Robust Automatic Face, Gender and Age Recognition Using ABIFGAR Algorithm

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Abstract- The face recognition system attains good accuracy in personal identification when they are provided with a large set of training sets. In this paper, we proposed Advanced Biometric Identification on Face, Gender and Age Recognition (ABIFGAR)algorithm for face recognition that yields good results when only small training set is available and it works even with a raining set as small as one image per person. The process is divided into three phases: Pre-processing, Feature Extraction and Classification. The geometric features from a facial image are obtained based on the symmetry of human faces and the variation of gray levels, the positions of eyes, nose and mouth are located by applying the Canny edge operator. The gender and age are classified based on shape and texture information using Posteriori Class Probability and Artificial Neural Network respectively. It is observed that the face recognition is 100%, the gender and age classification is around 98% and 94% respectively.

Index Terms- Posteriori Class Probability and Artificial Neural Network, Canny edge operator

I. INTRODUCTION

Gender recognition is a fundamental task for human beings, as many social functions critically depend on the correct gender perception. Automatic gender classification has many important applications, for example, intelligent user interface, visual surveillance,collecting demographic statistics for marketing, etc. Human faces provide important visual information for gender perception.Gender classification from face images has received much research interest in the last two decades. In the early 1990s various neural network techniques were employed to recognize gender by frontal faces (Golomb et al.,1991; Brunelli and Poggio, 1992), for example, Golomb et al.(1991) trained a fully connected two-layer neural network, SEXNET,which achieves the recognition accuracy of 91.9% on 90 face images. Recent years have witnessed many advances (Yang et al., 2006); we summarize recent studies in Table 1. Moghaddam and Yang (2002) used raw image pixels with nonlinear SVMs for gender classification on thumbnail faces; their experiments on the FERET database (1,755 faces) demonstrated SVMs are superior to other classifiers, achieving the accuracy of 96.6%.In BenAbdelkader and Griffin (2005), local region matching and holistic features were exploited with Linear Discriminant Analysis (LDA) and SVM for gender recognition. On the 12,964 frontal faces from multiple databases (including FERET and PIE), local regionbased SVM achieved the performance of 94.2%. Lapedriza et al. (2006) compared facial features from internal zone (eyes, nose,and mouth) and external zone (hair, chin, and ears). Their experiments on the FRGC database show that the external face zone contributes useful information for gender classification. Baluja and Rowley (2007) introduced an efficient gender recognition system by boosting pixel comparisons in face images. On the FERET database,their approach matches SVM with 500 comparison operations Mäkinen and Raisamo (2008).systematically evaluated different face alignment and gender recognition methods on the FERET database. More recently face appearance and motion cues are combined for gender recognition in videos (Hadid and Pietikäinen, 2009).A common problem of the above studies is that face images acquired under controlled conditions (e.g., the FERET database)are considered, which usually are frontal, occlusion-free, with clean background, consistent lighting, and limited facial expressions.However, in real-world applications, gender classification needs to be performed on real-life face images captured in unconstrained scenarios; see Fig. 1 for examples of real-life faces. As can be observed, there are significant appearance variations on real-life faces, which include facial expressions, illumination changes, head pose variations, occlusion or make-up, poor image quality, and so on. Therefore, gender recognition in real-life faces is much more challenging compared to the case for faces captured in constrained environments. Few studies in the literature have addressed this problem. Shakhnarovich et al. (2002) made an early attempt by collecting over 3,500 face images from the web. On this difficult data set, using Harr-like features, they obtained the performance of 79.0% (Adaboost) and 75.5% (SVM). Recently Gao and Ai (2009) adopted the probabilistic boosting tree with Harr-like features, and obtained the accuracy of 95.51% on 10,100 real-life faces. However, the data sets used in these studies are not public available;therefore, it is difficult for benchmark in research community. Kumar et al. (2008, 2009) recently investigated face verification on real-world images, where many binary ‘‘attribute’’ classifiers (including gender) were trained.

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They reported the performance of 81.22% on gender classification; however, as they mainly focused on face verification, they did not fully study gender recognition on real-life faces. In this paper, we use a recently built public database, the Labeled Faces in the Wild (LFW) to investigate gender classification on real-world face images. The public database used in this study enables future benchmark and evaluation.

Fig.1. Examples of real-life faces.

The paper is structured as follows. Section 1 describes local binary patterns. In Section 2, learning LBPH bin using Adaboost is discussed. Section 3 presents extensive experiments. Finally Section 4 concludes the paper.

