Gender Perception From Faces Using Boosted LBPH (Local Binary Patten Histograms)

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***Abstract*—Automatic Gender classification from faces has several applications such as surveillance, human computer interaction, targeted advertisement etc. Humans can recognize gender from faces quite accurately but for computer vision it is a difficult task. Many studies have targeted this problem but most of these studies used images of faces taken under constrained conditions. Real-world applications however require to process images from real-world, that have significant variation in lighting and pose, which makes the gender classification task very difficult. We have examined the problem of automatic gender classification from faces on real-world images. Using a face detector faces from images are extracted aligned and represented using Local binary pattern histogram. Discriminative features are selected using Adaboost and the boosted LBP features are used to train a support vector machine that provides a recognition rate of 93.29%.**

Keywords— Local Binary Patterns, Boosted Local Binary Patterns, Gender Recognition, Facial Land-marks detection, Face Localization.

I. INTRODUCTION

Automatic Classification of demographic characteristics of humans like sex, age and ethnicity by the use of computer vision has received added attention by the researches in past few years. Correct recognition of gender for human beings is vital for many social tasks. For humans recognizing sex is very natural and many studies have shown that humans can distinguish males from females with more than 95% accuracy just from faces [1]. Automatic classification of gender plays significant role in a lot of applications such as surveillance, targeted advertisement, Human interaction with computer and collection of demographic information for marketing etc. In past few decades research interest in classifying gender automatically has increased.

To recognize sex on frontal images, in 1990's neural network based techniques were used [2, 3]. In [2] a two layered fully connected neural network, SEXNET, was trained that acquired a precision of 91.9% on 90 images of faces. Moghaddam and Yang in [4] used raw pixels of images and trained a nonlinear SVMs using RBF kernel. They experimented on the FERET database using 1,755 face images, achieving 96.6% accuracy. In [5] a nonlinear SVM-RBF was trained on features extracted by Principal Component Analysis. The experiment was conducted on Mixture of FERET, BioID and AR database using 200 male and 200 female images and reported an accuracy of 92.25%. H. C. Lian and B. L. Lu in [6] used local binary pattern histograms and trained a nonlinear SVM-Polynomial on CAS-PEAL database using 1800 male and 1800 female images and reported an accuracy of 94.08%. In [7] a convolution neural network classifier is trained using raw pixel values. Classifier was trained on FERET database using only frontal images of 1152 males and 610 females, achieving an accuracy of 97.2%. In [8] a comparison of internal zone facial features such as mouth, nose and eyes are compared with external zone facial features such as chin, hair and ears. They experimented on FRGC database and showed that facial features for the external zone contribute important information for recognition of gender. X. M. Leng and Y. D. Wang in [9] trained a FUZZY SVM using features extracted by Gabor. They used FERET (160 male 140 female), BUAA-IRIP (150 male 150 female) and CAS-PEAL (400 male 400 female) and reported accuracies of 98%, 93% and 89% respectively. L. Lu and P. Shi in [10] trained a nonlinear radial bias function kernel based support vector machine on features extracted by 2D principal component analysis. The experimented with FERET (400 male and 400 female) and CAS PEAL (300 male and 300 female) databases. They reported an accuracy of 94.85% and 95.33% respectively on two databases.

A familiar problem with the above research studies is that experiments used databases containing images taken under constrained conditions. One of the examples of such databases is FERET database that contains images with uncluttered background, slight variations in expression and lighting conditions that are consistent. Images in real-world on the other hand have wide variations in lighting, facial expression and cluttered backgrounds. Therefore for classifier to perform well in real world requires images from real-world to be classified correctly. Fig 1 shows examples from real-world and images taken under constrained conditions. Images taken in controlled environments have clean backgrounds compared to images in real-world that have wide variations in head pose, lighting and cluttered background. Therefore recognition of gender becomes challenging task in real-world compared to constrained environment. There are also research studies in literature that have targeted this issue. In [11] Bayesian network was trained on web images of 16000 males and 16000 females. Images were taken under unconstrained conditions. They reported an accuracy of 89%. In [12] 3500 images of face were gathered from the web. Using features that are Haar-like, they trained Adaboost and SVM classifier and obtained a precision of 79% for Adaboost and 75.5% for support vector machine. In [13] probabilistic boosting tree was trained using features that are Harr-like and a prerecession of

95.51% was reported on 10,100 actual-world images. C. Shan in [14] used boosted local binary pattern histograms and trained an SVM classifier. He showed that boosted local binary pattern with Feature vector dimension of 500 using SVM classifier can achieve accuracy of 94.81%.

