Gender Classification based on Fusion of Facial Components Features

***Abstract*—The last few years have seen a great interest in image processing and as a result research in this field has been undertaken into the classification of gender based on face components because of its applications in database searching, marketing and knowledge that the human face carries a lot of information which may be extracted and used for many various purposes. This paper presents gender classification based on the fusion of facial components, eyes, nose, mouth, forehead and cheeks as many factors such as occlusion may affect visibility as they block the camera from viewing a facial image and to offset the effect of some features which have a lower classification rate. An artificial neural network with back propagation is used here for classification. The findings of this research showed us that with fusion the accuracy rates of components with lower classification can be improved. A good example being the mouth having a percentage accuracy of 75%, however after fusing it with the feature vector of the nose which has an individual classification of 90% we get an accuracy of 87%. This is of great use when large part of the component with a higher classification accuracy is occluded.**

***Index Terms*—Components, classification, components, fusion.**

I. Introduction

Gender classification refers to the process of determining gender based on facial features. There are a number of biometrics which may be used to classify gender such as the face, eyes, fingerprint and hand shape amongst many others however this paper focuses on the fusion of facial components to classify gender. This classification is very important for humans as it then determines how one communicates with others based on their gender. The ability to classify gender is a very easy task for humans, however passing this ability to computers is complex but achievable. Even if the face is cropped to remove all gender cues, we can identify gender with very high accuracy [1]. Automatic recognition and analysis of faces is one of the most challenging tasks in object recognition [2]. Previous research studies have shown that a human can categorize between male and females with great ease, recording a classification of above 95% [3] from faces. From the face there is a wide range of information one can get such as age, race, gender, scars and tattoos which can be used for various purposes as discussed below.

In order to classify gender, the face images should undergo analysis which will be undertaken in this paper as well. Successful analysis allows many interesting applications in human computer interaction, security industry and psychology, among others. Automatic gender classification is also a useful preprocessing step for face candidates before the recognition of the person and thus make the face recognition since it is possible to halve, in a case of equal amount of both genders, the number of face candidates before the recognition of the person and thus make the face recognition twice as fast [4], hence gender classification can be seen here used as an input to face recognition increasing the speed of recognition systems. There are a number of approaches to gender classification which can be undertaken which are appearance and geometric based. The geometric based methods are based on the relationships distances that exist between facial components. Geometric relationships between these points are maintained but other useful information may be discarded [5].

Appearance based methods on the other hand perform operations on pixels on an holistic or local level, at the local level the face is divided into defined regions such as eyes chin among others. There are a number of advantages of appearance methods over the geometric approach, one being that geometric relationships are naturally maintained which is very important when the gender discriminative features are not known exactly and they are sensitive to variations in appearance(view and illumination amongst others) [5]. Geometric features requires accurate feature extraction as to use locations of facial features for classification the ratios of distances are used and hence need to be very accurate.

Gender classification has been carried out by various researchers using facial components such as [1], [6], [7], who have mainly used one feature.However a distinguishing factor between our research and that done by previous researchers is that we have fused our facial features, at vector level with aim of improving classification accuracy. Very few researchers have applied fusion to improve gender classification rates [8], [9].

II. Literature Review

This section gives an overview on face detection. A number of databases have been used in face recognition. The most popular being the Facial Recognition Technology (FERET) Database as used in a number of papers such as Bissoon [10] and [11]. Another database used in face recognition is FG-NET database which was released in 2004 [12], which is used in this research. Golomb et al [6], put forward a neural network based method to be able to distinguish between the two genders. They went on to use a database containing 90 images equally split between males and females. They referred to their 2-Layer fully connected neural network as SEXNET. The accuracy reported on this paper was 91.8% [13], in this paper the images were manually aligned.

However in this paper we detect the Region of Interest (face) using Haar Cascades .Golomb et al got an average error rate of 8.1% compared to an average error rate of 11.6% he got with five human subjects [14]. This was a great stride for computer vision as SEXNET had a lower error rate marking room for improvement in the years that followed.

Hu et al [15]use the Local Directional Pattern for feature extraction and compares the classifications rates of three classifiers, the Local Directional Pattern, Local Binary Pattern and Principal Component Analysis using the FG-Net Database. In their experiments Hu et al used 200 facial images as the training sample and 100 facial images as the test sample in the database. The findings of their paper had the Local Directional Pattern (LDP) perform best with a recognition rate of 95% [16], LBP 93% followed by PCA with 85%. These experiments had very good results considering that they did not use any feature reduction techniques. In this paper we used feature reduction techniques LDA and PCA. Important facial feature points are detected and unnecessary points are discarded in this technique using PCA as stated by Khan et al [15]. Hence using feature reduction techniques may also lead to the loss of important features for classification hence they should be used only when necessary to reduce dimensionality.

