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FUSION OF GEOMETRIC AND TEXTURE FEATURES FOR SIDE-VIEW FACE RECOGNITION USING SVM

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Abstract: Biometric recognition systems have been getting a lot of attention in both academia and the industrial sector, one of such aspects of biometrics attracting interest is side-view face recognition, the side-view of the face is known to hold unique biometric information of subjects. This study embarks on contributing to the research of side-view face biometrics by proposing the fusion of geometric and texture features of the side-view face. Local Binary Pattern (LBP) was used for the extraction of texture features and the application of Laplacian filter was used for the extraction of geometric features, both features were tested in side-view face recognition individually before fusion of the two features in order to observe and note the effect of fusing the two features has on the performance of side-view face recognition, the experiments carried out in the proposed recognition system utilized Support Vector Machine (SVM) for classification, the training of the system was done using the histograms of the texture and geometric features extracted and labelled for every individual subject in the dataset. All experiments were done on the National Cheng Kung University (NCKU) faces dataset.

Key words: Side-view face recognition, Local binary pattern, Histogram fusion, SVM, Laplacian filter.

1. Introduction

It is clear that the processes of identification and verification has seen an evolution in the way these processes are being carried out, the traditional methods of these processes are slowly being replaced and being automated and integrated with biometric systems. As these systems grow and become sophisticated so is the growing need of security, biometric systems are being used in providing robust systems due to their growing sophistication and efficiency. Biometric systems use a process known as pattern recognition to carry out authentication or identification processes, biometric systems are mainly categorized based on the modalities used for the systems, which are physiological and behavioural modalities [2]. One of the most popular and well accepted biometric systems in both the research sector and the industrial sector is the face biometric systems, systems based on the face biometric modality use the human face for the pattern recognition process. Most facial biometric systems have been designed and developed for the frontal facial view, these kinds of systems require a relatively controlled scenario for an efficient recognition or identification process to be carried out, the control environment usually means a system is limited in its robustness, where a factor such as the viewing angle may pose a challenge to a recognition or identification system [12]. One of the most popular recognition systems for the human face recognition is the Viola-Jones technique of facial recognition systems, this system uses a process which involves the extraction of a specific feature from a detected facial image input which has to be a full-frontal view image, the specified feature is extracted through what is known as a window which is automatically scaled based on the size of the detected face, figure 1 below shows the steps of this algorithm through a typical recognition system flow chart.

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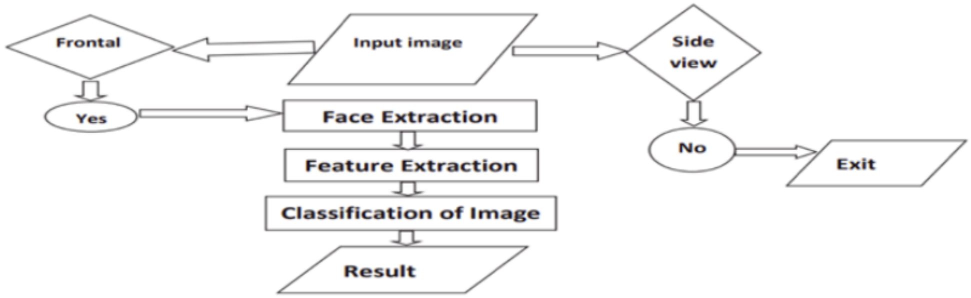

FIGURE 1. Typical Facial Recognition Flowchart[2]

As most systems and algorithms of facial recognition are designed and built to work with full frontal facial images, this makes the use of facial images with non-full-frontal pose images such as facial side view images in such systems challenging for the systems to recognize sand authenticate [1]. Both two dimensional (2D) and three dimensional (3D) facial images have been used in the field of facial image recognition systems, and studies and reports have shown the use of 3D facial images yielding more performing systems when compared to 2D facial recognition systems, however 2D facial images recognition systems are also significantly well performing, and it is also noteworthy that 3D systems require a lot more computing resources than their 2D systems counterpart which require a lot less computing power to work efficiently [13]. There are several 2D face recognition feature analysis systems that have been prominently used over the years and some of them are as follows: eigenfaces approach and geometric features-based approach, this study attempts to utilize two different approaches to facial features in side view, which are the texture based feature and the geometric based feature, the two chosen features will be applied using Local Binary Patterns (LBP) and Laplacian filters for texture and geometric features respectively.

