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Soft biometric classification using local appearance periocular region features

Jamie R. Lyle *, Philip E. Miller, Shrinivas J. Pundlik, Damon L. Woodard **

School of Computing, Biometrics and Pattern Recognition Lab, Clemson University, Clemson, SC 29634, USA

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ABSTRACT

This paper investigates the effectiveness of local appearance features such as Local Binary Patterns, Histograms of Oriented Gradient, Discrete Cosine Transform, and Local Color Histograms extracted from periocular region images for soft classification on gender and ethnicity. These features are classified by Artificial Neural Network or Support Vector Machine. Experiments are performed on visible and near-IR spectrum images derived from FRGC and MBGC datasets. For 4232 FRGC images of 404 subjects, we obtain baseline gender and ethnicity classifications of 97.3% and 94%. For 350 MBGC images of 60 subjects, we obtain baseline gender and ethnicity results of 90% and 89%.

1. Introduction

The periocular region biometric has lately gained attention as an alternative method for recognition where the face and iris modalities are captured under non-ideal conditions [1,2]. Several studies have shown the periocular region to be one of the most discriminative regions of the face for partial face recognition [3–6]. The periocular region, when used independently, has achieved limited success in highly controlled settings. Recent work has been done to investigate periocular recognition under non-ideal conditions [7]. Other studies have investigated using the periocular region to boost performance in identification tasks by fusing with face or iris information [8]. Previous work has also postulated that periocular region features can be used independently for soft biometric classification [9]. Soft biometric information can be used to describe an individual in broad categories, but is not specific enough to identify the individual uniquely [10]. Soft biometric information can include attributes such as gender, ethnicity, or even age. While the soft biometric information does not uniquely identify a subject, it can narrow the search space or provide additional information to boost performance during recognition tasks.

Few studies have been performed using the periocular region for soft biometric classification. Merkow et al. investigated gender classification of the periocular region using Local Binary Patterns (LBP) and pixels as features with LDA and SVM as classifiers achieving 85% performance on images collected from the web [24]. Lyle et al. performed gender and ethnicity classification using the same features and SVM classification. They achieved 93% for gender and 91% for ethnicity using images derived from the FRGC database [9]. Due to the popularity of facial recognition, face images have been used quite frequently to obtain both gender and ethnicity information. Table 1 details other key approaches in gender and ethnicity classification which use facial images. The majority of the approaches listed use very small images or feature vectors to perform classification while achieving very good results. A few detail the variables present in the dataset such as varying illumination and expression. Most of the approaches rely on appearance based features. For classification, the most popular schemes are Support Vector Machines (SVM), Artificial Neural Networks (ANN), and Adaboost (including various boosters). In most cases the approaches were evaluated using *k*-fold cross-validation. While the feature vector size differs, this paper endeavors to apply the most successful, widely used approaches for face classification to soft biometric classification of periocular images.

The goal of this paper is to investigate the effectiveness of different classifiers and periocular features across varying conditions according to soft biometric classifications. We explore the utility of various features, classifiers, sub-regions of an periocular image, and different combinations thereof. Within this work we concentrate on gender and ethnicity classification using the periocular and eye regions comparing the results to similar full face experiments. Fig. 1 shows examples of periocular regions belonging to the different classes used in this work. For this work we define the periocular region as the region surrounding the eye

* Corresponding author.
** Principal corresponding author.
E-mail addresses: jlyle@clemson.edu (J.R. Lyle), pemille@clemson.edu (P.E. Miller), spundli@clemson.edu (S.J. Pundlik), woodard@clemson.edu (D.L. Woodard).

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Table 1
A summary of the gender and ethnic classification approaches using face images. The recognition results are the best combined results reported [9].

