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FACE RECOGNITION USING COMBINATION OF CODEBOOKS FROM FRAGMENTED PATTERNS

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ABSTRACT

In this study, the proposed approach is based on extracting small fragments of face by Adaptive Window Positioning (AWP) procedure was used for attribute extraction, which efforts on the face image into 16 small fragments of size (16x16) such that it is big enough to include ample data about the style of the person and small enough to ensure a good identification achievement. Positioning windows over the face image and clustering similar face image fragments into clusters - the codebook. Fragments are then collected separately to obtain two codebooks, primary and secondary. Once the codebooks are generated, each face samples are represented by as a probability distribution of the patterns in the codebook. Then represents the combination of codebook designs for each person such that the number of categories in each codebook differs as a task of the face image. Two faces are then matched by calculating the dimension between their respective codebooks. Experimental outcomes illustration face recognition using windowing technique with combination of codebook is more efficient than other. The highest average estimation proportion of 98.15% is got for 80 individuals' of publicly available ORL dataset including differences in illumination, posing, and expressions.

Keyword: face image, adaptive window positioning, feature extraction, primary and secondary codebook design, face recognition.

1. INTRODUCTION

In face recognition, personal facial attribute extraction is the key to creating more strong schemes. A lot of algorithms have been planned for solving face recognition issue. Kotani *et al*. [1] have projected a new information-processing system named Vector Quantization (VQ) codebook area data processing which differs from the traditional methods of processing system. Depended on this procedure, we have progressed a very simple yet highly reliable face confession technique by utilizing windowing method with generated two Codebook. VQ algorithm [2] is well known in the field of sample coding. Input sample is first split into small sets, which are represented as input vectors in VQ procedure. Each input vector is then corresponding with code- vectors in a codebook by computing dimensions between them. In this study, a theoretical codebook scheme technique is projected. At first, a systematically organized codebook is created depended on the allocation of code designs abstracted from facial samples [3]. Main contribution of the projected technique is windowing method related with generating codebook includes fingerprint of each font and code for each possible character procedure. Each attribute of the major fragment is collected to form a vector. This scales and converts every attribute discretely to a fixed dimension on the training set [4-5]. This attribute allows the projected method to follow rapid generation of new fonts. Combining of two codebooks represents is final optimized codebook for facial samples will be generated. It can denote the attributes of the facial samples more adequately. This study is ordered as follows. First, background and related works, proposed system will be presented in detail in Section 3. Suggested codebook combining scheme of code patterns and will be defined in Segment 4. Experimental outcomes related with the algorithms will be conferred in Division 5. Lastly, we make a conclusion in Segment 6.

2. BACKGROUND PROBLEM

Finding of faces in static or video pictures is an important but challenging problem in processor vision that has applications in image retrieval schemes and biometrics [7-8]. It is an essential first-step in face recognition where the objective is to localize the spatial extent of a face in order to define the identity of an individual in an image. Number of systems have been planned in the literature for distinguishing faces [9]. Face recognition function is challenging as faces could occur at various scales, orientations, positions and pose in an uncontrolled background. In general, face finding approaches can be categorized into three broad classes [10]: intensity-based approaches, rule-based approaches and attribute-based procedures. Intensity-based procedures utilize classifiers that process directly on the point intensity of the sample without trying to extract any facial attributes. The input to these classifiers is a set of sample point values or simple additive attributes calculated on the point ratios. In this class, machine training approaches that employ "Support Vector Machines" SVMs [11] is utilized to discriminate face and non-face objects.

The second class includes of rule-based approaches which utilize the knowledge of the elements of the face such as the eyes and mouth, and their Face finding utilizing statistical and multi-resolution texture attributes Manian and Ross [12]. These approaches is that the number of possible rules in actual world face samples is big all of which cannot be determined.

