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Gender Classification through Fusion of Holistic and Region-based Facial Patterns

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Abstract

In this study, a robust gender prediction system is proposed to fuse global and regional facial representations through score and feature level fusion. In order to extract facial features for gender classification, Binarized Statistical Image Features (BSIF) approach is applied on holistic and regional features of face images. The extracted features are then concatenated to combine the region-based information at feature level fusion. Then the optimized sub-set of features is selected using Particle Swarm Optimization (PSO) method. Finally, the holistic and regional features are combined at score level fusion to produce the final set of scores for gender classification. This study applies Weighted Sum (WS) rule strategy for score level fusion. The experimental results are performed on Multiple Biometric Grand Challenge (MBGC) and CASIA-Iris-Distance databases with consideration of subject-disjoint training and testing evaluation to testify the validity of the proposed gender classification system. The experimental results of the study demonstrate the success of the proposed scheme for gender prediction.

Keywords: Gender classification, Region-based BSIF, Information fusion, Optimized feature selection

Bütünsel ve Bölge Bazlı Yüz Kalıplarının Birleştirilmesi Yoluyla Cinsiyet Sınıflandırması

Öz

Bu çalışmada, evrensel ve bölgesel yüz görünüşlerini skor seviyesi birleştirme ve öznitelik seviyesi birleştirme yoluyla bir araya getirmek için güçlü bir cinsiyet tahmin sistemi önerilmektedir. Cinsiyet sınıflandırmasında yüz özniteliklerini çıkarmak için, İkili İstatistiksel Görüntü Öznitelikleri (BSIF) yaklaşımı yüz görüntülerine bütünsel ve bölgesel olarak uygulanmıştır. Ardından çıkarılan öznitelikler bölgesel bilgilerin öznitelik seviyesi birleştirmesi düzeyinde bir araya getirilir, Optimize edilmiş öznitelik alt kümesi, Parçacık Sürü Optimizasyonu (PSO) yöntemi kullanılarak seçilir. Son olarak, bütünsel ve bölgesel bilgiler, cinsiyet sınıflandırması için nihai skorları üretmek amacıyla skor seviyesi birleştirme seviyesinde bir araya getirilir. Bu çalışma, skor seviyesi birleştirme için Ağırlıklı Toplam (WS) kuralı stratejisini kullanmaktadır. Deneysel sonuçlar, önerilen cinsiyet sınıflandırma sisteminin geçerliliğini test etmek amacıyla Multiple Biometric Grand Challenge (MBGC) ve CASIA-Iris-Distance veritabanlarında,

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özne-ayrık eğitim ve test değerlendirmesi dikkate alınarak gerçekleştirilmiştir. Çalışmanın deneysel sonuçları cinsiyet tahmin sisteminin başarılı olduğunu göstermiştir.

Anahtar Kelimeler: Cinsiyet sınıflandırması, Bölgesel BSIF, Bilgi kaynaşımı, Optimize edilmiş öznitelik seçimi

1. INTRODUCTION

Gender classification plays an important role in several face application scenarios such as surveillance, human computer interaction, content-based searching and indexing. In general, different biometric traits are used to predict the gender of individuals [1-10]. The focus of this study is on gender classification using facial information in images. In fact, fusion of holistic and regions of facial information first at feature level fusion and then at score level fusion produces the optimized proper information to estimate the gender of individuals.