Approach	Features	Classifier	Variables	Dataset	Recognition	
					Ethnicity	Gender (%)
Gutta et al. [11]	Grayscale pixel intensities	Ensembles of RBFs using DTs	–	FERET	92% (Caucasian, South Asian, East Asian, African)	96
Moghaddam and Yang [12]	Low-res grayscale images	SVM	–	FERET	–	97
Balci and Atalay [13]	PCA eigenvectors	Multilayer Perceptron		FERET	–	92
Wu et al. [14]	Grayscale pixel intensity	LUT weak classifier based Adaboost	–	FERET, WWW images	–	88
Hosoi et al. [15]	Gabor wavelet transform with retina sampling	SVM	Illumination	HOIP, misc. images	Asian—96%, European—93%, African—94%	–
BenAbdelkader and Griffin [16]	Local and global features (eigenfaces)	SVM, FLD	Illumination expression	FERET, PIE, Univ. of Essex	–	94
Lapedriza et al. [17]	DOG, LOG filters on facial fragments	Adaboost, Jointboost	Illumination	FRGC	–	92
Lu et al. [18]	Range and pixel intensity	SVM	–	Univ. of Notre Dame, Michigan State Univ.	98% (Asian, non-Asian)	91
Yang et al. [19]	Normalized face	SVM, LDA, Adaboost	Automatic detection	Chinese snapshot, FERET	–	97
Yang and Ai [20]	LBP, Haar like features	Adaboost	Expression	FERET, PIE, Chinese snapshot	97% (Asian, non-Asian)	93
Makinen and Raisamo [21]	Grayscale pixel intensity, Haar like, features, LBP	SVM, NN, Adaboost	Automatic detection	IMM face dataset, FERET	–	84
Xu et al. [22]	Haar (appearance)	SVM	–	FERET, AR, WWW images	–	92
Gao and Ai [23]	ASM based landmarks for normalization (grayscale intensities)	SVM, Adaboost, Probabilistic Boosting Trees (PBT)	Illumination expression pose	Chinese snapshot, consumer images	Ethnicity specific gender classification	97

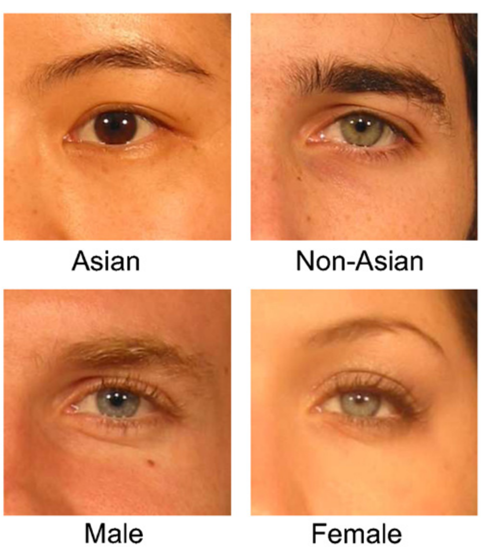

Fig. 1. Examples of right periocular region images for different classes in the FRGC dataset. Top row shows the ethnicity classes while the bottom row shows the gender classes considered in this work.

which may or may not include the eyebrow. The periocular experiments for this work have the eye masked out. The eye experiments include the iris, sclera, eyelashes and some of the eyelid, in reality, the inverse of the periocular mask. These regions can be seen in Fig. 2. This paper investigates whether periocular images contain enough information to accurately obtain similar soft biometric classification performance to that acquired from full face images. The images used in this work are subsets of the FRGC and MBGC face datasets. The experiments utilize appearance cues present in periocular images using multiple low level

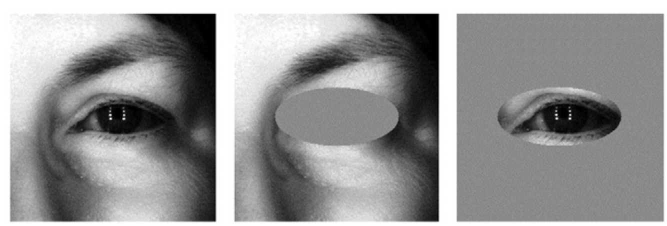

Fig. 2. Example of the different masks on the periocular region. From left to right: original MBGC periocular region, periocular mask, eye mask.

features. These features include various texture measures such as: Histograms of Oriented Gradients (HOG), Local Binary Patterns (LBP), and a Discrete Cosine Transform (DCT) of the LBP features. These features are chosen on the assumption that the success of similar texture features in separating the different classes in face images would translate well to periocular images. Color information is also utilized in the visible light images using Local Color Histograms (LCH). For classification, both ANN and SVM classifiers are used to provide a comparison of two widely used classification schemes. As an investigative work, the focus of this paper is to establish a baseline for comparison. To achieve this focus, the complexity of the classifier was kept to a minimum, so boosting was not included at this time. Performance is evaluated using stratified 5-fold cross-validation.

Fig. 3 shows the overall view of the proposed approach. The approach is divided into separate training and testing phases for both classifiers used. In the training phase, features are extracted from the preprocessed periocular images, which are used for training the classifiers. Gender and ethnicity training proceed separately and four classifiers are trained, two SVM and two ANN. In the testing phase, appearance features are extracted, given to the classifiers as input, and the classifiers output a class label associated with gender or ethnicity. The next section describes