evaluate the gender categorization capability of the chosen classifiers on the given feature sets, an experimental protocol has been devised, based on the FRGC2.0 dataset. The dataset is composed of about 40,000 images from 466 subjects of different races, 43.93% are female and 56.07% are male. Images were taken at different illumination conditions, and with different facial expressions.

The aim of the experimental trial is to compute the classification models trained on data having specific values of C, E, and R. Towards this end, the algorithms described in Section 2.2 are trained selecting controlled images – two studio lights – related to "Caucasian" subjects (the most recurrent in the FRGC2.0) showing a neutral expression. In other words, the classifiers are trained on a set Γ_t in which, for each subject j, $|\underline{\gamma_j}|$ is equal to the total amount of images $\gamma_{jk} \subset \underline{\gamma_j}$ such that $(C = c2l) \wedge (E = BlankStare) \wedge (R = W)$.

It is well-known, from machine learning literature, that classifiers performance may vary with different parametrization tunings. In order to provide a fair comparison among classifiers, the FRGC2.0 validation set Σ is divided into two parts. The first part is composed of the images related to the 291 subjects also occurring in Γ. This partition – denoted as Σ_v – is used just for parameter tuning. Σ_v is established with the same criteria applied for Γ:

$$\Sigma_v : \text{for each subject } j,\ \sigma_{jk} \subset \underline{\sigma_j} \text{ such that } (C = c2l) \wedge (E = BlankStare) \wedge (R = W)$$

Concerning the test set, we consider the partition of Σ composed of the images from the 175 subjects *not occurring* in Γ. Nine different test sets are extracted and organized in three groups:

- Σ_a: for each subject j, $\forall \sigma_{jk} \subset \underline{\sigma_j} \in \Sigma$ such that $\underline{\gamma_j} \notin \Gamma$ and $(E = BlankStare) \wedge (R = W)$. The rationale is to have the same facial expression and race of the training set, in order to have a baseline for the comparisons. This group is composed of three test sets, i.e., $\Sigma_{a,c2l}$, $\Sigma_{a,c3l}$, $\Sigma_{a,u}$, representing test sets in which σ_{jk} has a value of C equal to $c2l$, $c3l$, and u, respectively.
- Σ_b: for each subject j, $\forall \sigma_{jk} \subset \underline{\sigma_j} \in \Sigma$ such that $\underline{\gamma_j} \notin \Gamma$ and $(E = BlankStare)$. In this group are involved images that are not constrained to a particular value of R. The rationale is to compare the accuracy of the classifiers with respect to the race. Also this group if composed of three test sets, i.e., $\Sigma_{b,c2l}$, $\Sigma_{b,c3l}$, $\Sigma_{b,u}$.
- Σ_c: for each subject j, $\forall \sigma_{jk} \subset \underline{\sigma_j} \in \Sigma$ such that $\underline{\gamma_j} \notin \Gamma$ and $(E = Happiness)$. The rationale is to compare the accuracy of the classifiers with respect to different facial expressions. Also this group is not constrained by a particular value of R. It is composed of three test sets: $\Sigma_{c,c2l}$, $\Sigma_{c,c3l}$, $\Sigma_{c,u}$.

Cardinalities and label distributions of the sets are reported in Table 1.

4 Experimental Results

The first experimental trial is aimed to train a gender categorization model based on 1-NN, APC, and SVM. A parameter grid search involving both APC and SVM is performed, as follows:

- Concerning APC, we explore the parameter δ related to the pheromone intensity as described in [12].
- Concerning SVM, we consider a C-SVC with a Radial Basis Function (RBF) kernel. In particular, we explore the parameter space related to both cost c and the parameter g of the kernel RBF.

We test the obtained models on Σ_v, and the results of these experiments with the best parameter configuration – in terms of accuracy – are shown in Table 2. For all experiments described, when referring to APC and SVM, the parametrization in Table 2 was applied.

In the next experiment, the performance of 1-NN, APC, and SVM, trained on Γ_t using PV features, and tested on the test sets described in Section 3 are evaluated. The obtained results are summarized in Table 3.