Several studies investigate the performance of different biometric characteristics on gender classification using different methods and classifiers. The authors of [1] estimate the gender of individuals by computing the facial embedding of faces based on a neural network system. The focus of [2] for predicting gender from face images is on extracting the geometric features including distance between eyebrow to eye, eyebrow to nose top, nose top to mouth, eye to mouth, left eye to right eye, width of nose, width of mouth. The extracted features are then classified using an artificial neural Network. In [3], the classification of gender is performed using the Multiscale facial fusion feature method. The extraction of features for fusion is done using Local Binary Pattern (LBP) and Local Phase Quantization (LPQ) feature extractors and Support Vector Machine (SVM) employed for the purpose of classification. Gender classification based on iris features is proposed in [4] using an SVM classifier. In addition, the authors employ Principal Component Analysis (PCA) to reduce the dimension of feature vectors. In [5], prediction of gender through palm print biometric is performed using convolutional neural network (CNN) architecture. The work outperforms the gender classification of subjects through palm print by using a two-stage method to fine-tune the VGGNet. The classification of gender using fingerprint biometric is proposed in [6] using a fusion of LBP and LPQ feature extractors and SVM classifier. The focus of [7] is on face-ocular multimodal biometric systems for a person gender prediction. The authors utilize Uniform Local Binary Pattern (ULBP) descriptor to extract the features of modalities. They applied a Backtracking Search algorithm (BSA) and SVM classifier to predict the gender of individuals based on the optimized feature sets of modalities. Prediction of gender using pattern information of frontal and dorsal hand images is introduced in [8]. The authors of this study classify the hand images using CNN. The gender classification for hand back skin texture (HBST) is done in [9] using sparse representation (SR) technique and nearest neighbor classifier. The concentration of [10] for person gender classification is on a multimodal biometric system involving face, iris, and fingerprint traits. The authors predict gender by extracting the deep features based on AlexNet structure. In [11], the authors implement a model to combine handcrafted features with CNN to overcome challenges such as illumination, pose variations and the necessity of voluminous training sets. Proposing two convolutional neural networks using the central difference convolution layer and the vanilla convolution layer is considered in [12] to predict gender of face images. The authors of [13] introduce a CNN-based approach for gender classification of face images to construct the feature images first using raw patterns to represent a set of salient features for a CNN-based network as input to extract more salient features. Finally, the fused extracted salient features are given to SVM for gender classification.

The current work aims to implement a method based on the fusion of holistic and regions of facial patterns through score and feature level fusion. The facial features for the prediction of gender are extracted using Binarized Statistical Image feature (BSIF) [14] method on holistic and regions of face images. The extracted features then are concatenated to combine the region-based information at feature level fusion. In order to select the optimized sub-set of features for further classification this study utilizes Particle Swarm Optimization (PSO) [15] method. Finally, the fusion of holistic and regions of faces is performed at score level fusion to generate the final set of scores for gender classification. This study applies Weighted Sum (WS) rule strategy for score level fusion. In order to validate the robustness of the proposed scheme, the experimental results are performed on Multiple Biometric Grand Challenge (MBGC) [16] and CASIA-Iris-Distance [17] face databases with consideration of subject-disjoint training and testing evaluation for gender classification. The contribution of this study is therefore to implement a robust gender classification system based on the face biometrics of individuals which is able to present more remarkable facial information in high security scenarios to represent the subjects' gender of unrecognized attempts. Additionally, marketing research applications can use the proposed gender prediction system to offer their products based on the gender of persons which is provided by the system.

The rest of the paper is organized as follows. Section 2 goes into details of the BSIF feature extraction method for face biometric; Section 3 describes PSO feature selection technique to select an optimized subset of features. The explanation of the proposed gender prediction scheme is done in Section 4. A description of databases, assessment protocols and experimental results is in Section 5. Finally, Section 6 draws some conclusions.

2. FACIAL FEATURE EXTRACTION FOR GENDER PREDICTION

In order to extract the facial features to classify the gender of subjects, this study employs Binarized Statistical Image feature (BSIF) technique. BSFI method was introduced by Kannala and Rahtu [14] as a texture-based feature extractor technique. The idea behind BSFI method is to use concepts implemented in Local Binary Patterns (LBP) and Local Phase Quantization (LPQ) approaches. In fact, both approaches are considered as statistics of labels calculated in the local pixel neighbourhoods via filtering and quantization. Additionally, BSIF method aims to automatically learn a fixed set of filters using a small set of images in place of using hand-crafted filters. This texture-based feature extractor characterizes the texture properties within sub-regions using the code values of pixels histograms. The bit values of BSIF binary code string are calculated by binarizing the response of a linear filter using a threshold at zero. The base of BSIF method is on introducing an image patch X of size l × l pixels with considering a linear filter of the same size as Wi. Consequently, the calculation of filter response is done according to the equation (1).

$$s_i = \sum W_i(u,\ v)X(u,\ v) = w_i^T\ x \qquad (1)$$

where w and x are vectors involving pixels of Wi and X. Therefore, the binarized feature bi extracted using BSIF is calculated by assigning bi = 1 if si > 0 and bi = 0 otherwise. In this algorithm, learning the filters Wi is done using Independent Component Analysis (ICA) by maximizing the statistical independence of si [18].