2. Literature Review

Studies in facial recognition have been significantly pushed by the progress of computational technology of the past few decades, these technological advancements have made it possible to model mechanisms in such a way that they could possibly be as good or even more robust than the human visual perception. Facial recognition has seen a huge rise in interest due to its efficiency and non-invasive characteristics of the modality, this makes it suitable in many kinds of system and even in systems which do not require the cooperation of a subject for a recognition or identification process to be performed on them. Facial recognition systems go as far back as 1964 where Woodrow Wilson Bledsoe conducted computerized facial recognition experiments with an objective of simply identifying a specific image from a large number of images, in this study Bledsoe reported challenges faced by the study which were as follows: variation in accuracy with respect to variation in inclination and facial poses of the subjects, the intensity/angle of lighting, and the variation in facial expressions of subjects [17]. In a study by [6], subject markers were utilized by an operator which were measured and compared by the system to perform the facial recognition in each input photograph image, despite the earlier start of studies on facial recognition systems, automated facial recognition systems only really started in a 1971 [10], the study used an automated system to automatically extract and analyse facial features which included measurements of the nose, chin, and eye region, the study used the Euclidean distance classifier [23]. Over the years there have been proposal and utilization of several methods for facial recognition systems, the classification of the existing methods of facial recognition systems is complex, however they can still be categorized into three major categories which are: local based methods, holistic based methods and hybrid-based methods of facial recognition.

Holistic methods according to [11] are the systems which implement a method which uses the entire facial regions in their recognition process, this method includes the eigenface and fisher facial recognition techniques, local based facial recognition methods are the methods of facial recognition which specify local characteristics from a facial image to analyse such as the region of the mouth, eyes or nose.

local based methods have been very successful in facial recognition systems especially when compared with holistic based methods of facial recognition systems because they have an advantage whereby they are not as sensitive to variations in lamination and poses of the facial images been analysed but its accuracy performance is highly dependent on the efficiency of the features extraction method applied. Hybrid based recognition methods are as the name implies, a combination of both local based methods and holistic based methods in an attempt to use the best of what both of them have to offer as a single method in a facial recognition system.

2.1. Side View Face Recognition

This reported side view face recognition was in the 1970s [18], where the study was carried out by profiling side view facial images' silhouettes and was used for recognition, the study reported an impressive performance of up to 90 percent accuracy while auto correlations and K nearest neighbour was used as the classification algorithm of the facial recognition system, the study used a total of ten subjects. Another study [20] used facial labelling of facial landmarks on side view facial images as shown in figure 2 below, they used this labelling to wrap and register the facial features which they then applied Principal Component Analysis (PCA), Local Binary Pattern (LBP), and Linear Discriminant Analysis (LDA), and compare them, the study showed LBP having the better performance of the three applied methods with a performance accuracy of 91.1%.