Sun et al [17] put forward the idea that feature selection is an important issue for the gender classification and went on to show that Genetic Algorithms can perform this task well. They used Principal Component Analysis to extract features and create feature vectors which he used as input for the four classifiers Bayesian, neural network, Support Vector Machine (SVM) and Linear Discriminant Analysis (LDA). They went on to compare the performance of these four classifiers. The SVM classifier achieved the best classification rate 95.3% [4].

Bissoon et al [10] addressed the gender classification problem using Principal Component Analysis tackled the gender classification problem by using the PCA and LDA and comparing their results in three experiments. The most successful round of testing included a success rate of 83% when the PCA algorithm was applied, with an overall success rate of 85%reached when the LDA algorithm was applied to the system .The use of LDA leads to an increase in classification rate. LDA based algorithms outperform PCA based one, since the former optimizes the low dimensional representation of the objects with focus on the most discriminant feature extraction while the latter simply achieves object reconstruction [18], [19].

Not much research has been done on gender classification based on feature fusion. A research was carried out by [9] put forward a system which classified gender based on facial features, nose, eyes ,mouth ,chicks and external features such as hair and clothes using the SVM with various kernels. Most research work does not include clothing when classifying gender as it tends to have a large variations, however [9]states that from their observations male clothing is simple as compared to that of females and thus he used it in his experiments. The SVM classifier was used with the RBF kernel giving the highest classification of 82.9 on the features individually. Fusion of all facial features gave an accuracy of 89.5 and that of clothing hair and face gave an accuracy of 90.8%.

Jaswante [1] implemented back propagation neural networks to classify gender obtaining a classification rate of 100%.In their research the geometric approach was used .The architecture of the system was comprised of four hidden layers and one output layer. However the dataset is created by taking 100 images from the CIPM institute, which limits the results comparability with those of other researchers who used benchmarked datasets such as the FERET.

The results gained from fusion have resulted in improved results [19],who stated that by combining classifiers the accuracy is better than using a single classifier using weighted majority voting, they found the genetic algorithm to have the best results whenever used as a union of classifiers and was applied to the Stanford University Medical Students (SUMS) face database achieving a 94% accuracy rate. [20].

A combination of geometric and appearance based approach is also applied. Psychological experiments show that sub-face individual features comprising of brows, eyes, nose, mouth and chin when seen in isolation, carry a lot of gender information [8].The Discrete Cosine Transform, LBP and the geometric based feature are used. Majority voting is used to classify gender with the experiments carried out on two datasets the AR and ethnic. The results of this experiment showed that the novel geometric distance feature.

III. Methodology

The framework below outlines the steps taken right from loading the image through all the analysis stages upto finally classifying gender as shown in figure 1. These steps involved in this framework are the one taken when carrying out the experiments.

A. *Region of Interest detection*

In this research face detection is carried out by the Viola Jones algorithm. We first detect our Region of Interest, then get the three components to be used in this research which are the nose, mouth and eyes. The region of interest is drawn out using the two vertexes of a rectangles given then face height and width. The Region of Interest is represented by a rectangle drawn around the facial area. After which we It uses Haar-like features, a scalar product between the image and some Haar-like templates [21].

B. *Preprocessing*

After the three facial features are applied we then have to get them into the appropriate sizes to make the process faster or easier. Since the database we are using contains mixed

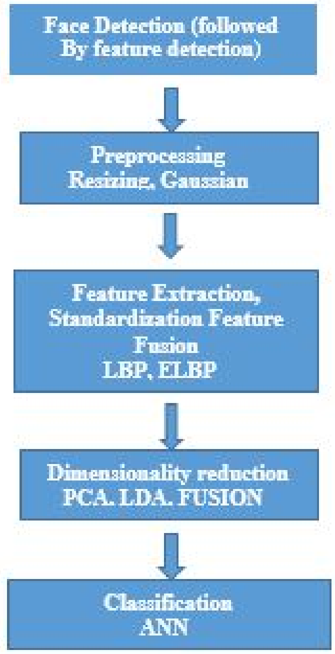

Fig. 1. System framework

color and gray-scale images we have to convert all of them to one channel, grayscale images. Grayscale representations are often used when one is extracting descriptors instead of operating on color images directly is that grayscale images simplify the algorithms processes they have less computational requirements [22]. After the image has been turned into a gray scale we resize it to be of dimension 120by120 this is done to maintain uniformity and also so that all the matrices will be of the same size.

The facial features are detected as shown in figure 2 below. The eyes ,nose and mouth are detected by the use of Haar cascades, however the forehead, cheeks are drawn out by using prior knowledge of their location for example the forehead is above the eye hence we just move up a distance slightly more than the eye boxs enclosing radius and use the eye radius as the foreheads shorter side.

