Automatic Gender Identification from Children Facial Images Using Texture Descriptors

Ayesha Iftikhar, Rehan Ashraf, Asim Saeed, Srinivas Alva and Rajmohan Pardeshi

Abstract Soft biometric such as gender significantly works to enhance the performance of biometric systems and also having applications in human–computer interaction, content-based indexing and retrieval, demographic studies, security, and surveillance. Gender identification among adults is easy as compared to in children, due to similarity of facial skin texture and appearance of faces. In this paper, we have introduced a technique to identify/classify the gender from facial images of children. In our method, we have applied three basic steps namely preprocessing, feature extraction, and classification. In preprocessing stage, face detection and normalization are performed. To extract the powerful features, we have computed different texture descriptors and after feature extraction process and SVM is applied for classification purpose. We have achieved the encouraging results in our experiments.

Keywords Gender identification in children · Facial images · Texture descriptors · Support vector machines · Soft biometric

1 Introduction

Biometric technology facilitates unique identification and verification based on physiological and behavioral attributes of a person. Physiological attributes include fingerprint, retina, palm, and face. Body movement, voice, handwriting, gait, etc., are considered as behavioral biometrics. Whereas in large biometric systems, soft bio-

A. Iftikhar · R. Ashraf
Department of Computer Science, NTU, Faisalabad, Pakistan

A. Saeed
Department of Computer Science, Beijing Jiaotong University, Beijing, China

S. Alva
Department of Computer Science, Gujarat University, Ahmedabad, India

R. Pardeshi (✉)
Department of Computer Science, Karnatak College, Bidar, India
e-mail: madhurrajmohan1@gmail.com

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metrics such as age, gender, eye color, hair color, gives additional information about the person and helps to enhance the performance. With rapid development in technology, biometric became popular in different applications such as national citizen identification framework, access control, law enforcement, security and surveillance [1], and automatic monitoring. But success of these applications is restricted only up to adult population and not scaled for children.

As per the report of The National Database and Registration Authority (NADRA) of Pakistan [2], being one the largest citizens biometric data agency, it is lagging for the children biometric services. In the future, major required applications of biometric technology for children are vaccination monitoring, flood relief, offering of financial benefits, reunification during disaster management, etc. In [3, 4], authors studied and they explained the issues faced by children such as child sexual abuse, exploitation, child pornography, and prostitution. To overcome these kinds of problems, biometric will play a vital role. Now, while developing such large biometric system for children of any country, soft biometric such as gender will play a major role in enhancement of accuracy.

Biometric data acquisition from children is a major challenge, in such case, the current study is focused on facial information due to its easy way of recording and it also does not need any special technical requirements. The remainder of the paper is structured as follows: In Sect. 2, we have presented related work. In Sect. 3, we have briefed our method and Sect. 4 dedicated for experiments and discussion. We concluded in Sect. 5.

2 Related Work

Gender classification (GC) from face image is getting attention of researcher from past few years. In comparison with humans, machines find difficult to classify the gender automatically. GC from face is very useful research because face has many discriminant features which can be used to identify human gender. Many methods have been proposed for GC from face images. In [5], author proposed novel approach from face images for GC by using local texture pattern as feature descriptor. Support vector machine (SVM) is used for classification purpose. FERET database is used and compared with other comparable works. Author uses LZP (local zigzag pattern) as a feature descriptor. Gender classification from face is becoming very popular. In [6], author uses hybrid approach by fusion of face appearance features and geometry feature. Researcher picks Haar wavelet for representation of appearance features and Adaboost algorithm for the selection of strong features. In [7], complex value neural network serves as a classifier and LBP with PCA feature extraction techniques for gender categorization by face. This paper also compares the complex value with real value neural network. Author in [8], proposed gender recognition by top half face based on local appearance feature. This research is suitable in that condition where the lower part of face is hidden. In [9], author classifies gender by face from appearance base method. Compare the nonlinear SVM classifier performance with traditional classifier like linear, quadratic, nearest neighbor as well as with modern RBF (radial base function) classifier. Study focuses on low-resolution thumbnail (21 × 21) images of front face images. In [10], authors presented a novel approach for gender classification from frontal facial images with SVM classifier and ICA Features. In paper [11], author presented a scheme for identification of children based on multimodal biometric. In paper [12], authors presented algorithms for newborn face recognition using principal component analysis (PCA), linear discriminant analysis (LDA), integrated principal analysis (IPA), speeded up robust features (SURF), local binary pattern (LBP), integrated component analysis (ICA). In [13], author proposes a novel approach by integrating face and soft biometric trait to improve the result about 5.6% on face biometric by use of 210 newborn data.