FIGURE 2. Manually labelled facial landmarks

Another study [15] carried out an innovative technique whereby both left and right-side view facial images of subjects were taken and used to detect and select the eye region of the subjects using an algorithm to create a single facial image from the two-side view facial images of subjects, the processed image is used to train the system after a median filter is applied to rid of possible noise, this study concluded the region of interest in side view facial images are the nose and eye regions of the facial images. [14] a study which successfully developed an algorithm to detect the eye brow region of facial images for both right and left side view face images made it possible to identify whether an input side view image was either left side or right side view face image, this enabled their facial recognition system to specify which facial images and their features to analyse in the automatic recognition process, the study also utilized local features for the recognition process of the side view facial images, and the vectors of LBP and Grey Level Co-occurrence Matrix (GLCM) were formed. [16] carried out a study which investigated facial recognition with respect to facial expressions in a multi view facial image which was a study motivated with handling non full frontal face images in a face recognition system, the study utilized local descriptors in the face images in the form of histograms, they used LBP for feature extraction in the form of grid set uniform sampling which were a division of 46 sub blocks of the facial image, the multi pose variation of the subjects was handled through the use of viola jones for facial regions extraction from the input images, the pose variation were in 0◦ ,15◦, 30◦, 45◦, 60◦ , 75◦ and 90◦ as can be seen for the respective angle of pose respectively in figure 3 below.

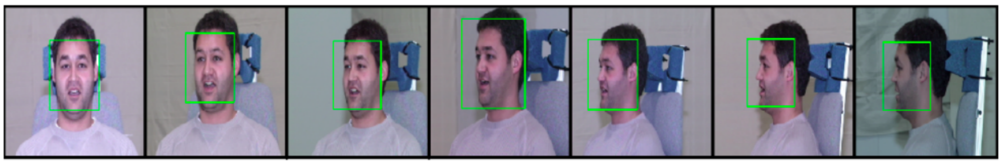

FIGURE 3. Subject face image in multiple pose variation [16]

The dataset used for this study had 4200 images, and the classification method used for the study in the experiments was Support Vector Machine (SVM).

2.2. Local Binary Pattern (LBP)

Local Binary Pattern (LBP) is an algorithm which is also an operator which is best described as a texture descriptor, LBP is used to extract and provide the texture information from the contours in an image of any kind of object. Unlike the visual perception of the human eye, LBP can distinguish between colours from the contours of an image, LBP is a very powerful descriptor because the texture information of an image is capable of giving information about the outline of an image [4], LBP descriptor was developed with working with images that are monoscriptal in as a feature, LBP uses eight closest pixel neighbours, where the LBP resulting pixel value depends on the value of the neighbouring pixels surrounding it, LBP also works by highlighting the edges of an image which in turn gives it a chance of obtaining better description of the texture of an image. LBP as an operator uses the following steps to carry out its function: it first starts by dividing the input image into n parts, however the most advised number of divisions of an image for an LBP operator is 16 because it gives efficiency for both accuracy and time taken to carry out the LBP operation on an image. LBP then uses a 3x3 mask with respect to the centre pixel of the mask, and then proceeds to apply the following formula as seen in formula 2.1 below.

$$LB(px_t - px_c) = \begin{cases} 1, px_t \geq px_c \\ 0, px_t < px_c \end{cases} \tag{2.1}$$

Where px_t is the pixel being analysed, and px_c is the centre pixel of the matrix, This is used to calculate and obtain new pixel values for the matrix in a manner where all neighbouring pixels are compared to the centre pixel, where the centre pixel is greater than the neighbouring pixel a binary value of 0 is assigned to the pixel as its new value else it is assigned 1 and the new pixel value [4], the new pixel value are then extracted as a vector of binary values which is then used to generate an LBP histogram from the acquired binary values, the total histograms gotten for an image are then concatenated into a spatially enhanced histogram as defined by formula 2.2 below.

$$H_{ij} = \sum_{x,y} I\left\{f_l(x,y) = i\right\} I\left\{(x,y)\,\epsilon\, R_j\right\}, \qquad i = 0, ..., n-1, j = 0, ..., m-1 \tag{2.2}$$