Fig. 1. Examples of images taken under constrained conditions (ROW 1 from FERET [26] database) and images from real-world (ROW 2 from LFW [24] database)

II. SYSTEM OVERVIEW

Recognizing gender from faces whether there is a single face or multiple faces in the image requires, face detection and then determination of gender. Fig 2 shows the pictorial illustration of gender recognition system

Fig. 2. Gender Recognition System Overview.

A. *Detection of Face*

From figure 2 it can be seen in order to get a decision for gender, face from the image is needed. Therefore faces are first localized, using some face detector. In 2006 P. Viola, M. Jones [15] proposed a new face detection technique and since then their face detector has been the defacto face detection standard. Haar Cascade classifier (As it uses haar like features) is used to localize faces. Once the face is localized, it is aligned and re-sized to 64 x 84 sizes as show in figure 3. For face alignment first facial landmarks are detected, using facial land mark Detector based on Deformable Part Model described in [16]. Using the eye corners (left eye corner and right eye corner) and measuring the angle between eyes, rotation about x-axis is removed. Thus the eyes are aligned as shown in figure 3.3

B. *Gender Recognition*

Features are extracted from localized faces. Local binary pattern histograms are used to represent faces. Finally decision (male/female) is made by the trained classifier. Two classifiers are trained, support vector machine with RBF kernel and Adaboost for classification purpose. It is shown through experiments that discriminative features learned using Adaboost from multi-scale LBPH (local binary pattern histogram) feature pool contain more discriminative information for classification of gender.

Fig. 3. 3.1) Original Image 3.2) Detected Facial landmarks 3.3) Cropped, Re-sized and Aligned face

III. FACE REPRESENTATION WITH LBPH

The original LBP pioneered by Ojala et al. [17] works on a neighborhood of 3x3 pixels, by thresholding the neighborhood by the value of center pixel. The label is obtained for the central value by multiplying with the power of two and finally all the values are summed. Figure 4 illustrates the basic operation of LBP (local binary pattern). The local binary pattern in decimal can be expressed by following equation:

$$LBP\ (x_c, y_c) = \sum_{p=0}^{7} s(i_p - i_c) 2^p \qquad (1)$$

Where i_P and i_C are neighbor and central pixel values respectively, and s(x) is equal to 1 if x greater than or equal to 0 and 0 otherwise. For neighbors equal to eight for each label there are 256 possible combinations ($2^8 = 256$).

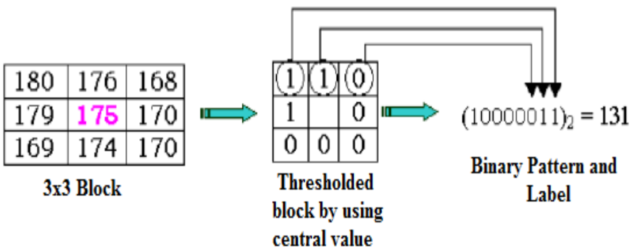


Fig 4. Illustration of Local Binary Pattern Calculation

Two extensions were made to the original operator by Ojala et al [18] later on. Firstly To acquire the strong features at different scales, circular neighborhood of different sizes is used. The Bi-linear Interpolation of the pixels and circular neighborhoods acknowledge any number of pixel and radius in the neighborhood. The representation (P, R) designate a surrounding of P coordinately separated sample points on a circle that has radius R. Secondly to characterize the image textures, they suggested using smaller subset containing 2^P Local binary patterns, generated by LBP (P, R) operator. This smaller subset of pattern is called uniform local binary patters.

The Uniform patterns at most contain only two bit-wise changes from 0 to 1 and from 1 to 0. Some Uniform pattern are 00000000, 11111111 00100000 etc. Ojala et al noticed from experiment performed on texture images noticed that 90% of all pattern are uniform in a neighborhood of (8, 1). As figure 5 shows most information is captured by uniform local binary patterns.