The third class contains of attribute-based approaches and a big number of procedures improved for face finding fall in this class. These contain the utilize of edge attributes, skin color thresholding, ear, form from shading, etc. to localize/recognize faces. Edge attribute approaches collection edges utilizing heuristics, and elements are labeled and corresponding to pre-computed reproductions [13]. In color-based face recognition, the

skin color pixels are distinguished by thresholding in a color ears such as RGB, normalized RGB or YCrCb. Post-processing processes contain the utilize of morphological processes to remove non-face points and locate facial eares. Statistical multiresolution Gaussian pyramid attributes have been utilized in [14] for face recognition. Since a human face has a different texture related to other entities, this property is estimated to exertion well for face recognition.

3. PROPOSED SYSTEM

The face sample is physiological attribute and is a enhanced biometric information as the images can be gotten without the co-operation of an individual as well as can also be taken with reasonable dimension. Olivetti Research Laboratory (ORL) dataset is applied to estimate the achievement of proposed technique. ORL This research represents the well-known ORL face database that is taken at the Olivetti Study Laboratory in Cambridge, UK [15, 16]. The ORL dataset includes 400 Grey samples matching to ten various samples of 40 dimension subjects. The tests have been achieved on ORL dataset with various number of training and testing samples. the new set-up, the numbers of training samples are various from 80 part to 40 part that is initially 80% of total samples is utilized in training and remaining 20% for analysis.

The methodology starts with binarization of face image followed by division of components which represents black color from image into small segments. Similar segments are then grouped together into clusters which serve to recognize the face. The overall proposed model is illustrated in Figure-1. Each of these components is discussed in detail in the subsequent segments.

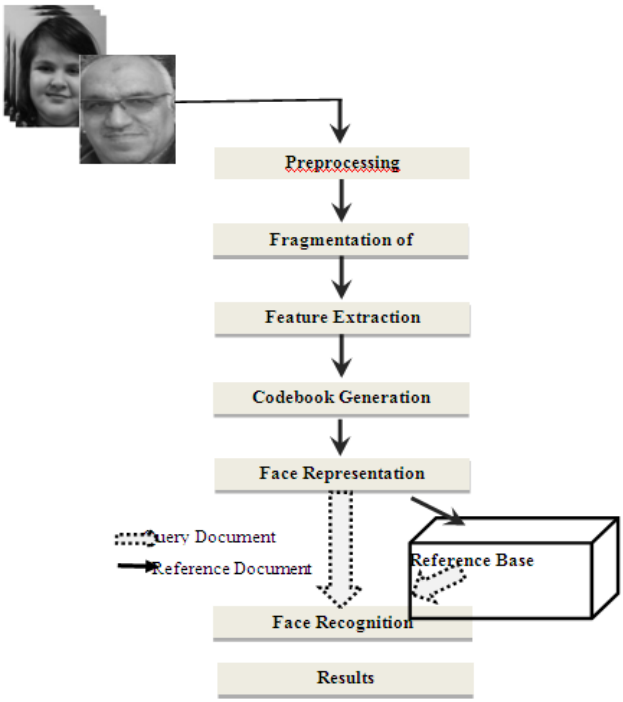

Figure-1. An overview of the proposed methodology.

3.1 Pre processing

The Face images are pre-processed to get only face part using scanning involves color to gray scale image conversion; the gray scale image, Image cropping; only the face section of the sample is cropped. The sample is changed to binary prior to cropping [17]. The cropped dataset and check sample may have various measurements; hence the face sample is resized to 120*120 length. After finding the related elements, the next stage is to split the face into small sections in order to extract the patterns of face photo. The next section discusses the technique used to divide face image into fragments. All subsequent steps are then carried out on the binary image.

3.2 Feature Extraction

The proposed methodology characterizes the face of a given sample by considering small invariant fragments to exploit the redundancy in image. Division of face image into small fragments is a very important step in the proposed method. The proposed approach not only considers these image parts, but also the adjacent parts which are related to these major fragments. These adjacent sections are got by splitting the face image into fragments. Both the major and adjacent parts are then congregated into separate codebooks which are utilized to illustrate the face of individual. The planned approach splits the binarized text sample applying the shape explained in Figure-2. The central window includes the major fragment while the four small windows denote the parts that connect to the major fragment.

