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Face Recognition under partial visibility: Classifiers Fusion based Approach

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Abstract:- This project presents new technique for partial face recognition. It provides feasible way to locate the positions of two eyeballs, near and far corners of eyes, midpoint of nostrils and mouth corners from face images. This approach would help to extract useful features on human faces automatically and improve the accuracy of face recognition. A whole partial face recognition system proposed is based on SVM and KNN. Support Vector Machines (SVM) can be used for feature extraction and dimension reduction. K-Nearest Neighbor Classifier is a class of non-parametric method used in statistical classification. The method classifies objects based on closest training.

Keywords: *-Partial Visible Conditions, Classifiers Fusion, Scaling, Translation and Rotation*.

I. INTRODUCTION

Biometrics refers to the automatic recognition of persons based on their physical or behavioral attributes. Several biometric traits such as signature, voice, fingerprint, iris, retina, ear and face have been explored. But Face recognition technology is more efficient and widely accepted by public compared to other biometrics due to its invasive property. Face images can be captured from a distance and the identification does not require interacting with the person. Face recognition finds many applications in the field of access control points, law enforcement, security and surveillance systems, victim and missing person identification, medical diagnosis and treatment planning and computer game industry etc. Feature extraction method include support vector machine (SVM) under the condition that samples obey the multi variant normal distribution. One of the greatest challenges in face recognition systems is to recognize faces around different poses and illuminations. The first step of face recognition is the identification of an efficient method to reduce the dimensionality, feature extraction and finally Classification.

II. REVIEW OF LITERATURE

According to Francesc Tarres and Antonia[1] the problem of face recognition under partial occlusion and different facial expression. In this work they present a new technique for face recognition that can cope with partial occlusion or strong variations in facial expression. This technique can be considered as the complementary of the eigen features approach because the entire face image except the region of a local feature is used, instead of using only the region of the local features(re draft the sentence). Athinodoros G.Georghiades[10] explains the problem is to find illumination cone models for Face Recognition under variable lighting and pose (redraft). They present a generative appearance-based method for recognizing human faces under varying light and viewpoint using a small number of training images of each face taken with different lighting directions, the shape and the face can be reconstructed. Hariprasad E.N. and Jayasree M. [9] discusses about the problem is to find face detection is the necessary first step for most of the face analyzing algorithms for example - face recognition. We present a novel method for detecting human faces from digital color images based on Speeded Up Robust Features (SURF) and Support Vector Machines (SVM). classifier to make a practical face detector. We built a frontal face detector using this approach and found to be very promising for further research.

III. PROPOSED METHODOLOGY

Support Vector Machines (SVM) are one of the most useful techniques in classification problems. One clear example is face recognition. However, SVM cannot be applied when the feature vectors defining our samples have missing entries. This is clearly the case in face recognition when occlusions are present in the training and/or testing sets. SVM is a binary classification method that finds the optimal linear decision surface based on the concept of structural risk minimization. The decision surface is a weighted combination of elements of the training set. These elements are called support vectors and characterize the boundary between the two classes.