In [14], researcher investing the GC by using face image of per person. For this purpose, two types of features have been used. First appearance base and other is geometric base for appearance base (LBP and DCT) used and for geometry base (GDF) is used. GDF is based on the physical changes in male and female faces. In [15], author said that gender classification is challenging task on real-world face images due to nonsupport environment. Authors used (LFW) database. LBP with Adaboost is employed for the selection of discriminant features and obtained 94.81% result. Viola–Jones algorithm is used for face detection and image dimension is 250 × 250. In [16], author claims that LBP histogram is good and different feature for the gender classification task from face images. Author compares his technique with more sophisticated Gabor filter technique and result was outperformed with raw pixel values as a feature are computationally less expensive. GC used in many other problems like it can reduce the search space for face recognition software. In [17], author projected 2DPCA (2D principal component analysis) for face recognition and test on ORL, AR, and Yale well-known databases. The ORL database assesses the performance under varied limitations of light and movement. The AR database computes the system working under the limitation of change of time in face expressions in light variation. When light and face expressions both vary, then Yale database is used to evaluate the system performance. 2DPCA is more simple than PCA. In accuracy term, it is most suitable than PCA. In [18] paper, author proposed a novel technique for GC by designing multi-resolution feature extraction method on the idea of local phase quantization (LPQ) by monogenic and intensity image. Features with LPQ are obtained from input image. SVM is used for classification. Author compares experiment result with two unconstrained LWF and groups public database. When the proposed result compares with other state-of-the-art approaches, the competed accuracy rate was 97.0% with LWF and 91.58% on group dataset. In [19], authors shown that, gender identification accuracy greatly affects with different age groups. Author claims that by using state-of-the-art method experimental study on big dataset of 8000 images from 0 to 93 age range display accuracy of GC on adult faces is 10% higher than the young and senior faces. Author studies that aging effect on human motivates to find which features on shape and texture differences on face can combine to tell about gender of human. LBP and HOG used to estimate the gender characterization difference with age. In [20] paper author introduce child robotic method for interaction to estimate age and gender by 3D body matrix in real-world multi-party circumstances.

From our quick review presented in above paragraphs, it is clear that soft biometric plays a major role in human–computer interaction and enhancement of accuracy of biometric-based personal identification. Most of the work is dedicated toward adult biometric, whereas very limited focus is given toward children. In this paper, we have presented a method for gender identification from facial images of children.

3 Proposed Method

Our aim is to identify the gender from facial images of the children. To achieve this, we employed the three steps, preprocessing, feature extraction, and classification. In preprocessing, we have detected the face and normalized to a standard size. Histogram of oriented gradients (HOG) [21], uniform local binary patterns (ULBP), and Gabor wavelet transform (GWT) [22] based texture descriptors are used for feature extraction. These global approaches are found suitable for facial feature representation. SVM is considered for the classification. Block diagram of the proposed method is shown in Fig. 1.

3.1 Preprocessing

Images in our dataset are unconstrained in nature and having huge variation in illumination, background, size, pose and expressions; therefore, FEI tool [23, 24] is used to detect and normalize the face region. In preprocessing, we first detected the face region. Input image of size 240 $\times$ 260 is provided as input and FEI tool returns cropped normalized facial region. Output of face detection is shown in Fig. 2.