The proposed shape for division of writing consists of one major window along with four adjacent small windows termed "as N, S, E and W (North, South, East, and West) as shown in Figure-2. In former comparable researches, a square window of an empirically specified size (16x16 pixels) is placed on the component to get small face image forms [18-19]. Once the major boxes are located, taking every major window as reference, the proposed technique computes the starting coordinate of adjacent boxes on the four sides. The size of North and South adjacent windows is 4x16 pixels and the size of East and West adjacent windows is 16x4 pixels. These small windows are big enough to provide information about the strokes which are related with the major window. The North and South windows are then rotated by 90 degrees and all the four adjacent boxes are sequenced. The idea of extracting redundant face image patterns using the proposed shape is explained in Figure 2 where the three forms in the major window are very much comparable but the relating parts in the adjacent boxes are all different. Division of face image is carried out by dividing the entire face image using the windows discussed in the above section. The technique first position the main window on the face image from left to right and top to bottom by following the ink trace. In relation to that, the pseudo-code of fragmentation process is given in Algorithm 1. After having represented the main and adjacent fragments by a set of features, next step is to cluster the fragments. But before clustering, features are

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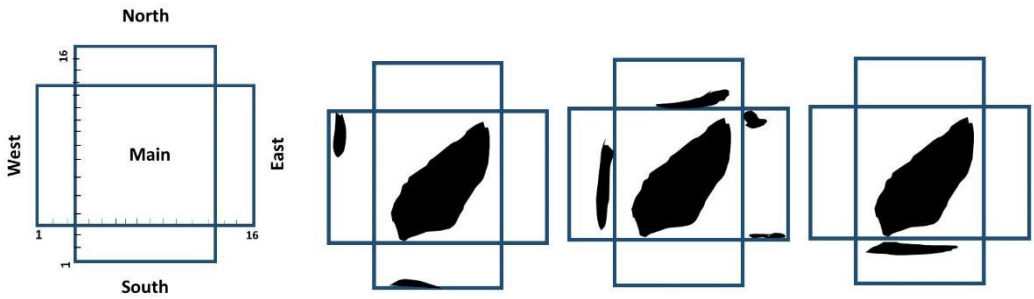
compared using a (dis) similarity measure. The connection between two face image fragments is specified by calculating the Euclidean dimension between their respective attributes:

$$Dis(p,q) = \sum_{i=1}^{\dim} \sqrt{(p_i - q_i)^2} \quad (1)$$

where, Dis represents distance of feature vectors of two fragments, p and q,
i= 1, . . ., dim(dim is the number of features considered).



(a) (b)

Figure-2. (a) The main window of 16x16 pixels with Four adjacent windows, after rotating North and South window by 90o, (b) 3-fragments sharing the same design in the Major fragments but different in the adjacent fragments.

Algorithm 1. Fragmentation of face image

```
Input: Binary face image
Output: Main and adjacent fragmants information
Begin:
 Identify the connected components of image I
 Set MainWinSize ← 16
 Set AdjWinSize ← 4
 Set numOfWin ← 0
for each component do
   Extract component region from Image I using stored
   information
   Calculate the size of component in Row and Column
   \\ dividing component in equally spaced vertical lines
   for i- 1 → Rows, increment by MainWinSize do
      Set j ← 1
      \\ finding black pixel from left to right and top to
      \\ bottom
      while j < Columns do
         for k - 1 → MainWinSize do
            if CImg(i+k,j) is black
               Store (x,y)coordinate of main window
               numOfWin - numOfWin + 1
               i ← i + MainWinSize
            end if
         end for
         j ←j+1
      end while
   end for
   \\ Computing adjacent window using (x,y) coordinate of
   \\ main window
   for i = 1 → number of numOfWin do
      Select the ith window coordinate
      Identify coordinate of North window (x,y-AdjWinSize)
      Identify coordinate of South window (x,y+MainWinSize)
      Identify coordinate of East window (x+MainWinSize,y)
      Identify coordinate of West window (x-AdjWinSize,y)
   end for
end for
end
```