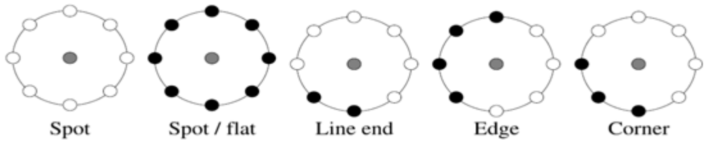
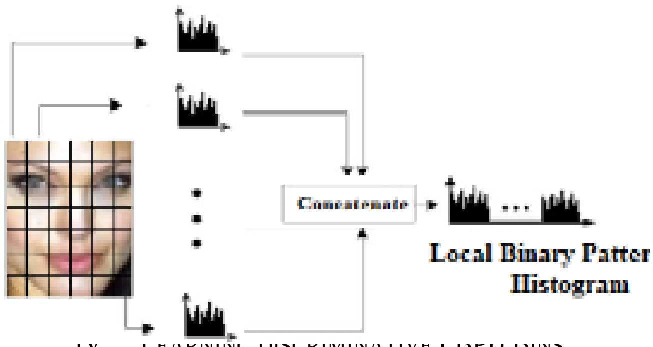


Fig 5. Some Uniform Local Binary Patterns

Thus for each uniform pattern there is a separate label and a single label for non-uniform pattern. Thus producing and LBP operator, designated by LBP (P, R, U2), that generates smaller no of patterns as compared to regular LBP operator without losing much information. Images after having labeled using local binary patterns operator, the histogram of these labeled images can be utilized as a descriptor for texture. Images of faces thus can be thought of combination of micro-patterns that can easily be characterized by local binary patterns. To globally describe the images, many current studies suggest, to break down the face image into non-coinciding sub-regions (shown in fig 6), and concatenate the extracted local binary pattern histograms for these sub-regions in spatially amplified or enhanced histogram. Such feature histogram characterizes local texture and shape of the face image globally.



IV. LEARNING DISCRIMINATIVE LBPH BINS

Fig 6: Face Representation Using Local Binary Pattern Histogram

The feature vectors (LBPH) so obtained contain bins that are not all discriminative for the representation of face. Adaboost is used to learn LBPH bins that are discriminative for face representation, an approach similar to the one described in [14, 21]. The boosting algorithm (Adaboost) described in [20, 21] uses an uncomplicated and effective strategy for learning a classification function that is nonlinear using a stage wise approach. Adaboost works with a weak learner (classifier) whose responses are just better than random guessing and by learning small no of weak classifiers iteratively Adaboost produces a strong classifier having high prediction rate. Adaboost keeps a distribution over set of examples (feature vectors) and during each iteration a weak classifier is selected that is able to minimize the weighted error rate. The distribution is updated such that more weight is given to examples that were classified wrong. Thus giving more importance to misclassified examples compared to correctly classified examples. The weak classifier is similar to the one used in [15] and shown in equation below.

$$\mathrm{h_j}(x) = \begin{cases} 1 & if\ \ p_j\ f_j(x) \le p_j \vartheta_j \\ 0 & Otherwise \end{cases} \qquad (2)$$

The weak learner $\mathrm{h_j}(x)$ is made up of feature $f_j(x)$ which comes from single LBPH bin and p_j here is used as parity indicating the direction for the sign of inequality and finally the threshold value ϑ_j .

V. TRAINING THE CLASSIFIER

Images from three different databases are used for training and testing purpose. Table 1 gives the distribution of images from different databases in the data-set. Faces from the images in the data-set are localized aligned and re-sized to 64 x 84 sizes for training and testing purpose Images from LFW are aligned so the images of faces can be detected by the face detector. Only those images are considered for which ground truth can be established (male/female) that is images of infants are not considered, and faces that can be detected using Haar cascade face detector. In this study we have only considered images with frontal faces with very little variations in pose.

TABLE I. DISTRIBUTION OF IMAGES FROM DIFFERENT DATABASES IN DATA-SET

Database	***Male Images***	***Female Images***	***Pose***	***Total***	***%of data set***
Ferret [26]	512	500	Frontal	1012	14.85
SUMS	200	200	Frontal	400	5.9
LFW [24]	3200	2200	Variou s	5400	79.2
Total				6812	