3. OPTIMIZED FEATURE SELECTION USING PSO

This study attempts to overcome the problem of high dimensionality for feature level fusion part of the proposed method and consequently selecting the optimized subset of feature sets by applying Particle Swarm Optimization (PSO) approach on concatenated facial features. PSO is introduced by Kennedy and Eberhart [15] concentrating on learning optimized solutions in a search space. The algorithm is initialized using a population of random solutions, called particles, and evaluated using a fitness function. Every particle in this algorithm can be seen as a point in an n-dimensional feature space and the *i*th particle is shown as $x_i = (x_{i1}, x_{i2}, \ldots, x_{in})$. PSO memorizes the two best values of each iteration called pbest and gbest. The algorithm records the position of best fitness value for each particle using pbest as $p_i = (p_{i1}, p_{i2}, \ldots, p_{in})$, p is the population size. The best particle index among all particles of the population is represented by gbest. Additionally, the velocity of ith particle of PSO algorithm is considered as $v_i = (v_{i1}, v_{i2}, \ldots, v_{in})$. The particle's new velocity is therefore computed according to their previous velocity, distances of its current position from its own best position and groups best experience. The procedure of updating particles is demonstrated in equations (2), (3) and (4).

$$v_i = wv_i + c1 \times rand1(\ \ )(P_i - x_i) + c2 \times rand2(\ \ )(gbest - x_i), \quad (2)$$

$$x_i = x_i + v_i, \quad (3)$$

$$x_i = \begin{cases} 1, & if \ \frac{1}{1+e_i^{v}}, \\ 0, & if \ otherwise, \end{cases} \quad (4)$$

In the above equations, w, c1 and c2 stand for inertia weight and acceleration constants while rand1(), rand2(), and rand3() are separate random numbers respectively. The value of w, c1 and c2 in this study is set as 16, 1 and 2 respectively as introduced in the original PSO. In addition, the concentration of fitness function of this study to select the optimized feature sets is on maximizing the classification rate. Selection of optimized feature sets in this study is performed using binary PSO with consideration of bit strings of length M consisting of "0" and "1", where M represents number of features. The bit string "1" means the feature selected while 0 means not selected. This study sets the population and iteration size of the binary PSO feature selection method as 20 and 30 experimentally.

4. PROPOSED GENDER PREDICTION SCHEME

The focus of this section is on introducing a pipeline to increase the gender classification rate of individuals and consequently improve the performance and security of the face recognition systems. The proposed gender prediction scheme explores the sub-regions of face images and then combines with the holistic information extracted from images. The block diagram of the proposed scheme is depicted in Fig 1. The extraction of ROI of face images to predict the gender in this study considers two scenarios. The first scenario includes four sub-regions as left periocular region, right periocular region, nose, and mouth regions.

In the second scenario, the face image is divided into three vertical parts as upper, middle, and lower to provide enough information for gender prediction of subjects. BSFI feature extractor is employed on all extracted regions and entire face separately, the extracted features therefore are fused at feature level fusion. The most relevant and optimized subset of features are selected using the PSO algorithm to improve the performance of the system. In the next step of the proposed method, the matching scores of entire face, ROI regions and vertical parts are combined using Weighted Sum Rule (WS) technique at score level fusion. The fusion is performed based on the WS strategy to combine several matchers by applying sum of their relevant matching scores according to weight values as indicated in equation (5).