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As discussed in the previous sections 3.2, each main and adjacent fragmented pattern is represented by set of features. This section now discusses the methodology to group similar fragments, which are extracted using major and adjacent windows, into groups also known as codebook. In the clustering, based on the features, closely related fragmented patterns are grouped together to form a class. Patterns in each class of cluster are dissimilar to the patterns of other classes. In a cluster, each individual class represents a set of invariant patterns in face image. The proposed technique generates two different sets of clusters after matching the features of invariant patterns. The set of redundant patterns generated after clustering is also termed as codebook. In the proposed methodology, once the face is split into parts, it groups similar parts into clusters to generate the codebooks. While generating the codebook, the proposed technique not only considers the main fragment, but also considers fragments adjacent to the main fragment. This results in two codebooks are namely, the primary codebook and the secondary codebook. Hereinafter, instead of using the term cluster, codebook has been used to represent a cluster. The proposed methodology has been implemented on specific face personal, and universal codebooks as discussed in the following sections. In this study, for each individual face sample, a separate codebook of fragmented patterns, main and adjacent, is generated. The numbers of categories in each related codebook, primary and secondary, are not known because it varies from taster to taster. The proposed technique therefore needs to choose a clustering algorithm that does not need to know a priori number of clusters. In this research, hierarchical clustering is employed to group main and adjacent face image fragments separately and generate face personal for ccodebooks. The details of the hierarchical clustering algorithm are presented in the following section.

After representing each fragment by set of features, hierarchical clustering groups the fragmented patterns based on similarity to build a hierarchy of clusters. This clustering approach starts with every object as a single category and merges objects into the parts until all objects are in one collection. The projected procedure requests to describe a dimension ratio letting evaluation of two parts. The operation of a hierarchical clustering is illustrated in Figure-3.27. As an example, seven labelled patterns are shown in Figure-3.a, in this research these seven labelled pattern can be consider as seven fragmented windows, which is then group together in a single cluster. Figure-3.b represents the binary tree corresponding to the patterns in Figure-3.a. In the binary tree, each patterns are the leaves, each branching points are the similarity between sub-trees. Horizontal cuts using different line patterns in the tree represents classes.

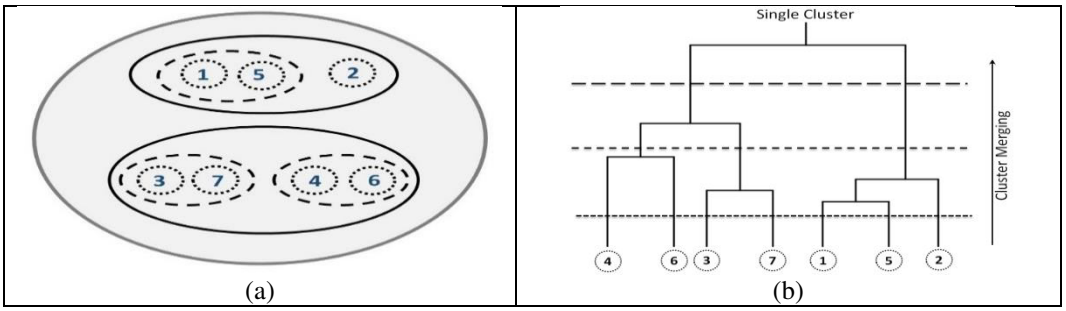


Figure-3. Points falling in hierarchical cluster in (a), Binary tree of hierarchical clustering in (b).

The distance between the two classes can be calculated as the minimum, maximum or the average of the dimensions between attributes of patterns in different clusters. This research employed the average-link method for clustering. In this method, the distance between two categories is defined as the average of the dimensions between all the objects in the two categories. This method is expressed by the next equation.

$$Dist(c_i, c_j) = \underset{x \in c_i, y \in c_j}{avg} Dist(x, y) \quad (2)$$

where, c_i and c_j be two categories. Dist defines the dimension between c_i and c_j.

In adding, since the number of parts for every person face is not known, this approach uses the dimension criterion to represent the number of cluster. For every person the projected performance generates the clusters from the main as well as adjacent boxes. In this study, major and adjacent clusters are also termed as primary and secondary codebooks respectively.