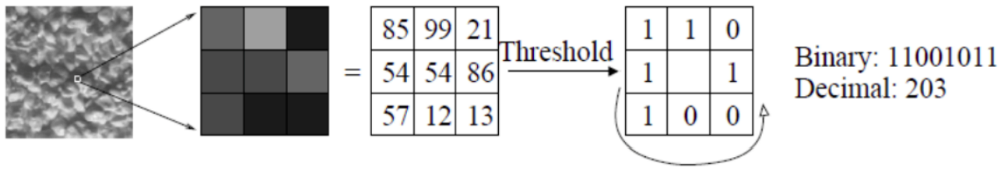

FIGURE 4. Basic LBP operator function on image

The entire LBP operator function on an image can be seen as described in figure 4 below

LBP as an operator has been used over the years in several studies and has also been proven to be a very powerful texture feature extractor, the use of LBP in facial recognition system can be seen in [4] where the authors achieved a performance rate of up to 90% accuracy in the facial recognition system in which they applied LBP to the FERET facial dataset. Another study which used LBP for side view face recognition is [21] where they applied LBP on the National Cheng Kung University (NCKU) dataset, they applied LBP on both left and right side face images of the dataset, after which they used a distance based classifier to gauge the performance of their recognition system, they achieved different accuracy performance for the right side images and left side images of the dataset, with 67% performance for the right side face images and 74.19% accuracy performance for the left side view images.

2.3. Support Vector Machine (SVM)

Support vector machine is a classification algorithm which is discriminative, SVM as a classifier has also seen applications in regression challenges, however the major function of the SVM classifier lies in its used a function which performs classification using hyperplanes, using an N-dimensional plane SVM is capable of distinctively identifying data, where the features of class type is denoted by N, and every class type is situated on a different side of the hyperplane as can be seen in figure 5 below. SVM also has multidimensional hyperspace functions, SVM has kernel functions which enables it to map classification regions within a space [5].

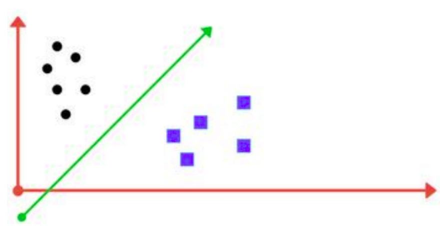

FIGURE 5. SVM hyperplane showing two distinct classes

2.3.1. SVM in Facial Recognition

Zhang et al. [22] carried out a facial expression recognition in which they applied SVM for classification in their experiments, they used a variation of SVM known as the fuzzy multi class SVM for their classification phase of their study and achieved an accuracy performance of 96.77%. another study which used SVM in their facial recognition system classification is a study by Richhariya and Gupta [7], this study used a variation of SVM known as the iterative universum twin SVM in which they used datapoints in their datasets which were not associated with any of the classes being trained to supervise the training of the classes data. Another study which used the SVM classifier in a facial recognition system study is study by Wang et al. [19] which they used in on extracted LBP features from a facial image dataset, their system was a facial recognition system which operates in real-time which showed promising recognition accuracy performance. Julina and Sharmila [9] used the SVM classification algorithm on Histogram of Gradients (HOG) features which they extracted from the AT & T face dataset, this study took on the challenge of multi variation in pose and lighting with their study to which they achieved an impressive accuracy performance of up to 90.2 %.

2.4. Feature Fusion

There have been studies over the years which have carried on the researches to fuse multiple features of a dataset in an attempt to gain better performance than otherwise using a single of the multiple selected features in an experiment. A study by Santemiz et al. [18] carried out a study in which they used HOG and LBP features together and classified them using SVM after they have fused them using sum rule fusion, this study arrived at a performance accuracy of 89%. Another similar study is that of Chen et al. [3] which used HOG-TOP fusion on geometric warp features and acoustic features of a face image dataset. A study which used the same multiple feature fusion as proposed by this study is that of Jiddah and Yurtkan [8], however they used the Euclidean distance classifier on human ear dataset to which they also reported an improvement in accuracy when compared to using any of the two features individually in the facial recognition system

3. Methodology

This study has been proposed to fuse two features; geometric and texture features of side view face images, and using the SVM classifier for classification. Our methodology for this study seeks to use LBP to extract the texture features from our sideview facial images, and use Laplacian filters to extract the geometric features from the side view face images. The methodology of study follows an outline as follows: the NCKU dataset images were pre-processed to rid the image of redundant data, after which LBP and Laplacian filter were used to extract texture and geometric features of the images respectively, the histogram of the images were then extracted and fused together using histogram concatenation, the concatenated histograms were then classified using SVM and tested for recognition accuracy. Figure 6 below shows a general outline of the methodology using a block diagram.