From table 3, SVM outperforms all classifiers, reporting an accuracy greater than 90% on all test sets with $C = c2l$ and $C = c3l$ in both groups Σ_a and Σ_b. SVM is also the best performing classifier for $C = u$. Concerning $\Sigma_{a,c2l}$, the SVM accuracy is more than 10% higher than both 1-NN and APC. The classification results related to $\Sigma_{a,c2l}$ can be regarded as a reference, because it is composed of images having the same value of C, E, and R used to compute Γ_t.

Considering the results related to $\Sigma_{a,c3l}$, the accuracy of all classifiers is very close to the one reported for $\Sigma_{a,c2l}$. As a consequence, we can conjecture that

Table 2. Parameter optimization for the considered algorithms. The table is organized as follows: The first column shows the name of the algorithms, and it is followed by three groups of columns, reporting the results of the optimization considering PV, Gabor and LBP features. Each group of columns is composed of two subcolumns, reporting the accuracy (column "Acc.") of the computed model, and the related parameters (column "Par.").

Classifier	**PV**		**Gabor**		**LBP**	
	Acc.	**Par.**	**Acc.**	**Par.**	**Acc.**	**Par.**
`1-NN`	97.54%	–	98.99%	–	96.59%	–
`APC`	95.90%	$\delta = 2$	99.07%	$\delta = 0.1$	94.27%	$\delta = 50$
`SVM`	98.80%	$c = 2,\ g = 0$	99.46%	$c = 2,\ g = 2$	97.29%	$c = 16,\ g = $ 2e-06

Table 3. Evaluation results using PV features. The table is composed of four columns. The first one ("Test set") denotes the test set on which classifiers has been evaluated. The three following columns report the accuracy performance (in percentage) related to 1-NN, APC, and SVM (columns "1-NN", "APC", and "SVM", respectively).

Test set	**1-NN**	**APC**	**SVM**
$\Sigma_{a,c2l}$	83.60%	84.86%	95.80%
$\Sigma_{a,c3l}$	81.70%	84.15%	95.01%
$\Sigma_{a,u}$	64.10%	67.99%	76.39%
$\Sigma_{b,c2l}$	81.31%	82.38%	91.37%
$\Sigma_{b,c3l}$	81.10%	82.69%	91.78%
$\Sigma_{b,u}$	63.89%	66.70%	75.49%
$\Sigma_{c,c2l}$	80.03%	80.54%	88.07%
$\Sigma_{c,c3l}$	81.00%	81.15%	89.07%
$\Sigma_{c,u}$	65.83%	68.08%	78.19%

all considered classifiers are robust with respect to controlled illumination variations. From the results obtained from images captured in an uncontrolled environment – $\Sigma_{a,u}$ –, the performances of the classifiers decrease. SVM still provides the best classification performance, but its accuracy is about 20% lower than the one reported for both $\Sigma_{a,c2l}$ and $\Sigma_{a,c3l}$.

Considering the results related to Σ_b, the same results described for Σ_a hold: SVM outperforms the other classifiers, and there is a lack of performance for $C = u$. The resulting accuracy of all classifiers is very close to that reported for Σ_a. However, as discussed in Section 3, the images comprised in such test sets are not constrained from a particular value of R. As a consequence, we can conjecture that classifiers performance are not affected by race variations. The same conclusions can be drawn from the results related to the group Σ_c, in which also E (facial expression) is not constrained.

As for Gabor features, the results of the performed experiments are summarized in Table 4. Also in this case SVM outperforms the other classifiers, reaching an accuracy greater than 90% on all test sets having $C = c2l$ and $C = c3l$. SVM is also the best performing classifier for $C = u$. Concerning $\Sigma_{a,c2l}$, SVM accuracy is more than 5% greater than APC accuracy, and about 9% greater than 1-NN

Table 4. Evaluation results using Gabor features. The table is organized as Table 4.

Test set	1-NN	APC	SVM
$\Sigma_{a,c2l}$	82.88%	86.53%	91.92%
$\Sigma_{a,c3l}$	83.44%	87.48%	92.95%
$\Sigma_{a,u}$	64.66%	68.70%	78.68%
$\Sigma_{b,c2l}$	83.20%	86.57%	90.60%
$\Sigma_{b,c3l}$	83.71%	87.13%	91.62%
$\Sigma_{b,u}$	65.37%	68.18%	77.99%
$\Sigma_{c,c2l}$	74.44%	80.75%	90.14%
$\Sigma_{c,c3l}$	74.11%	81.61%	90.81%
$\Sigma_{c,u}$	63.48%	64.86%	71.12%

Table 5. Evaluation results using LBP features. The table is organized as Table 3.