4. EXPERIMENTAL RESULTS

The procedure of face recognition includes identifying the individual based on facial attributes. Hence it is essential to extract the attributes from a given face sample. The input face sample in RGB color ear was first changed to grayscale sample as presented in Figure-4 (a) denoted Original sample. Then, the photo was smoothened with median filter and converted to binary as shown in Figure-4 (b). 4(c) the sample was resized. Dark areas are assumed to be regions which have intensity lesser than the range intensity of the entire sample. So the threshold which distinguishes dark and light regions is chosen as average intensity of the sample as shown in Figure-4 (d). After finding, the dark and light areas are parted into 2

pictures. The not light photo is illumined by multiplying it with factor c calculate in Eq. (5).

Let μ_{in}signify the average value of volume in the dark areas and μ_{out} signify the average value of amount in the lighter areas. R, G and B signify the red, green and blue symbols of a sample correspondingly. The energy task must include the variation between μ_{in} and μ_{out}. Since color samples have 3 elements, the energy task is measured as the Euclidean dimension between μ_{in} and μ_{out} for all 3 elements. The wanted lighting is supposed to be a value multiple 'c' of white light. The rate of c, once increased with the dark area, must minimize the variation between the rate light inside and the rate light external the dark areas. Ability task can now be defined as presented in Eq. (3)

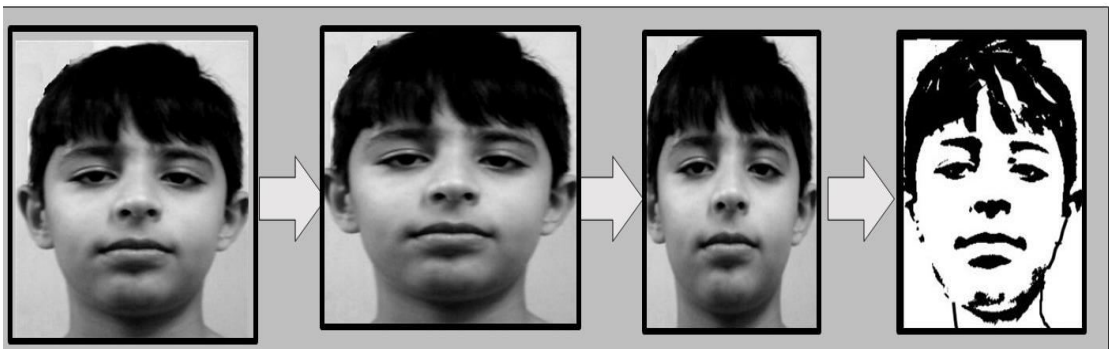
$$E(c) = [(c\mu_{in}^{R} - \mu_{out}^{R})^2 + (c\mu_{in}^{G} - \mu_{out}^{G})^2 + (c\mu_{in}^{B} - \mu_{out}^{B})^2] \quad (3)$$

The copied of this procedure is set to 0 in order to get the value of c which minimizes the function.

$$\frac{dE}{dc} = 2.[\mu_{in}^{R}(c\mu_{in}^{R} - \mu_{out}^{R}) + \mu_{in}^{G}(c\mu_{in}^{G} - \mu_{out}^{G}) + \mu_{in}^{B}(c\mu_{in}^{B} - \mu_{out}^{B})] = 0 \quad (4)$$

Explaining this equation for c offers:

$$c = \frac{\mu_{in}^{R}.\mu_{out}^{R} + \mu_{in}^{G}.\mu_{out}^{G} + \mu_{in}^{B}.\mu_{out}^{B}}{\mu_{in}^{R}.\mu_{in}^{R} + \mu_{in}^{G}.\mu_{in}^{G} + \mu_{in}^{B}.\mu_{in}^{B}} \quad (5)$$



(a) (b) (c) (d)

Figure-4. The various phases of the pre-processing part, (a) Original sample, (b) Binary and converted sample, (c) Resized photo, (d) Thresholded segment

The proposed division technique which introduces the concept of secondary or adjacent windows allows capturing additional information connected to the main window as shown in Figure-4. This extra information is likely to improve the achievement of the classical codebook based methods. For each connected component of an individual sample, the proposed technique fragments the face image using the proposed methodology.