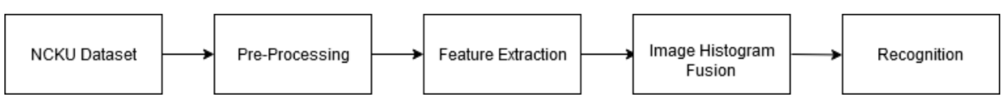

Figure 6. Methodology block diagram

3.1. National Cheng Kung University (NCKU) dataset

The National Cheng Kung University (NCKU) dataset is a side view face dataset which is publicly available to the research community courtesy of the National Cheng University, the dataset contains images of a total of 90 subjects with 12 female subjects and 78 male subjects, with each subject having a total of 37 images making a total of 6660 images for all subjects, with a 50:50 ratio for left side face and right side face images, a sample of the NCKU dataset can be seen in figure 7 below. Each image is captured with a resolution of 640x480. For the purpose of the experiments carried out in this study the images were pre-processed to rid the original images of any redundant data in order to speed up the computational process and rid the images of noise, during the pre-processing the images were resized to 128x128 pixels, a sample of a processed image can be seen in figure 8 below. Also, only images of the right side with pose variations that are actually side view face images were used for our experiments which are the 70 to 90 degrees pose variations, which brings our experiment images to a total of 450 images.

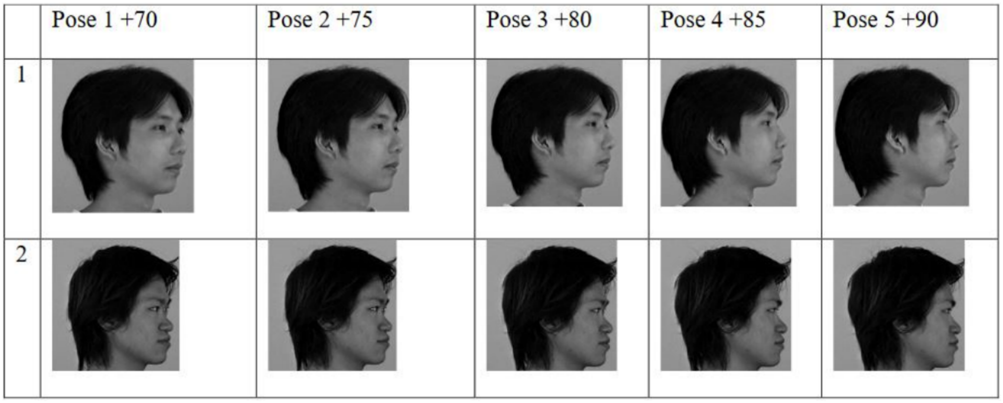

Figure 7. NCKU dataset sample images

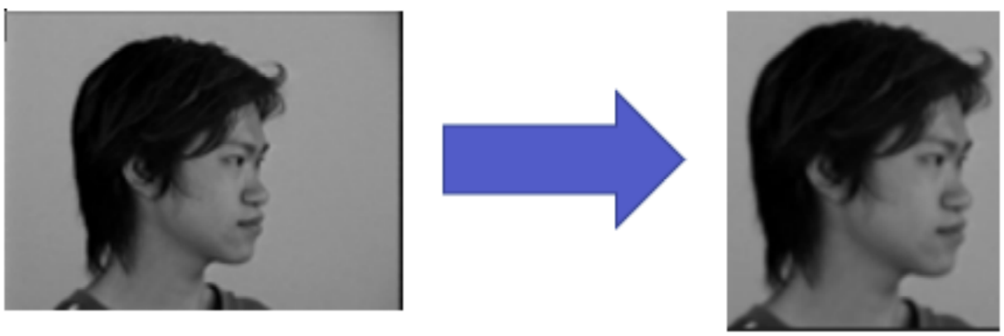

Figure 8. Original image (left), processed image (right)