Test set	1-NN	APC	SVM
$\Sigma_{a,c2l}$	79.63%	81.93%	90.89%
$\Sigma_{a,c3l}$	81.30%	81.06%	91.36%
$\Sigma_{a,u}$	53.80%	51.34%	51.98%
$\Sigma_{b,c2l}$	82.79%	85.03%	91.73%
$\Sigma_{b,c3l}$	82.53%	83.76%	92.13%
$\Sigma_{b,u}$	49.08%	52.35%	54.44%
$\Sigma_{c,c2l}$	80.08%	81.97%	90.40%
$\Sigma_{c,c3l}$	77.43%	78.65%	89.32%
$\Sigma_{c,u}$	56.84%	54.70%	55.41%

accuracy. Considering the results related to $\Sigma_{a,c3l}$, the accuracy of all classifiers is very close to the one reported for $\Sigma_{a,c2l}$. Also for $\Sigma_{a,u}$, a lack of classifiers performance is reported. SVM still produces the best classification results, but its accuracy is about 14% smaller than the one reported for both $\Sigma_{a,c2l}$ and $\Sigma_{a,c2l}$. The performance of both 1-NN and APC also decrease of about 20%. Considering the results related to Σ_b, the same results described for Σ_a hold: SVM outperforms the other classifiers, and there is a lack of performance for $C = u$. The accuracy reported for all classifiers is very close to that reported for Σ_a.

The last experiment performed is similar to the previous one, but LBP features were used instead of Gabor features. The obtained results are reported in Table 5.

Also in this case, SVM is the best performing classifier – in terms of accuracy. From the results related to Σ_a, Σ_b, and Σ_c, the same conclusions made for both PV and Gabor features can be drawn. This fact confirm our conjecture that gender classification is independent from the values of E (facial expression) and R (race), and also from controlled illumination variations. However, differently from the previous experiments, LBP features are almost useless in the uncontrolled cases $\Sigma_{a,u}$, $\Sigma_{b,u}$, and $\Sigma_{c,u}$.

5 Conclusions

The gender categorization problem has been analyzed trying to understand which factors critically affect the accuracy of available technologies. The proposed protocol exploited the dimensions of the FRGC2.0 database, analyzing the sensitivity of a two-steps feature extraction-classification approach with respect to three different classifiers and three orthogonal types of features.

The results of our empirical analysis can be summarized as follows:

- Gender categorization is independent from the race of the subjects. Our results show that training an inductive model on a set of images composed of subject of only one race, the accuracy of the classifiers is about the same if in the test set we involve subjects of different races.
- The accuracy in gender categorization does not change in a noticeable way for controlled changes of illumination. We showed that, training classifiers on FRGC2.0 controlled images with two studio lights, and testing them on controlled images with three studio lights, the accuracy result is almost the same of the test performed on controlled images with two studio lights.
- Different facial expressions do not influence in a noticeable way the gender categorization accuracy applying SVM to Gabor and LBP features. A marginal degradation is reported for PV features, starting from a 96% accuracy obtained for $\Sigma_{a,2cl}$. This fact is probably related to the iconic information content of PV features, while both Gabor and LBP features are mainly related to the frequency image content.

As a final comment, our analysis confirms that race, facial expression, and illumination condition are almost irrelevant for gender categorization from human faces. Obviously, relaxing the constraints for race and expression, the identification performance decreases. But this finding is independent from both classifiers and features.

Concerning the adopted classifiers, SVMs always outperform the other classifiers. The analysis performed in this paper confirms that Gabor features are an effective choice in the case of uncontrolled environments. Moreover, elementary features such as raw pixel values can be usefully applied for gender categorization.

As future work, we are planning to investigate additional dimensions of FRGC2.0, e.g. age, and to extend our analysis to other datasets, including masking and face occlusions. In addition, we plan to extend our analysis to additional feature representation and state-of-the-art gender classification methods, and carefully consider the statistical significance of the classifier results.

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