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Human Face Recognition Using EigenFace, SURF Methods

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Abstract. One such complicated and exciting problem in computer vision and pattern recognition is identification using face biometrics. One such application of biometrics, used in video inspection, biometric authentication, surveillance, and so on, is facial recognition. Many techniques for detecting facial biometrics have been studied in the past three years. However, considerations such as shifting lighting, landscape, the nose being farther from the camera, the background being farther from the camera creating blurring, and noise present render previous approaches bad. To solve these problems, numerous works with sufficient clarification on this research subject have been introduced in this paper. This paper analyzes the multiple methods researchers use in their numerous researches to solve different types of problems faced during facial recognition. A new technique is implemented to investigate the feature space to the abstract component subset. Principle Component Analysis (PCA) is used to analyze the features and use Speed up Robust Features (SURF) technique Eigenfaces, identification, and matching is done respectively. Thus, we get improved accuracy and almost similar recognition rate from the acquired research results based on the facial image dataset, which has been taken from the ORL database.

Keywords: Human face detection, Face recognition, Facial detection, Eigen-face, Methods, SURF.

1 Introduction

One such optical pattern recognition problem is face recognition [1]. After entering a random image as input in the face recognition system, it will explore the database and identify the person as output. Usually, a face identification system contains four components [2] as shown in Fig. 1: detection, alignment, feature extraction, and matching, the refining steps are localization and normalization (face detection and alignment) before face identification (extraction and matching) is done [3]. Facial image identification separates the facial region from the background. However, face tracking equipment [4] is used to trace the recognized faces in a video. Face alignment focuses on acquiring more precise localization and thus normalizing faces.

On the other hand, face recognition gives a rough measure of every identified face's position and scale. Facial elements such as eyes, mouth, nose, and facial layout are situated [5]. Using the location spots, the face image given as input is standardized, in respect of geometrical characteristics such as pose and size, using geometrical distortion or transforms. The face goes through more normalization procedures regarding photometrical characteristics such as illumination and grayscale. After standardizing the face geometrically and photometrically, attribute selection is executed to give the necessary information that helps differentiate between faces of various persons and steady in respect of the geometrical and photometrical variations [6]. In the case of face matching, the input face's obtained attribute vector is compared with that of the registered faces existing in the database. Whether a match is found with sufficient confidence, it offers the name of the face as output and if no match is found, an anonymous face is specified. Artificial Intelligence has been properly used to overcome signal processing issues for 20 years [7]. Researchers suggested various models related to artificial neural networks. It is a tough procedure to figure out the most reliable neural network model for solving real-life problems.

Fig. 1. The infrastructure of a Face Recognition System.

The following building blocks typically comprise facial recognition systems:

- ***Face detection.*** The first and important stage for facial recognition is Face Detection, which is used to recognize faces in photographs. It is a result of the identification of artifacts. A face detector locates the whereabouts of the faces inside an image and if any face is traced then the coordinates of a bounding box for all of them are returned. This is depicted in Fig. 2(a).
- ***Face alignment***. The objective of face alignment is to scale and similarly trim facial images using a group of related points situated at certain positions in the image. Using a landmark detector, a group of facial markers is located in this method. We intend to look for the optimal affine evolution adjusted in the reference points for 2D alignment. Two facial images are oriented in Fig. 3(b) and 3 (c) using the same related points. Face fractalization (varying the posture of a face to frontal) can be implemented by other critical 3D orientation algorithms i.e. [16].

- ***Feature Extraction:*** While portraying the face, the pixel values of a facial image are mutated into a close-packed and distinguishing attribute vector, called template. Logically, each face of the same individual should point to related attribute vectors.
- ***Face matching***: In the face matching process, a similarity score is obtained by contrasting two templates which show the probability that they are part of the same individual. Face representation is indeed the most vital element of the face identification system and the literature review is focused on in Section II.