3.2. Feature Extraction

This section explains the methodology used for the feature extraction procedure for both of our geometric and texture feature in order to achieve the proposed fusion of geometric and texture features in our side view facial image recognition system.

3.2.1. Texture Feature Extraction

The texture features used in the experiments of this study were extracted using the LBP algorithm with the LBP procedure explained in section 2.2 of this paper as proposed by Ojala et al. [16]. figure 9 below shows a sample image from our experiments after the LBP operator has been applied on an image to highlight the texture features of the image.

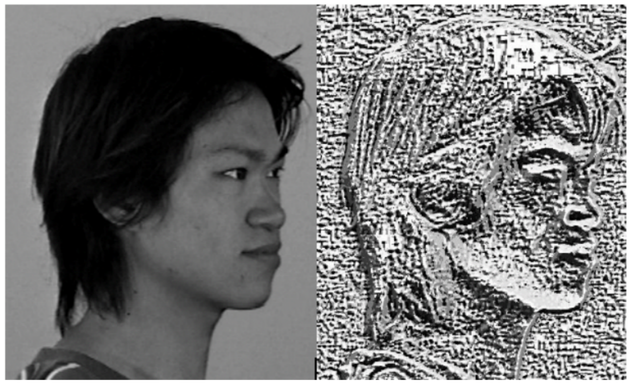

FIGURE 9. Greyscale Image (Left), Corresponding LBP (right)

3.2.2. Geometric Feature Extraction

The geometric features used in the course of the experiments of this study were extracted by the utilization of the Laplacian filter, Laplacian filter is a known image filter which is known to highlight and extract the geometric features of an image. Figure 10 below shows a sample image from our experiments after a Laplacian filter has been applied on a side view facial image and the geometric features of the image have been highlighted.

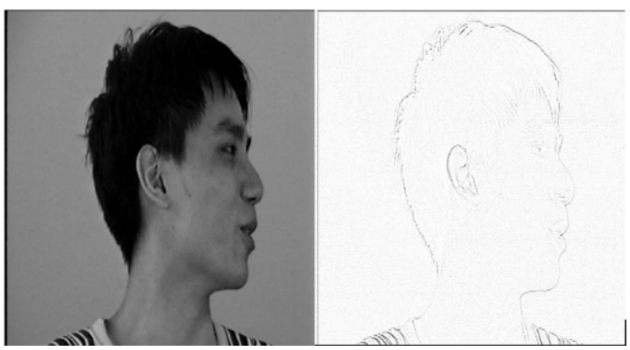

FIGURE 10. Greyscale image(left), Laplacian image (right)

3.3. Image Histograms

Part of the proposed methodology of this study is the use of image histograms of the extracted features from the image, it has been identified as one the efficient ways for the fusion of features and hence the choice to use the image histograms of the extracted features. These extracted image histograms were concatenated for the purpose of the fusion of the features, figure 11 below shows a sample image histogram from our study.

3.4. Classification

The classification phase of this study used SVM for its classification, the training and testing of the classification process used a ratio of 80:20 for training and testing respectively, which brings our training images to a total of 360 and testing images to 90. Also, k-fold cross validation was used to obtain the average of the accuracy performance of our proposed facial recognition system.