Fig. 1 Flow diagram of proposed method

Fig. 2 Face detection and normalization using FEI tool

3.2 Feature Extraction

Selection of suitable features extraction technique is the significant step in designing of any image classification or retrieval system. Our main focus is on efficient feature extraction from face images to obtain discriminating features for gender classification. In this regard, we used uniform local binary patterns (ULBP) variant of LBP [22, 25], histogram of oriented gradients (HOG) [23], Gabor wavelet transforms (GWT).

Uniform Local Binary Pattern (ULBP): Local binary pattern (LBP) is one of the very efficient texture descriptors, and it labels the pixel of an image based on thresholding operation, later post-thresholding sequence of 0 and 1 considered as binary number further which is represented by its equivalent decimal. The same process is repeated for whole image. The histogram of these labels $2^8 = 256$ is used as texture descriptor. Further, it can be optimized by considering only limited intervals as given in (Ojala et al.), which gives only 59 descriptors. Once the labeled image $IL(x, y)$ is obtained, we can define the histogram of LBP as:

$$H_i \sum_{xy} IL\left\{(x, y) = 1\right\}, i = 0, 1, 2, \ldots, n - 1 \tag{1}$$

where n is number of labels and $IL\{A\}$ is 1 if true or 0 if false. In Fig. 3, we have shown working of local binary patterns.

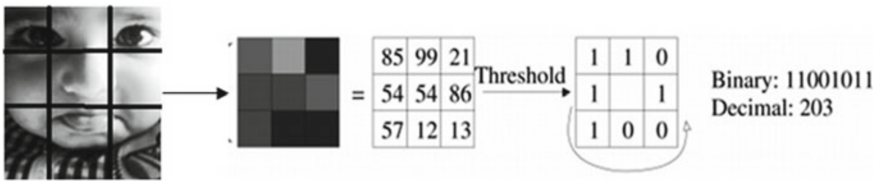

Fig. 3 Computation of local binary pattern

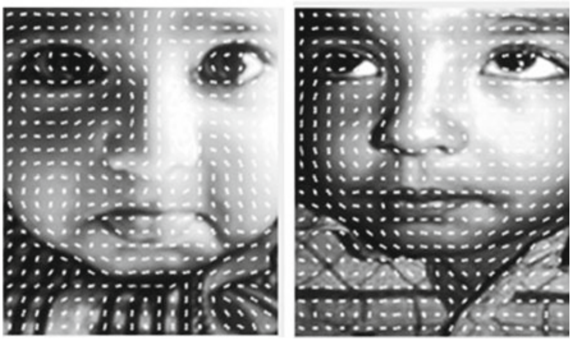

Fig. 4 Visualization of HOG descriptors applied to facial image of children

Histogram of Oriented Gradients (HOG): In image processing, HOG [20, 24, 26, 27] is very popular descriptor used for object detection. In local image portion, it counts the occurrence of gradient. The basic idea behind the HOG descriptor is: (1) It divides the image into small linked section and each section is called cell, and for each cell, it calculates the HOG magnitude and direction for each pixel within the cell and then, (2) According to the gradient, orientation discretizes each cell into angular bins. (3) Each cell pixel has gradient weight according to angular bin. (4) Groups of connected cell are called blocks and grouping of cells into block is base for grouping and normalization of histogram. Following Fig. 4 shows the HOG visualization on our dataset. We use different HOG cell size in our work like 16×16, 32×32 and 64×64.

Gabor Wavelet Transfrom (GWT): Gabor wavelets [28, 29] are powerful tool to highlight the texture regions in image. In the literature, Gabor wavelets are widely used to extract the texture information for various image processing and computer vision applications. Gabor wavelet is the group of Wavelets; [30] mathematically represented as:

$$\phi(x, y, w_0, \Theta) = \frac{1}{2\pi\sigma^2} \mathrm{e}^{-(x_0^2+y_0^2)/2\sigma^2} [\mathrm{e}^{jw_0x_0} - \mathrm{e}^{-w_0\sigma^2/2}] \tag{2}$$

To compute the texture descriptors based on Gabor wavelets, we have applied GWT at six different orientations and five scales which gives us total 30 transformed images. Then, from each transformed image, we have computed mean and standard deviation to form fixed size compact feature vector of size 60.