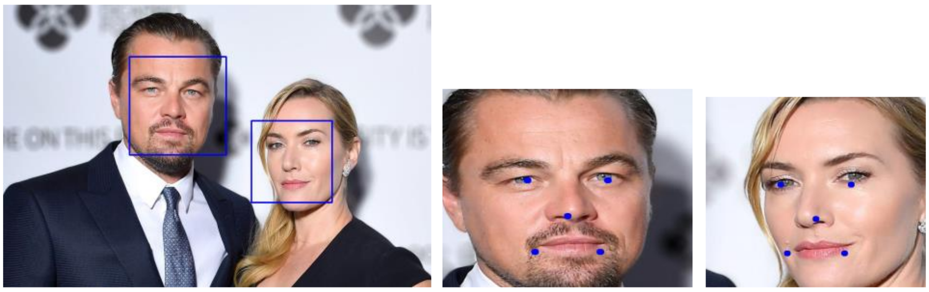

Fig. 2. (a) Face Detector; (b) Aligned Faces and Reference Points.

The primary features of the current study are:

- In this system, two key features of face recognition such as Eigenface and SURF have been demonstrated with the help of PCA components.
- Four different types of eigenvectors (6, 10, 20, and 190) have been computed based on the Euclidean and Manhattan distances.
- Besides, Euclidean and Manhattan distances were also shown the predicted accuracy of five different persons based on various types of input images to make this unique approach.
- Both SURF (64 and 128) and SIFT (128) are examined on different dimensions along with the doubled image sizes of those dimensions.

The following sections of this paper contain: comprehensive related works of face recognition have been added in Section 2. In section 3, a sufficient description of the collected dataset is given and a descriptive analysis of the introduced features has been explained with required working diagrams. An intuitive comparison of results is generated for showing their performance on the given dataset to make it more understandable with the aid of graphs in section 4. In the final section 5, this paper's overall idea has been made to show its capability.

2 Relevant Works

Multiple prevailing face recognition types of research use PCA (Eigenfaces) for face identification. Some of the current works are illustrated. In [8], the authors brought in

updated procedures, or scores [9 – 10], for uniformity of the face to make the investigation easier. Scores are calculated using only the pixel data of the images in the database (and the weighted mean of the pixel data). A 3D face database is used to eliminate undesirable errors in the calculation of uniformity from issues in 2D images, i.e. illumination. Based on the scores, statistical tests [11] are carried out in different subgroups of the database to differentiate the uniformity of the face, and then the result of face recognition is compared with similar subgroups. A significant variation in face uniformity scores between the subgroups of men and women is observed and the result of face identification is contrasted. The database is then split into most uniform subjects and least uniform subjects based on the uniformity scores and the face identification outcome is contrasted. They realized that using uniformity in face identification, using the mean-half-face, is helpful for their analysis. They discovered analytical importance between male and female subjects' face uniformity in the 3-dimensional database, including variation in face identification precision [12]. In full face, the least uniform subjects generate greater face identification precision than the most uniform subjects.
Nevertheless, face identification precision is globally increased when mean-half-face is used in the experiments instead of full face. A computerized face identification system has been made in [13], to analyze the possible use for office door access control. Eigenfaces' procedure depending on the principal component analysis (PCA) and artificial neural networks [14] have been used. Training images can be acquired offline either by pre-recorded and trimmed facial images or online by using the system's face recognition and identification training components on the actual front-facing images. For the rotational angle of the person's head from -20 and +20 degrees, the device may distinguish the face at a reasonable pace at a distance of 40 cm and 60 cm from the frame. The experimental result confirmed the impact of illumination and stance on the facial recognition device. The authors used principal component analysis (PCA) in [15], to obtain attributes of facial images and to implement face identification, sparse representation-based classification (SRC) algorithm is employed. Experimental outcome depicts that when the ideal illustration is properly scattered, it can be effectively resolved using convex optimization, which is referred to as an l1-minimization problem.
Furthermore, the homotopic algorithm can efficiently resolve the l1-minimization problem, hence for figuring out the object classes, sparse coefficients are employed. The authors suggest a strategy in [16] depending on an information theory method, where facial images are fragmented into a tiny set of distinctive attribute images known as "Eigenfaces", which in reality are the main elements of the preliminary training set of facial images. Identification is carried out by creating a new image into the subspace covered by Eigenfaces ("face space") and then by contrasting the location of the face in the face space with the location of the face of the known persons, the face is identified. An effective method to discover the lower-dimensional space is the Eigenface method. In reality, Eigenfaces are proprietary vectors that represent each dimension in face space and can be used as different face attributes. Both face forms may be described in the face collection as a linear fusion of singular vectors. To be exact, these singular vectors are the covariance matrices vectors. In displaying the significant characteristics, the eigenfaces played an essential function, thereby reducing the input size of the neural network.