For each space line, find the first black pixel from upper to down and left to right. Once the first black point is found, the main window is placed and its starting coordinate (x,y) is stored in an array. For the next main window, there is an increment of 16 pixels from left to right to get the next black pixel. Once all the pixels in the current line are checked then the technique searches the black pixel in next line of the component to place the main window. This process repeats until the main window slides on each of the lines and stores all the starting coordinates of the main window if black pixel is found. To utilize the adaptive windowing procedure to split it into sections as displayed in Figure-5.

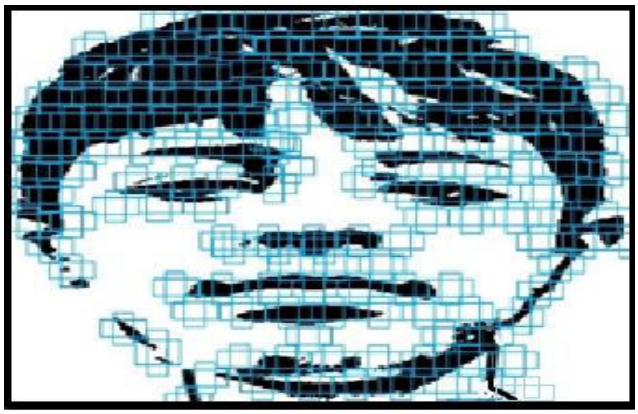


Figure 5. Windowing image.

Once the codebook for major and neighboring windows are produced, the planned procedure types the categories giving to the cardinality and saves only those parts which have adequate server of boxes. As an example, primary and secondary codebooks shaped from major and neighboring split windows are explained in Figure-6a, and Figure-6b, respectively. In each codebook there are different number classes. Each part includes comparatively identical collections of similar forms, which are various to features in the last parts. These classes are separated by the black window in the codebook as displayed in Figure-6a and 6b.

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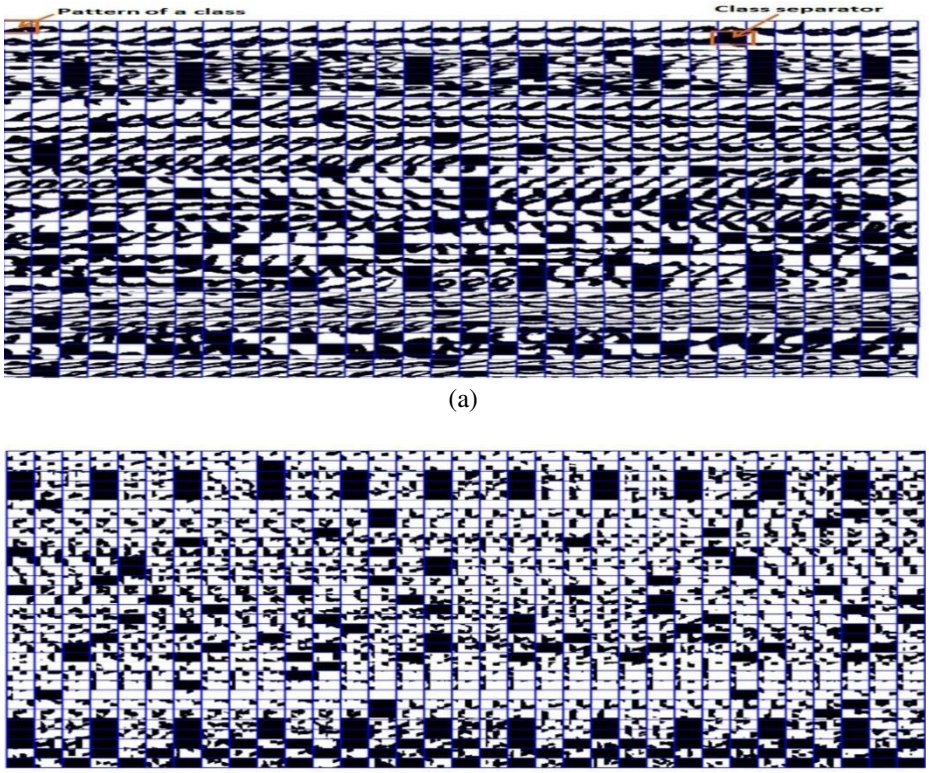