II. RELATED WORK

The image of a person's face exhibits many variations which may affect the ability of a computer vision system to recognize the gender. We can categorize these variations as being caused by the human or the image capture process.Human factors are due to the characteristics of a person, such as age, ethnicity and facial expressions (neutral, smiling, closed eyes etc.), and the accessories being worn (such as eye glasses and hat). Factors due to the image capture process are the person's head pose, lighting or illumination, and image quality (blurring, noise, low resolution).Head pose refers to the orientation of the head relative to the view of the image capturing device. The human head is limited to three degrees of freedom, as described by the pitch, roll and yaw angles [1].The impact of age and ethnicity on the accuracy of gender classification has been observed. Benabdelkader and Griffin [2], after testing their classifier with a set of 12,964 face images, found that a disproportionately large number of elderly females and young males were misclassified. In empirical studies by Guo et al. [3] using several classification method on a large face database, it was found that gender classification accuracy was significantly affected by age, with adult faces having higher accuracies than young or senior faces. In [4], when a generic gender classifier trained for all ethnicities was tested on a specific ethnicity, the result was not as good as a classifier trained specifically for that ethnicity. Studies have shown that a human can easily differentiate between a male and female (above 95% accuracy from faces [5]). However, it is a challenging task for computer vision. Nevertheless, such attribute classification problems have not been as well studied compared to the more popular problem of individual recognition. In this paper, we survey the methods used for human gender recognition in images and videos using computer vision techniques. In the detection phase, given an image, the human subject or face region is detected and the image is cropped. This will be followed by some preprocessing, for example to normalize against variations in scale and illumination. A widely used method for face detection is by Viola and Jones [6], which has an OpenCV implementation. The benchmark for human detection is based on using Histogram of Oriented Gradients (HOG) [7]. In the case of gait analysis, many methods use a binary silhouette of the human which is extracted using background subtraction. In feature extraction, representative descriptors of the image are found and selection of the most discriminative features may be made. In some cases when the number of features is too high, dimension reduction can be applied. As this step is perhaps the most important to achieve high recognition accuracy, we will provide a more detailed review in later sections. Lastly, the classifier is trained and validated with a dataset. Gender recognition is a within-object classification problem [8]. The subject is to be classified as either male or female, therefore a binary classifier is used. Examples of classifiers that have been widely used to perform gender recognition are Support Vector Machine (SVM), Adaboost,neural networks and Bayesian classifier. From our survey, SVM is the most widely used face gender classifier (usually using a non-linear kernel such as the radial basis function), followed by boosting approaches such as Adaboost. Nearest neighbor classifier and Markov models are also popular for gait-based gender classifiers.

III.METHODOLOGY

1. LOCAL BINARY PATTERNS

The original LBP operator (Ojala et al., 2002) labels the pixels of an image by thresholding neighborhood of each pixel with the center value and considering the results as a binary number.Formally, given a pixel at (xc,yc), the resulting LBP can be expressed in the decimal form as where n runs over the 8 neighbors of the central pixel, ic and in are the gray-level values of the central pixel and the surrounding pixel,and s(x) is 1 if xP0 and 0 otherwise.Ojala et al. (2002) later made two extensions of the original operator. Firstly, the operator was extended to use neighborhood of different sizes, to capture dominant features at different scales.Using circular neighborhoods and bilinearly interpolating the pixel values allow any radius and number of pixels in the neighborhood.The notation (P,R) denotes a neighborhood of P equally spaced sampling points on a circle of radius of R. Secondly, they proposed to use a small subset of the 2P patterns, produced by the operator LBP(P,R), to describe the texture of images. These patterns, called uniform patterns, contain at most two bitwise transitions from 0 to 1 or vice versa when considered as a circular binary string. For example, 00000000, 001110000 and 11100001 are uniform patterns.It was observed that most of the texture information was contained in the uniform patterns. Labeling the patterns which have more than 2 transitions with a single label yields an LBP operator,denoted LBP(P,R,u2), which produces much less patterns without losing too much information.After labeling an image with a LBP operator, a histogram of the labeled image can be used as texture descriptor. Each face image can be seen as a composition of micro-patterns which can be effectively described by LBP. In the existing studies (Ahonen et al.,2004), to consider the shape information, face images are divided into non-overlapping sub-regions (as shown in Fig. 2); the LBP histograms extracted from sub-regions are concatenated into a single,spatially enhanced feature histogram The extracted feature histogram describes the local texture and global shape of face images.The limitations of the above LBP-based facial representation arethat dividing the face into a grid of sub-regions is somewhat arbitrary,as sub-regions are not necessary well aligned with facial features,and that the resulting facial representation suffers from fixedsize and position of sub-regions. In Zhang et al. (2004), Sun et al.(2006), Adaboost was used to learn the discriminative sub-regions (in term of LBP histogram) from a large pool of sub-regions generated by shifting and scaling a sub-window over face images. In these studies, the Chi square distance between corresponding LBP histograms of the sample image and the template is used to construct the weak classifier.