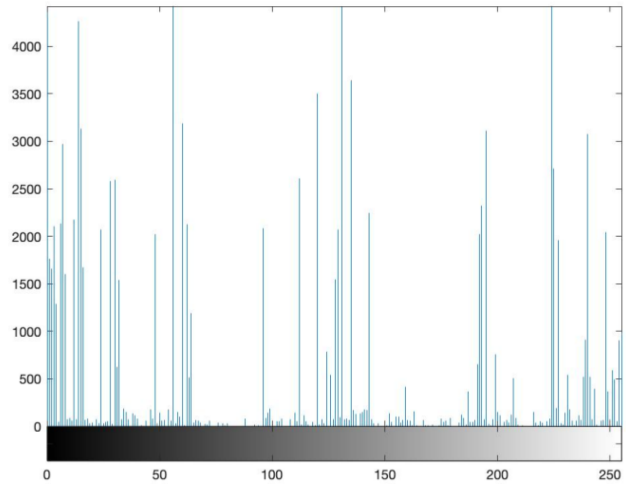

FIGURE 11. Sample Image Histogram

4. Results

The results of our experiments are reported in this section of this paper, the results are reported to show experiments carried out on individual features before their fusion, doing so enabled us to compare and contrast the performance of both geometric and texture features individually and when combined as one in the side view facial recognition system. Table 1 below shows the performance of the texture features when used alone in our proposed facial recognition system, as can be seen in the table after the k-fold cross validation the texture features achieved a recognition accuracy of 70%.

TABLE 1. Texture features accuracy performance

Iteration	Training Images	Testing Images	Accuracy (%)
1	360	90	77
2	360	90	74
3	360	90	67
4	360	90	81
5	360	90	55
Average			70

Table 2 below shows the accuracy performance of the geometric features used alone in the proposed side view face recognition system, the geometric feature significantly out performs the texture features with an increase of 15% accuracy in the performance, as can be seen after the k-fold cross validation the geometric feature achieved 85% accuracy performance in the proposed recognition system

Table 3 as shown below shows the performance of our proposed side view facial recognition system when both texture and geometric features are fused together and used as a single feature in the recognition system. The fusion of the features has shown promising results as expected, there was a significant increase in performance accuracy, the fusion of the features outperforms both texture and geometric features when used individually, the fusion of both features achieved an impressive 90% accuracy performance.

Table 2. Geometric features accuracy performance

Iteration	Training Images	Testing Images	Accuracy (%)
1	360	90	95
2	360	90	94
3	360	90	87
4	360	90	70
5	360	90	83
Average			85

Table 3. Geometric features accuracy performance

Iteration	Training Images	Testing Images	Accuracy (%)
1	360	90	96
2	360	90	88
3	360	90	87
4	360	90	87
5	360	90	76
Average			90

5. Results Discussion

The aim of this paper is to propose a side-view facial recognition system based on the fusion of both texture and geometric histograms rather than study they separately. Based on the results of the study we can see that histogram fusion outperform if conducted separately both textural and geometrical methods with an accuracy of around 90% noting that study utilized only 5 images per subject using the SVM classifier. Authors in [24] ave used the NCKU dataset where they have trained the first 37 images of all subjects where they have divided them into 3 subsets 2 for training and 1 for testing. They have proposed the use of Improved Random Regression Forests classifier with an optimal accuracy of 88.32% using the HOG method. Thus, even with a relatively smaller training set conducted in this study histogram fusion yields better results by utilizing the use of SVM classifier and would yield further greater results if trained with more images.

6. Conclusion and Recommendation

The experiments carried out to implement our proposed side view face recognition system have shown promising results as we have hoped it will based on the literature review done prior to the experiments carried out. This study paves a way for further studies with more comprehensive experiments to be carried out in order to produce an increase in accuracy and robustness in side view facial recognition systems, this study concludes by recommending this methodology to be carried out on a much more larger scale as it is known that SVM classifier increases performance with more data in its training phase, perhaps the use of other geometric and texture feature extractors to compare and contrast the performance gotten from the feature extraction methods used in this study.

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