March - April 2020
ISSN: 0193-4120 Page No. 7378 - 7384

Recognition of Partially Occluded Face using Block Based Mean Weighted Local Binary Pattern Feature and Adaptive Sparse Classifier

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Article Info
Volume 83
Page Number: 7378 - 7384
Publication Issue:
March - April 2020

Article History
Article Received: *24 July 2019*
Revised: *12 September 2019*
Accepted: *15 February 2020*
Publication: *07 April 2020*

Abstract
In recent literature related to the problem of face recognition under partial occlusion is a big challenge for the researchers who are working in this domain. The recognition performance of any face recognition system under partial occlusion needs to be improved.To shed some light in this area this paper addresses the face recognition problem partial occlusion due to scarf and sunglasses. Intially the face image is divided in to occluded and non occluded regions, the non occluded portion of the face image is only used for face recognition. For detecting the occluded area the input image is divided in to number of sub blocks and then each block is checked for occlusion using Fuzzy Segmentation. Mean weighted local binary pattern features are extracted from non occluded portion and are given to the adaptive sparse classifier in order to recognize the image. The method is implemented on different datasets and the results were promising.

Keywords; *Face Recognition, Occlusion, Fuzzy Segmentation, SVM, IOT, Mean weighted LBP.*

I. INTRODUCTION

The latest advancements in the computer science technology, results in high level of security for persons as well as organization to carry out transactions. To protect the privacy of an individual and organizations one needs a better and more secure authentic system. Humans normally try to identify the other persons using their face. So face biometric is becoming one of the most popular biometric in identifying humans even in millions of images. According to the survey conducted by NIST(National Institute of Standards and Technology) the face recognition systems developed today are able to achieve accuracy of 92% in 1.6 millions of face images.

There are other biometrics like retina, finger print , palm print etc., but face biometric is used in many domains because it does not require human involvement or cooperation. On the face images captured in well cooperated environments , the face recognition system perform better than images taken in poor illumination backgrounds and non controlled environments. There are other reasons such as occlusion, resolution and aging causes face recognition system to fail.

Organization of the remaining paper is as follows. In Section II literature survey is presented, Section III presents partioning of image in to sub blocks, Section IV describes occlusion detection and segmentation in an image. Section V describes the face recognition method using Mean weighted local binary pattern feature and adaptive sparse classifier. Section VI describes experimental results with discussion and Section VII concludes the research work with future directions.

Published by: The Mattingley Publishing Co., Inc.

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II. RELATED WORK

The occlusion present in the face image can greatly affect the recognition performance of any face recognition system. The partial occlusion present in the image handled in such a way that recognition accuracy must get some significant improvement. The features of an image in occluded area may not contribute in the classification, so many researchers segmented the occluded area from participating in the classification of face image. So this work also excluded the occluded part due to sunglass and scarf to achieve significant improvement in the recognition rate.

In order to identify occluded part in the face image , the image is divided in to number sub blocks and each block is verified if occlusion is present or not. Only the non occluded blocks are collected and t mean weighted local binary pattern features are extracted from non occluded image are used for recognition.

III. PARTITIONING THE IMAGE INTO SUB-BLOCKS

Image partitioning is an important factor to determine the functionality and the efficiency of face recognition system. In fact if images are divided into smaller and more manageable units, then it becomes easier to compress, store, access and retrieve the image data.

There are two types of approaches to FRS. They are Global and Region Based Approaches. Global approach uses the features of the entire image, which gives up retrieval effectiveness with the lack of spatial and topological information. But the Global approaches attain high efficiency in terms of extracting the features, space requirement, and image similarity measurement.

The Region Based approach decomposes the image into regions. The regions count and also the size of each region per image are variable in nature and the representation of obtained regions may also expensive with respect to storage point of view. These approaches employs high complexity image segmentation techniques to divide images into regions of high similarity, complex image analysis algorithms for feature extraction, high complexity distance functions for image similarity measurement and high space overhead but an improved retrieval effectiveness.