A. *Uniform Patterns*

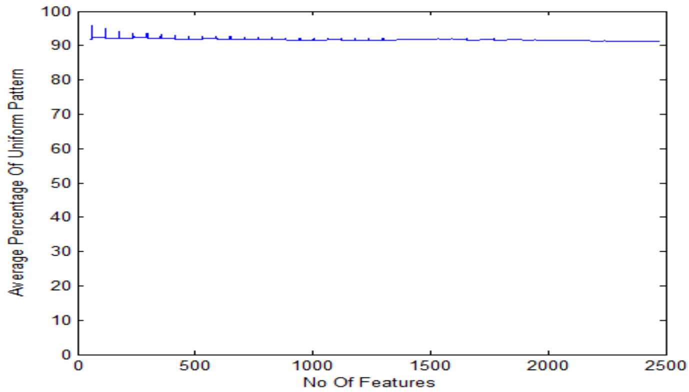


Fig 7: Graph of uniform pattern in the data set using LBP (8, 2) operator

Experimentally it was shown in [18] that 90% of texture information was contained in uniform patterns. To investigate this fact in the data set considered, LBP (8, 2) operator Was applied on all the images in the dataset. A similar trend was noted in the data set considered. For example in figure 7 the horizontal axis of the graph shows the no of features considered through the iteration and average percentage of uniform pattern in images in the data set. From the figure it can be seen that majority of the pattern in the images are uniform (approximately 91%). In figure 8 a comparison of LBP (8, 2, u2) vs. LBP (8, 2) is given. Each image of the Face was represented by 10,752 feature vectors (42x256 in case of LBP (8, 2)) and then using adaboost discriminative features were learned. In figure 8 vertical axis represent recognition rate for the choice of selected features that is the strong classifier performance. The comparison shows that strong classifier obtained by boosting for LBP (8, 2, u2) and LBP (8, 2) perform very similar, which again shows that patterns that are not uniform have no additional knowledge for discrimination of gender perception.

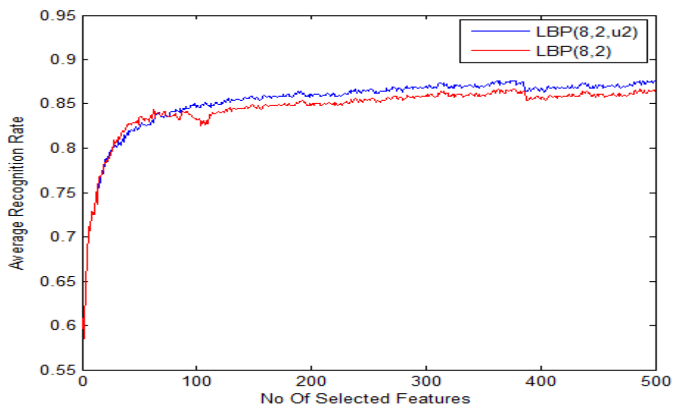
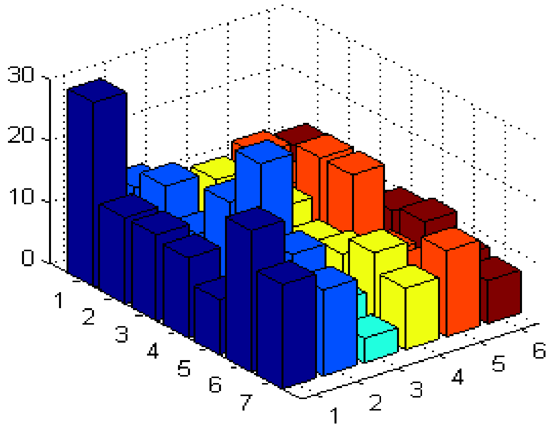


Fig 8: Comparison of LBP (8, 2, u2) recognition rates vs. LBP (8, 2)



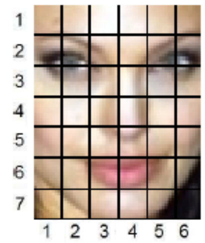


Figure 9: Top 500 Selected BINS by using LBP (8, R, u2) operator and Adaboost

C. Distribution of Features

The performance of multiple scale local binary patterns for classification of gender was investigated. To obtain the local binary patterns of different resolutions radius of samples is varied, that is R=1, 2 ….8. By varying the radius of samples, a feature vector of local binary histogram so obtained has dimension of 19824 (59x8x42). Using Adaboost discriminative features (LBPH Bins) from the pool of features are learned. Classification performance using different resolution local binary patterns is also investigated. Table 2 shows the classification performance obtained by applying local binary pattern operator of different radius. The dimensions are kept at 11 x 12 for every sub-region for all cases. Two classifier, Adaboost and SVM-RBF are considered in this experiment and a comparison of their performance is given. It can be seen from the table that multi-scale local binary pattern features contain more discriminative information for gender classification. Finally it is observed that SVM-RBF performs better than Adaboost and gives higher recognition rates.