2. LEARNING LBP-HISTOGRAM BINS

In the existing work, the LBP histograms are always extracted from local regions, and used as a whole for the regional description.However, not all bins in the LBP histogram are discriminative for facial representation. Here we propose to learn discriminative LBP-Histogram (LBPH) bins for better gender classification.Adaboost (Freund and Schapire, 1997; Schapire and Singer,1999) provides a simple yet effective approach for stagewise learning of a nonlinear classification function. Here we adopt Adaboost to learn the discriminative LBPH bins. Adaboost learns a small number of weak classifiers whose performance is just better than random guessing, and boosts them iteratively into a strong classifier of higher accuracy. The process of Adaboost maintains a distribution on the training samples. At each iteration, a weak classifier which minimizes the weighted error rate is selected, and the distribution is updated to increase the weights of the misclassified samples and reduce the importance of the others. Similar to Viola and Jones (2001), the weak classifier hj(x) consists of a feature fj which corresponds to a single LBPH bin, a threshold hj and a parity pj indicating the direction of the inequality sign:

3. EXPERIMENTS

We conduct experiments on the LFW database (Huang et al., 2007). LFW is a database for studying the problem of unconstrained face recognition, which contains 13,233 color face photographs of 5,749 subjects collected from the web. All the faces were detected by the Viola-Jones face detector (Viola and Jones, 2004), and the images were centered using detected faces and scaled to the size of 250x250 pixels. We manually labeled the ground truth regarding gender for each face. The faces that are not (near) frontal, as well as those for which it is difficult to establish the ground truth, were not considered (see Fig. 3 for some examples). In our experiments, we chose 7,443 face images (2,943 females and 4,500 males); see Fig. 1 for some examples. All experimental results were obtained using the 5-fold cross-validation. We partitioned the data set into five subsets of similar size, keeping the same ratio between female and male. The images of a particular subject appear only in one subset. As illustrated in Fig. 4, all images were aligned with commercial face alignment software (Wolf et al., 2009); the grayscale faces of 127x91 pixels were cropped from aligned images for use.

IV. RESULTS

To improve computation efficiency, we adopted a coarse to fine feature selection scheme: We first run Adaboost to select LBPH bins from each single scale LBP(8,R,u2), then applied Adaboost to the selected LBPH bins at different scales to obtain the final feature selection results. We plot in Fig. 2 the recognition performance of the boosted strong classifiers as a function of the number of features selected. We can see that the boosted strong classifier of multiscale LBP provides better performance than that of each single scale, achieving the recognition rate of 94.40%.

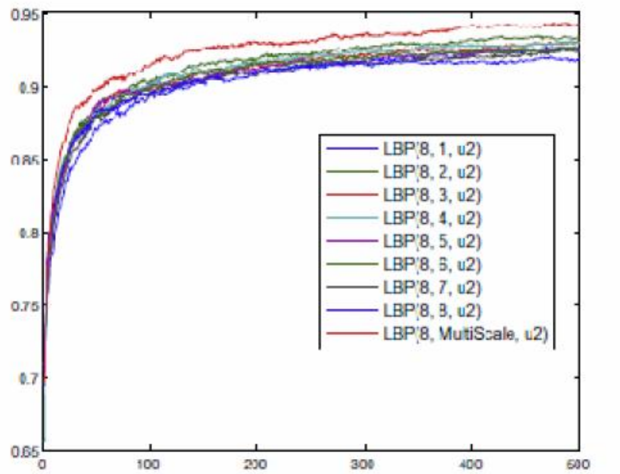

Fig.2.Classification Performance of boosted strong classifiers.

As observed in Table 2, the boosted LBP features also produce smaller standard variation. We see in Table 1 there is notable bias towards males in all experiments, as observed in existing studies (Shakhnarovich et al., 2002). This might be due to the unbalanced training data.

Approach			Recognition rates (%)		
Feature	Dimension	Classifier	Female	Male	Overall
Raw pixels	2,944	SVM	86.89	94.13	91.27 ± 1.67
Standard LBP	2,478	SVM	89.78	95.73	93.38 ± 1.50
Boosted LBP	500	Adaboost	91.98	95.98	94.40 ± 0.86
Boosted LBP	500	SVM	92.02	96.64	94.81 ± 1.10

Table 1.Experimental results of Gender classifications

VI CONCLUSION

In this paper, we investigate gender classification on real-life faces acquired in unconstrained conditions, a challenging but relatively understudied problem. We learn discriminative LBP-Histogram bins as compact facial representation for gender classification. By adopting SVM with the selected LBPH bins, we obtain the classification rate of 94.81% on the LFW database

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