There is great need for reducing the complexity of the Region Based approach and to improve the efficiency of Global approaches. So, a coarse segmentation frame work is presented which implements simple segmentation technique and an efficient image to image matching procedure to provide efficient and effective image recognition.

The coarse segmentation framework partitions the image into fixed sized sub-blocks. A coarse segmentation framework is for better representationof an image, minimizing computational and storage requirements. The grid structure used to partition the image is shown in Fig 3.1. In general the aggregate number of sub-blocks[29] for an image is calculated by Eq (3.1).

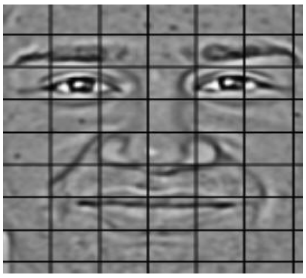

Fig. 3 Partitioned Image

Total no.of Sub-blocks=(No.of row pixels)/p X (No.of Column Pixels)/q (3.1)

Here p is the number of rows required in the image sub-block and q is the number of columns required in the image sub-block. The AR face dataset is the benchmark data set considered for experimentation. The dataset comprises images of size either 256 x 384 or 384 x 256. The image is partitioned into 24 (4 x 6 or 6 x 4) non overlapping sub-blocks.

The size of the image block is chosen in such a way

Published by: The Mattingley Publishing Co., Inc.

March - April 2020
ISSN: 0193-4120 Page No. 7378 - 7384

that it should improve the effectiveness at a cost of computation time. Smaller the block size may contain more details but increase the computation time as well. Conversely we increase the block size in order to reduce the computation time in that case we may lose the finer information. The number of sub-blocks per an image remains same. In the coarse segmentation framework each image can be represented formally as in Eq (3.2).

$$I = \# B_{ij} \quad where \quad i = 1 \ldots 4, j = 1 \ldots 6 \qquad \textbf{(3.2)}$$

data storage. For example, write "15 Gb/cm^2 (100

The image contains 24 sub-blocks subscripted from B_{11} to B_{46} as mentioned in Eq (3.2). Each one of these blocks is presently a function of the raw data obtained from the original image. These sub-blocks will serve as basic building blocks to recognize the images. The rotational invariant local binary pattern features computed on these sub-blocks serve as local texture descriptors [22].

IV. NOVEL MWLBP FEATURE EXTRACTION

SVM classifier is used for classifying the input image in to occluded or not and the conventional fuzzy c-means clustering is used to segement the non occluded part from occluded part in the image as shown in the following figure 4.1 a-c. Ihe fig a) shows the partially occluded images one is with scarf and the other is with sun glasses. In fig c) the result of segmentation of occluded part using fuzzy c-means clustering.

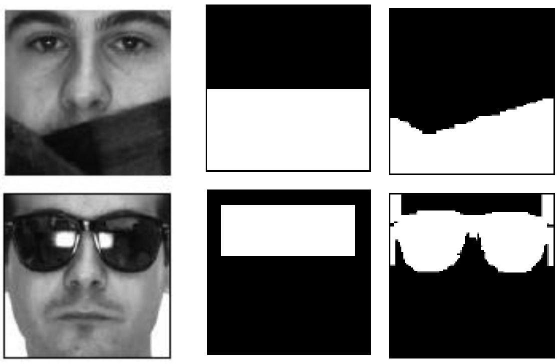

Fig 4.1 a) occluded image b)Thresholded image c)Segemented image

4.1 Local Binary Pattern (LBP) Extraction

In the basic LBP extraction , the image is partitioned in to 3X3 sub blocks and from 3X3 neighborhood, each pixel pi is examined and the eight neighboring pixels and their intensities are compared with the central pixel value cpi then the eight bit binary number is formed. The binary bit value is 0 if the neighbor pixel intensity is less than cpi otherwise it's value is 1 as given in equation (4.1). With these binary numbers a histogram is generated.

$$\text{f(pi-cpi)}=\begin{cases} \mathbf{1} \;\; \boldsymbol{if(pi} > cpi) \\ \mathbf{0} \; \boldsymbol{otherwise} \end{cases} \qquad \textbf{(4.1)}$$

Where cpi is the central pixel intensity value in a3x3 neighbourhood.