$$WS = \sum_{i=1}^{N} W_i S_i \quad (5)$$

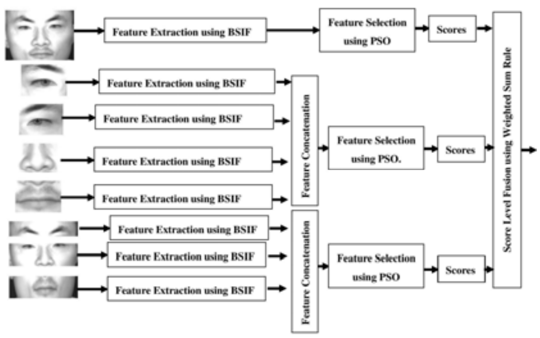

Figure 1. Block diagram of the proposed method

where N is number of matchers, W_i is weights corresponding to matchers and Si is matching scores. In order to compute the weights, this study considers user-specific method of weight computation [19] on a reference database. In addition, Manhattan distance measurement is employed in this study to produce the matching scores. In general, the proposed scheme attempts to combine several facial parts using feature and score level fusion strategies to study the effect of holistic and part-based information of faces on gender prediction of subjects.

5. DATABASES AND EXPERIMENTAL RESULTS

In order to validate the robustness of the proposed scheme, this section concentrates on the performed experiments of MBGC and CASIA-Iris-Distance databases with consideration of subject-disjoint training and testing evaluation. In general, MBGC database consists of images of 135 individuals under unconstrained conditions and using three challenge problems. The construction of database to perform the experiments is done using 75 males and 60 females to contain whole face, left periocular region, right periocular region, nose region, mouth region, upper partition, middle partition, and lower partition of each subject. The database therefore involves 1080 images in total. On the other hand, CASIA-Iris-Distance database images provide suitable information of both dual-eye iris and face patterns of subjects, the total number of images in this database is 2567 images of 142 individuals captured by a high-resolution camera at-a-distance of ~3 m. This study considers 100 individuals of CASIA-Iris-Distance database including 50 males and 50 females. In total, in order to construct the dataset for experiments, 800 images of this database with consideration of only one image of each subject (face, corresponding ROI and partitions) are selected. This study divides the images into two random parts as training and testing. In general, 50% of males and females are assigned to training and 50% to testing sets. The division to training and testing is done five times, and the last result is reported as average of five runs.

The first set of experiments is conducted to study the effect of holistic, region-based and partition-based facial patterns on gender prediction as represented in Table 1. The highest classification rate belongs to the proposed method for CASIA-Iris-Distance and MBGC databases as 90.12% and 94.11% respectively. The experiments for region-based and partition-based facial representations are performed with and without consideration of the entire face. The investigation of results shows that combining holistic information of individuals with region/partition-based patterns can improve the gender classification as reported in Table 1. In fact, involving the entire face when left periocular region, right periocular region, nose, and mouth regions are used improves 4.57% and 4.79% classification rate for CASIA-Iris-Distance and MBGC databases respectively compare to the using only entire face for gender prediction. Additionally, fusion of upper, middle, and lower part of the image with the entire face outperforms the gender prediction rate up to 2.45% and 3.29% as demonstrated in the table for CASIA-Iris-Distance and MBGC databases respectively. Therefore, according to the experimental results reported in Table 1, it can be stated that fusion of entire face and ROI's is effective for gender prediction of facial features.

It should be stated that, Manhattan distance measurement is employed to produce the matching scores and WS fusion strategy is used to combine region/partition-based facial patterns with and without the entire face in this study as mentioned before. In addition, the second set of experiments in Table 2 concentrates on the effect of selecting optimized features on gender classification. The experiments of Table 2 therefore, repeat the same experiments at feature level fusion with and without PSO. As reported in the table, the best gender classification rate belongs to the proposed scheme as 90.12% and 94.11% for CASIA-Iris-Distance and MBGC databases respectively when PSO feature selection method is employed. Additionally, all the experiments of both databases have improvement on gender prediction results when PSO feature selection is applied. In fact, investigation of the results demonstrates the effectiveness of optimized feature selection of the study using PSO which has improvement of 3.83% and 4.83% over the experiments without PSO feature selection strategy for the proposed method on CASIA-Iris-Distance and MBGC databases respectively. The improvement of the classification rate using PSO can be seen for other implemented methods as depicted in Table 2. On the other hand, in order to demonstrate the robustness of the proposed method Table 3 presents a comparison with the state-of-the-art gender classification methods on CASIA-Iris-Distance dataset. The comparison of the results of Table 3 shows the success of the proposed method over other handcrafted methods implemented in this study. Although the method implemented based on the Convolutional Neural Network (CNN) has the highest classification rate, the improvement compared to the result obtained using the proposed method is not so considerable as reported in the Table. It should be stated that, all the implemented state-of-the-art methods have been applied on entire face images used in this study.