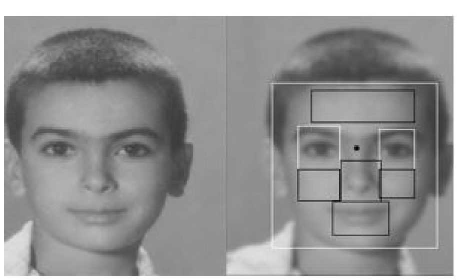

Fig. 2. Feature detection

C. Feature Extraction

Images in computers are represented in a complex way ,however since we intend to perform some mathematical operations may be applied upon them easily .The original Local Binary Pattern is used in this case taking a 33 block, where each pixel is thresholded against the center value as shown below with the final binary value converted to a decimal and these are the Local Binary Patterns.

The labeling of each pixel of an image by thresholding its P-neighbor values with the center value and converting the resulting binary string into decimal code using equation (1) below

$$LBP(x,y) = \sum_{n=0}^{k-1} s(i_n - i_m)2^n \tag{1}$$

In the equation above i_m represents the middle pixel at coordinate(x,y) and i_n represents the neighborhood pixels.

In the equation above i_m represents the gray level of the pixel at position (x,y) and i_n represents the gray level of the nth neighborhood pixel and k is the number of neighboring pixels considered.

$$s(x) = \begin{cases} 1 & \text{if } x \geq 0 \\ 0 & \text{if } x < 0 \end{cases} \tag{2}$$

D. Dimensionality reduction and feature fusion

After feature extraction we have to select the most important features and throw away the rest, as the data would be of high dimensionality and hence has to be reduced using Principal Component Analysis. PCA is a very well-known method of identifying patterns in data and expressing data in such a way that to highlight their similarities and differences [26] [23]. High dimensional data usually contains data which may have many irrelevant variables [24]. Hence we used PCA to reduce the feature vectors columns(dimensionality reduction).

Since we seek to solve a binary problem we then use LDA, as PCA only gives us the main variance of data. The main aim of LDA is to find optimal projection, vectors simultaneously minimizing the within-class distance and maximizing the between-class distance for the given data [25]. The drawback of using PCA before LDA is that in cases where there are few samples is that it may result in valuable texture information being discarded [26] The primary goal of feature fusion is to have one feature offset the classification weakness of another feature. As one component may also have a high level of noise associated with it, hence we fuse the mouth, which had the highest classification rate [18] with the eyes.

E. Standardization

Before feature fusion is performed we need to standardize our feature matrices, there are a number of ways to perform this and we have performed Z-score standardization on the two feature matrices before fusing them by addition. This can be done by performing the three steps that follow:

$$\mu = \sum_{1}^{n} \frac{x}{n} \tag{3}$$

Above μ is the mean ,n is the number of samples and x is the particular value to be standardized. One has to find the standard deviation as shown below

$$\sigma = \sqrt{\frac{\sum(x-\mu)}{n}} \tag{4}$$

Then standardizing each matrice value Z-score = $\frac{x-\mu}{\sigma}$

F. Back propagation Neural Networks

A neural network may be thought of as a set of interconnected neurons which operate together to perform a particular task [1]. There are different structures of neural networks which one may use from feed forward to back propagation neural networks. The fact that back propagation neural networks are simple has led to them being used in a wide range of applications and are the most common neural network structures [26] The back propagation neural network is hence used as our classifier in this research paper. However there a number of variables which need to be set such as the number of nodes and layers, weights and learning parameters.

IV. Results

The table below shows the accuracy results after carrying out classification based on single features and after fusion.

TABLE I
GENDER CLASSIFICATION USING SINGLE FEATURES

Feature	Accuracy
Nose	90%
Eyes	87%
Mouth	75%
Forehead	92%
Cheeks	89.2%

TABLE II
GENDER CLASSIFICATION USING FEATURE FUSION

Feature	Accuracy
Forehead+Eyes	93%
Forehead+Nose	94.6%
Forehead +Cheeks	93.7%
Nose +eyes	92%
Nose +Cheeks	91.3
Nose +Mouth	87%

From the results above it can be seen that fusion leads to improved classification rates. Even for features which themselves have a lower classification rate, like Mouth. When it is fused with a high classification rate feature like the nose, its classification rate is improved.

V. Conclusion

From the results it has been shown that gender classification using feature fusion is seen to offset the low classification rates at feature level too, as fusion of appearance ad geometric approach had been seen earlier to also improve the approach using the FG-NET dataset. A good example is that of the mouth which moves from 75% to a fusion accuracy classification of 87% when fused with as a combination with the nose. However our feature extraction technique requires enhancement especially when it comes to the forehead detection and cropping as hair is often cropped out too.The mouth has the lowest individual accuracy rate, this may be a result of some males having beards which has an effect on classification rate, reducing accuracy.

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