3.3 Classification

Support Vector Machine: SVM is supervised classifier based on statistical learning theory [31], introduced by Vapnik. Due to its strong learning ability and discriminating power, we have chosen SVM for difficult task of gender classification in childrens' facial images. The basic principle of SVM is that it tries to construct hyperplane separating the two linearly separable classes. Suppose we have n data vectors X_i. Seperation of each data item in two classes is carried out by a discriminant function $g(X) = W^T.X - b$.

$$g(X) = W^T.X_i - b \geq 1 \tag{3}$$

where y_i is the class either $+1$ (boy) or -1 (girl). In case on nonlinearly separable data, then the SVM can be extended with kernel function, for instance some of them are Cubic, Gaussian, and Polynomial.

4 Experiments

4.1 Dataset and Evaluation Protocol

Dataset: Due to the unavailability of the standard dataset for gender classification for child, we created our own dataset. To introduce more complexities, we have captured the face images with different smartphones having different configuration to get more variation in images. Facial images in our dataset having different poses, expressions, background, and resolutions. The informed consent is recorded from parents of volunteers during the process of data collection. We have considered total 752 images for our experiment purpose out of which 441 are boys and are 311 are girls. Samples from our dataset are shown in Fig. 5.

We have used tenfold cross-validation technique instead of traditional classification, to evaluate the performance of our method. The whole dataset is divided into 10 sub-parts. When any of one sub-part is used for testing, the other nine sub-parts used for training. This method is repeated 10 times, in such way that each sub-part will serve for both training and for testing.

4.2 Results and Discussion

The exhaustive experimental tests are carried out on our dataset to measure the performance of the proposed method. We have tested the performance of ULBP, HOG, and GWT with SVM Classifier. Linear SVM further extended with kernel trick to enhance the classifier performance. Detailed results of our experimental tests are given in Table 1. We have observed that quadratic SVM with histogram of oriented gradients of cell size 16 × 16 given high accuracy in gender identification in child with an average accuracy of 89%, for boy 92% and 86% for girl. ULPB and GWT

Fig. 5 Samples from our dataset **a** boys, **b** girls

Table 1 Gender identification accuracy using SVM with ULBP, GWT and HOG

Descriptors	Linear SVM		Avg. (%)	Quadratic SVM		Avg. (%)	Cubic SVM		Avg. (%)
	Boy (%)	Girl (%)		Boy (%)	Girl (%)		Boy (%)	Girl (%)	
ULBP	85	53	69	87	82	85	84	78	82
GWT	83	34	58	84	67	75	85	80	82
HOG (16 × 16)	88	74	81	91	86	88	**92**	**86**	**89**
HOG (32 × 32)	89	72	81	91	84	87	90	87	88
HOG (64 × 64)	78	62	70	85	77	81	86	84	85

with Cubic SVM given weak performance with the classification accuracy of 82 and 82%, respectively. Further we have also witnessed that, the Cubic SVM performed better as compared to Linear SVM and Quadratic SVM.

5 Conclusion

In this paper, we have presented a method for gender identification among children. This is the first approach when children gender identification considered for smartphone captured complex dataset having huge variations in pose, lighting, and expressions of children. We have evaluated the performance of different texture descriptors such as ULBP, HOG and GWT; it is observed that HOG with cell size 16 × 16 has good discriminating capacity as compared to ULBP and GWT. Support vector machine has performed better when extended with Cubic Kernel and given average accuracy of 89% for gender identification in child.

In the future, we will consider the combination of classifiers approach to enhance the performance of our system.

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