I

161	154	110
150	150	69
142	165	132

f(I)

1	1	0
1		0
0	1	0

LBP= $(11000101)_2 = 2^0+2^1+2^5+2^7=163$

Fig 4.2 Basic LBP Calculation

Now the LBP codes are caluculated by using the equation (4.2)

$$\textbf{LBP}=\sum_{i=0}^{7} \boldsymbol{f(pi-cpi)2^{i}} \qquad \textbf{(4.2)}$$

Published by: The Mattingley Publishing Co., Inc.

March - April 2020
ISSN: 0193-4120 Page No. 7378 - 7384

4.2 Mean weighted local binary Pattern Feature Extraction(Mwlbp)

In basic LBP central pixel intensity is considered for thresholding. But this may overlook the noise present in in nearby pixels. Since face images are almost uniform in order to make the conventional LBP robust the mean intensity of 3x3 neighborhood is taken for thresholding purpose and then the weights are calculated using the Eq (4.3)

$$\mathbf{f(pi\text{-}pm)}=\sum_{i=0}^{7} f(pi-pm)2^{i} \qquad \textbf{(4.3)}$$

The MWLBP features are calculated then mean and standard deviation of MWLBP features are computed. These features are used for classification of test face image.

V. ADAPTIVE SPARSE REPRESENTATION BASED FACE RECOGNITION

Sparse representation classification solves the problem ℓ_1 optimization to recover the coefficient vector V. One of the limitation of SRC is its speed. The time for solving is quadratic to the number of columns present in the training matrix V. It implies that if the number of samples or the columns in matrix V are increased or doubled, the time required for solving the will be quadrupled. The following figure shows the relationship between execution time and the number of samples considered for a face recognition problem. It shows that if the number of samples are increased, the execution time is also increased as shown in fig 5.1.

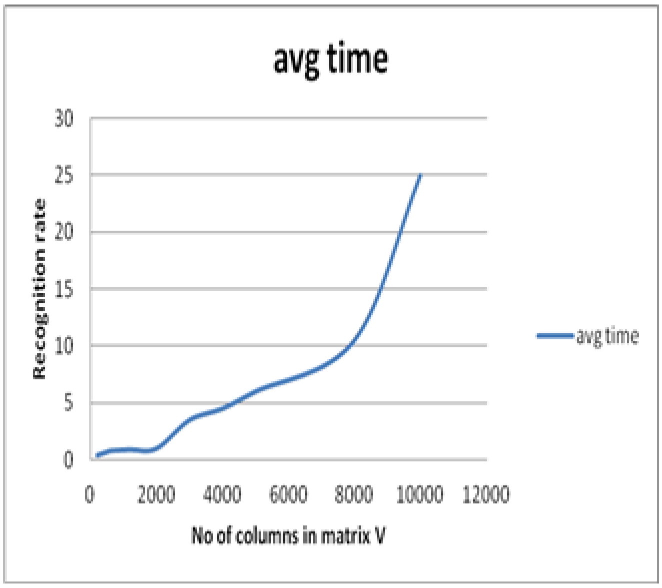

Fig. 5.1 .Relationship between no.of samples in SRC matrix and its execution time

In practical applications, face recognition problem contains so many classes and lots of training samples are available in each class. Also face is a relatively large dimensional space. To reduce the dimensionality several dimensionality reduction techniques are applied in the literature. However the number of training samples is still a big challenge in terms of time and space complexity of SRC algorithm. If reduce the number of training samples are reduced, it significantly reduces the running time of SRC. This motivates the study of adaptive sparse representation model which improves the efficiency of SRC by only selecting the representative samples from all the training samples using adaptive clustering scheme.