(a)

(b)

Figure-6. (a) person-specific primary codebook gotten from the major split boxes on a face tester, (b) person-specific secondary codebook gotten from the adjacent split boxes on a face tester.

Once the primary and secondary codebooks are produced for every person face, the following phase is to limit how to use this data to signify face recognition as discussed in the following section.

5. VERIFICATION

Both of these codebooks contain different information about an individual's face image and complement each other. Some persons which are not identified by the primary codebook can be distinguished by their secondary codebook and vice versa. It would therefore be a good idea to combine the two codebooks to compare two face images. When two face images are compared, the proposed technique first computes the distance between them using their primary and secondary codebooks separately. Let d_1 represent the distance between the distributions primary codebooks of the reference and test face images and d_2 represent the same distance for secondary codebooks. The final dimension between the two face images is calculated as a weighted combination of the two distances as shown in Eq 6.

$$combDist = (w_1 * d_1) + (w_2 * d_2) \tag{6}$$

where, *combDist* represents the final distance between two face images while w_1 and $w_2$are the weights associated with each d_1 and d_2 respectively. The value of w_1 and $w_2$are related as:

$$w_2 = (1 - w_2) \tag{7}$$

where, the value of w1 must stand between 0 and 1. In most of experiments, empirically the value of " w1=0.5", which corresponds to simple averaging of the two dimensions. For face verification, the proposed technique simply matches the dimension between two images with predefined decision threshold. It can be realized that combining the two codebooks outcomes in a better performance than each of the individual codebooks. Two different sets of face samples have been used. The outcomes of these assessments are described in Table-1. Perfecting the main windows with adjacent windows, and finally producing two single codebooks, offers additional data on the parts related to the major designs in the face image and serves to improve the achievement of the scheme in characterizing the person. This improvement is more significant once the two codebooks are produced applying different collections of face image tests allowing the illustration of face image in two different areas and accordingly enhancing the recognition proportions.

Table-1. Achievement on 80 persons of ORL dataset by applying various images to produce primary and secondary codebooks.

Task	Identification	Verification
Codebook	**RR**	**EER**
Primary	96%	4.50%
Secondary	96%	4.90%
Combined	98.2%	1.80%

The overall achievement is quantified by calculating the Recognition Rate (RR).The proposed face recognition approach outclasses the other five techniques for ORL dataset as displayed in Table-2.

Table-2. Performance evaluation of face recognition approaches applying ORL database.

Author	Approaches	RR
Proposed (2018)	Combination of Codebooks From Fragmented Patterns	98.15%
Fares (2017)	Using Eigenfaces	93.75%
Yulian (2009)	RS[E] Technique	94.22%
V.Kumar (2006)	Correlation filters	96.25%
Weiwei(2006)	Kernel Eigenfaces	94%
Jian (2004)	2DPCA Technique	95.45%

6. CONCLUSIONS

This paper was aimed at studying the application of the projected face acknowledgement techniques. The performance of the projected technique was first evaluated on window technique for extracted features with face codebook approach and appreciable recognition rates were achieved. In this way we encompass the efficiency of feature extraction for face recognition and the robustness of image strategy for face classification simultaneously. Later, the evaluations were carried out on universal codebook approach and achieved results which were very hopeful, so far the best outcomes on ORL database. Besides offering experimental outcomes, various evaluate and discussions of the outcomes are also described. Strengths and weaknesses of the planned performance are also checked in this study. The Euclidean dimension is applied for comparison through computed the values of RR. It is experimental that the value of RR is % 98.15.

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