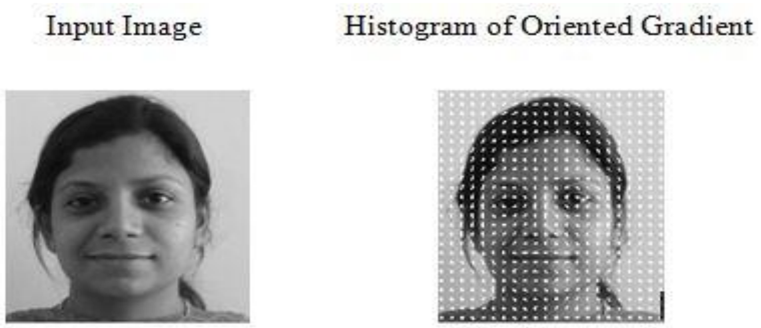


Fig 1

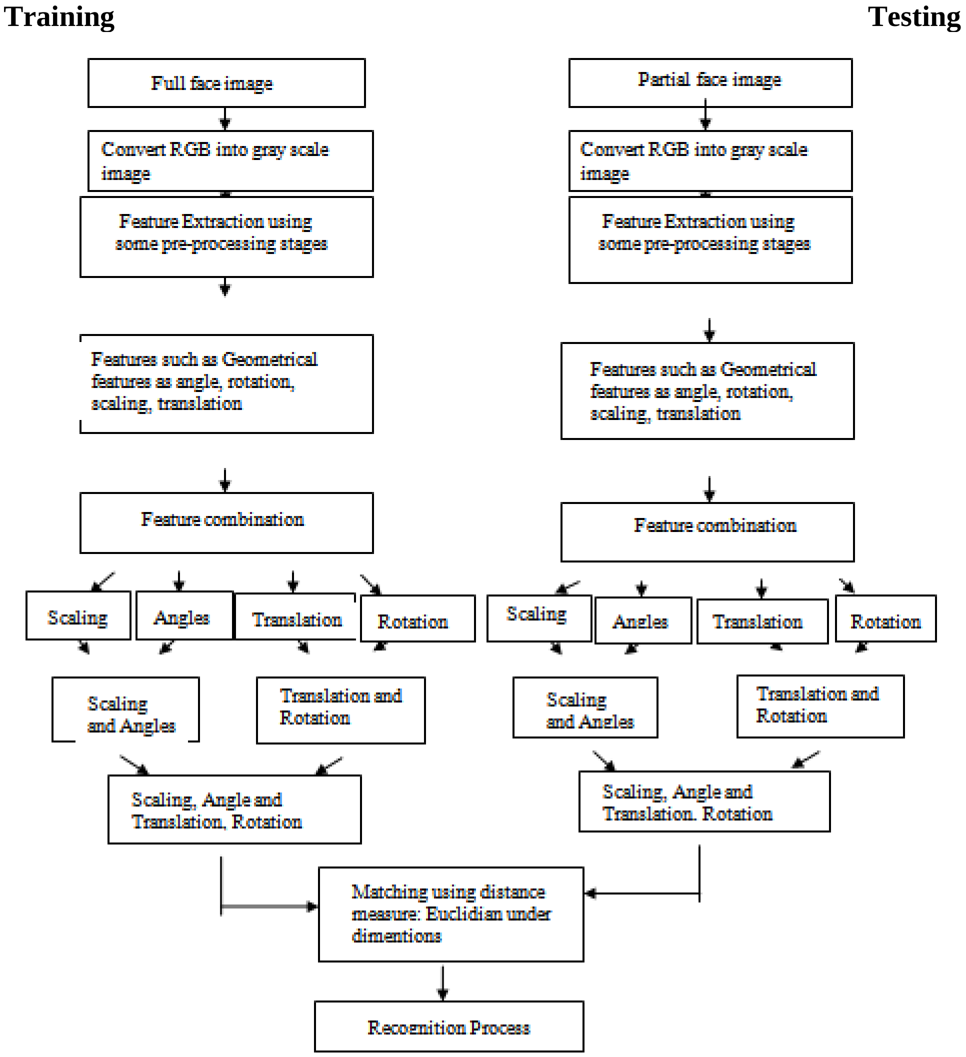


Fig 2 Block diagram of Proposed Model

Here, we have computes the normalization, which takes local groups of cells and contrast normalizes their overall responses before passing to next stage. Normalization introduces better invariance to illumination, shadowing, and edge contrast. It is performed by accumulating a measure of local histogram "energy" over local groups of cells that we call "blocks". The result is used to normalize each cell in the block. Typically each individual cell is shared between several blocks, but its normalizations are block dependent and thus different. The cell thus appears several times in the final output vector with different normalizations. This may seem redundant but it improves the performance. We refer to the normalized block descriptors as Histogram of Oriented Gradient (HOG) descriptors.

The final step collects the HOG descriptors from all blocks of a dense overlapping grid of blocks covering the detection window into a combined feature vector for use in the window classifier.

3.1 Pre-processing Stage

The full face image is resizing the images keeping an aspect ratio. RGB color image is converted into gray scale, because the intensity value of the gray scale is less than RGB images.

Resized image Gray scale image

3.2 Feature Extraction

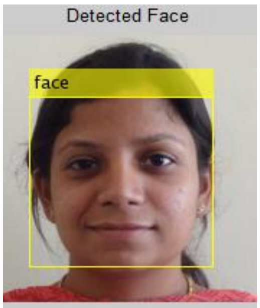
In feature extraction, we are using the HOG feature which is known as Histogram of Oriented Gradients. It is a feature descriptor used in computer vision and image processing for the purpose of object detection. The technique counts occurrences of gradient orientation in localized portions of an image.
Feature extraction methods consists of Scaling, angles, Translation and Rotations

IV. Experimental Results and Analysis

4.1 Dataset

Here we have taken our own created dataset tested with more than 600 images and compared with benchmark datasets like, YALE and LFW face datasets.

Face Detection



4.2 Feature Labeling

	1	2	3	4	5	6	7	8	9	10	11	12	13
1	6.6425	11.2837	6.1296	1.9204									
2	5.4965	8.9469	5.0528	1.7610									
3	5.9646	9.9616	5.6061	1.8117									
4	7.8487	13.3415	6.6770	2.0934									
5	6.6394	11.2960	6.0211	1.9411									
6	6.7523	11.7909	6.7223	1.8007									
7	5.4088	10.4531	5.5840	1.6862									
8	5.1473	9.4837	5.1293	1.6792									
9	7.0276	11.9999	6.8114	1.8768									
10	4.6049	8.2597	4.7116	1.6257									
11	8.5476	12.8246	7.7530	2.2019									
12	7.1462	11.4767	6.9423	1.8730									

Detected

Noise removing Image

4.3 Labeling the images

	1	2	3	4	5	6	7	8	9	10	11	12	13
1	1												
2	1												
3	1												
4	1												
5	1												
6	2												
7	2												
8	2												
9	2												
10	2												
11	3												
12	3												

V. CONCLUSION AND FUTURE WORK

In this work, a comparative analysis of exiting face recognition methods was presented to examine the performances of such existing methods in terms of their face recognition rates. The comparative analysis shows that the existing methods are need to enhance to attain the higher recognition rates. This lower performance in comparative analysis process has motivated to do a new effective face recognition method under face and illumination with higher face recognition rate. The new developed face recognition method under pose and illumination process utilized most renowned method to perform the face recognition process. The performance of the most renowned method provided higher face recognition rates than the methods are discussed in the comparative analysis.

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