Table 2. A comparison of SVM and Adaboost classifiers. (5-CV = Five Fold Cross Validation, 1055f= 1055 female face images, 1075m= 1075 male face images)

Method					**Classification Rate (%)**			
LBP Operator	**Features**	**Total No Of Features**	**Feature Vector Dimension**	**Classifier**	**Test Data**	**Male**	**Female**	**Overall**
LBP(8,2)	Boosted LBP	10752	500	Adaboost	1055f, 1075m	91.15	82.08	86.61
LBP(8,1,u2)	Boosted LBP	2478	500	Adaboost	1055f, 1075m	91.34	80.94	86.19
LBP(8,1,u2)	Boosted LBP	2478	500	SVM-RBF	5-CV	93.39	81.7	87.6
LBP(8,2,u2)	Boosted LBP	2478	500	Adaboost	1055f, 1075m	92.18	81.8	87.04
LBP(8,2,u2)	Boosted LBP	2478	500	SVM-RBF	5-CV	94.13	83.88	89.06
LBP(8,3,u2)	Boosted LBP	2478	500	Adaboost	1055f, 1075m	91.9	83.98	87.98

LBP(8,3,u2)	Boosted LBP	2478	500	SVM-RBF	5-CV	93.95	90.09	91.91
LBP(8,4,u2)	Boosted LBP	2478	500	Adaboost	1055f, 1075m	93.2	82.08	87.69
LBP(8,4,u2)	Boosted LBP	2478	500	SVM-RBF	5-CV	94.51	85.49	90.04
LBP(8,5,u2)	Boosted LBP	2478	500	Adaboost	1055f, 1075m	92.27	84.83	88.59
LBP(8,5,u2)	Boosted LBP	2478	500	SVM-RBF	5-CV	95.16	86.16	90.7
LBP(8,6,u2)	Boosted LBP	2478	500	Adaboost	1055f, 1075m	91.44	82.18	86.85
LBP(8,6,u2)	Boosted LBP	2478	500	SVM-RBF	5-CV	93.39	85.78	89.62
LBP(8,7,u2)	Boosted LBP	2478	500	Adaboost	1055f, 1075m	91.25	82.08	86.71
LBP(8,7,u2)	Boosted LBP	2478	500	SVM-RBF	5-CV	92.27	84.17	88.26
LBP(8,8,u2)	Boosted LBP	2478	500	Adaboost	1055f, 1075m	90.88	80.28	85.63
LBP(8,8,u2)	Boosted LBP	2478	500	SVM-RBF	5-CV	93.11	81.42	87.32
LBP(8,R,u2) R=1,....8	Boosted LBP	19824	500	Adaboost	1055f, 1075m	93.11	86.82	89.98
LBP(8,R,u2) R=1,....8	Boosted LBP	19824	500	SVM-RBF	5-CV	96.16	90.42	93.29

D. *Experiments with Real World Images*

Experiments on real world images gathered form the internet are conducted. Images that are taken are not the part of any the database used for training and testing the classifiers and every image contained multiple faces per image. Images below are processed by the proposed system. Faces with red rectangles around them are classified as females and with blue are classified as males.

Fig 10: Faces detected 6 correct classifications 6

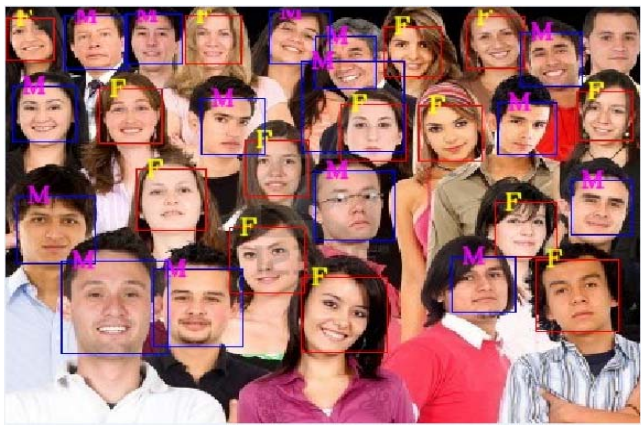


Fig 12: Faces detected 29 correct classifications 26

Fig 13: Faces detected 4 correct classifications 4

Fig 14: Faces detected 11 correct classifications 10

Fig15: Faces Detected 38 correct classifications 30

VI. Conclusions

This paper examines the problem of classifying gender on real-world images. The databases used are FERRET, LFW and SUMS databases for training and testing the classifiers. Adaptive boosting has been used to pick out (learn) discriminative Local Binary Pattern Histogram bins. Boosted Local Binary Pattern Histogram bins give a smaller representation of images of faces. SVM-RBF is trained on compact representation of faces which provides overall recognition rate of 93.29%. Faces from images are localized using face detector (haar Cascade Classifier) and faces are aligned using facial land-marks (left eye corner and right eye corner) detected by facial landmark detector based on Deformable Part Model [16]. Images from the web are gathered and processed by the proposed system and images contained multiple faces for example crowd of people etc and obtained good recognition rates.

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