5.1 Efficient Src Using Adaptive Clustering

In this section a method is proposed to reduce the number of columns in matrix V by using an efficient replacement of the original training samples. Face images from one subject form a subspace in the original m dimensional space. Considering the fact that many training face images might contain similar information, using all samples to represent a sub-space is not efficient. In this case, it would be more rational to characterize each class by a more representative and smaller set of sample vectors.

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A dataset with 100 classes with 150 sample per class or a total number of 15000 training face images are considered for experimentation. Assuming each face is a 60X60 image, the size of the training matrix V will be 3600X15000. If a matrix of size 100X3600 is used for feature extraction, then the original size of the matrix V it will be100X15000. For comparison, if the average number of samples per class is selected to be 10, the size of the matrix V will be reduced into 100X1000. Although random selection of the original training samples may reduce the number of columns in V , it cannot necessarily represent each class well.

Adaptive k-means clustering algorithm

Input: Data matrix V and the number of clusters Q

Step1:Intialize Q partitions

Step2: calculate mean vector for all clusters. Form the cluster centroid matrix CV

Step 3: While there is change in minimum one cluster do repartition assign each sample to the nearest cluster and then calculate CV.

Output: Cluster centers

VI. EXPERIMENTAL RESULTS AND EVALUATION

Different sizes of training matrices are used for evaluating the performance of proposed approach using Random Projection, Eigen Faces, Down Sampling, Laplacian, Fisher and Local Binary Patterns. It can be observed that for the same number of columns in the training matrix,the proposed method is showing higher recognition rates when compared to the conventional SRC and visualization is shown in fig 6.1.

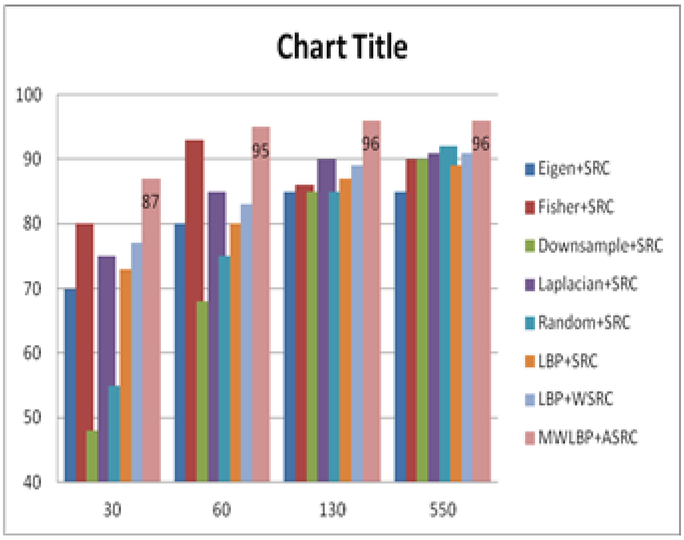

Fig. 6.1 Performance of different algorithms on AR face database applied on different feature dimensions.

Discussion

The Proposed technique has been implemented and tested using AR face image benchmark dataset and the retrieval performance is compared to existing region-based systems (Eigen+SRC, Downsample+SRC, Laplacian+SRC,LBP+SRC and LBP+WSRC). The performance of the proposed technique performed better when compared with other method

VII. CONCLUSIONS AND FUTURE RESEARCH ISSUES

The experimental results show the significantly improved performance of the proposed algorithm under severe illumination, partial occlusion and low quality images in uncontrolled imaging conditions. The best recognition rate using MATLAB 2013a indicated **28.15**% improvement with respect to accuracy. The proposed face recognition system can also be applied to recognize the face images in general that are occluded with hat, beard and so on.

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ISSN: 0193-4120 Page No. 7378 - 7384

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