Table 1. Gender classification rate of holistic, region-based and partition-based facial patterns using score level fusion (%)

	CASIA-Iris-Distance			MBGC		
	Male (%)	**Female (%)**	**Overall prediction (%)**	**Male (%)**	**Female (%)**	**Overall prediction (%)**
Entire Face	85.00	81.00	83.05±1.06	90.28	85.12	87.71 ± 0.45
L-periocular + R-periocular + Nose + Mouth	86.00	84.25	85.12± 0.91	90.50	87.40	88.95 ± 0.37
Upper + Middle + Lower	85.00	81.00	83. 00±0.88	88.38	84.67	86.52 ± 1.20
Entire Face + L-periocular + R-periocular + Nose + Mouth	90.25	85.00	87. 62±0.39	95.70	89.31	92.50 ± 0.22
Entire Face + Upper + Middle + Lower	87.00	84.00	85. 50±1.14	93.00	90.00	91.00 ± 0.36
Proposed Method	**92.50**	**87.75**	**90.12 ± 0.91**	**95.82**	**92.41**	**94.11 ± 0.18**

Table 2. Gender classification rate of holistic, region-based and partition-based facial patterns using feature level fusion (%)

	CASIA-Iris-Distance		MBGC	
	Overall prediction (%)		**Overall prediction (%)**	
	Without-PSO	**With-PSO**	**Without-PSO**	**With-PSO**
Entire Face	79.13±0.53	83.05± 1.06	82.69 ± 0.12	87.71 ± 0.45
L-periocular + R-periocular + Nose + Mouth	81.74± 1.04	85.12 ±0.91	84.44 ± 0.77	88.95 ± 0.37
Upper + Middle + Lower	80. 35±2.00	83.00 ±0.88	83.17 ± 0.95	86.52 ± 1.20
Entire Face + L-periocular + R-periocular + Nose + Mouth	84. 20±0.96	87. 62±0.39	86.94 ± 1.31	92.50 ± 0.22
Entire Face + Upper + Middle + Lower	81. 83±0.82	85. 50±1.14	86.23± 0.72	91.00 ± 0.36
Proposed Method	**86.29± 2.03**	**90.12 ± 0.91**	**89.28± 1.03**	**94.11 ± 0.18**

Table 3. Comparison of the proposed scheme with State-of-the-art methods for gender classification (%)

	CASIA-Iris-Distance		
	Male (%)	**Female (%)**	**Overall prediction (%)**
LBP + LPQ + SVM [3]	91.25	83.00	87.12 ± 1.37
Overlapped-ULBP +SVM [7]	91.25	85.75	88.50 ± 0.52
VGGNet + SVM [5]	**93.75**	**86.75**	**90.25 ± 1.80**
Proposed Method	**92.50**	**87.75**	**90.12 ± 0.91**

6. CONCLUSION

This study proposed a robust gender prediction scheme for fusion of global and regional facial representations through score and feature level fusion. The extraction of facial features has been performed using Binarized Statistical Image feature (BSIF) technique holistic and regions of face images to predict the gender of subjects. The feature level fusion of study considered concatenation of the region-based information of the features. In addition, Particle Swarm Optimization (PSO) method has been applied to select the optimized subset of feature at the feature level fusion with the purpose of improving the gender prediction rate. In total, eight different global and regional parts of facial images have been used in this study. Finally, the score level fusion of the work combines scores of these eight different facial parts to produce the final set of scores for gender classification. In total, the best classification rate achieved by the proposed method for CASIA-Iris-Distance and MBGC datasets as 90.12% and 94.11% respectively. The experimental results of the study demonstrated the success of the proposed scheme for gender prediction.

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