3 Research Methodology

3.1 Data Collection

The test was carried out by using the ORL database (face data) [17]. Within the training database, there are 190 images of 38 people (5 images for each person) and 40 images of different people (38 familiar and 2 unfamiliars) are present in the test database. In a straight-up, front-view posture, a photograph of the subject is taken. A picture has a similar unilluminated backdrop and 92×112 measurements. Besides, each picture is grayscale (intensity measures of gray are considered image attributes).

3.2 PCA Approach to Face Recognition

A sequence of data derived from logically linked variables [18] is converted by key component analysis into a collection of values for non-correlated variables called main components. The number of components may be smaller than or equal to the initial number of variables [19]. The first major variable has the largest potential variance. Under the constraint that it has to be orthogonal to the previous component, each of the effective components has the greatest possible variance [20]. We want to find the key components of the covariance matrix of facial images, in this case, eigenvectors. The first thing we need to do is to build a data set for training. The fundamental techniques followed by this have been depicted in Fig. 3 to show the overall working process.

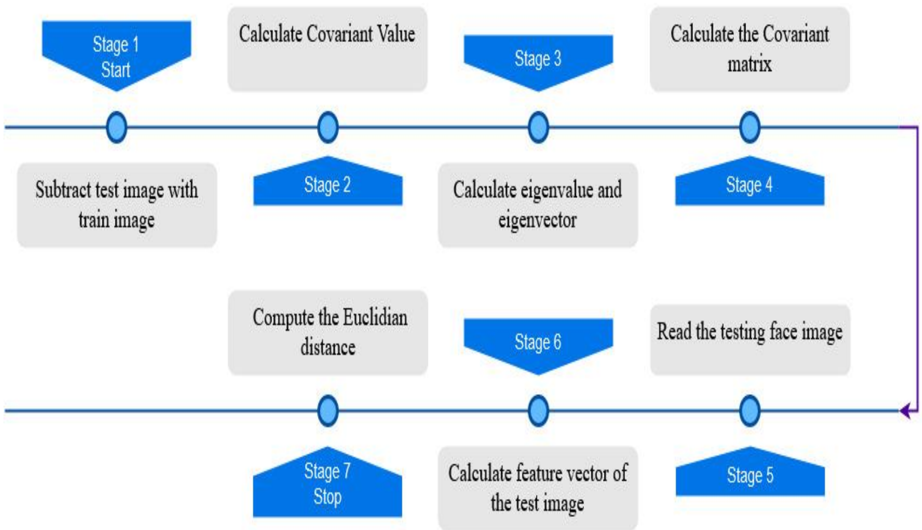

Fig. 3. Flow Diagram of PCA Approach

At first, the collected images were separated into two parts: training and testing to calculate the covariant value. After that, both eigenvector and eigenvalues were computed before getting the results from the covariant matrix. In the following stage, when the

matrix was calculated, the face image was read also. Subsequently, after calculating the feature vector of each image, the result was computed by Euclidian distance.
If A and B are two D-distance vectors, using charts [21], the distinction between them is overcome. Here are the following equations (1) and (2).

Manhattan distance: $d(A,B) = \sum_{i=1}^{D} |a_i - b_i|$ (1)

Euclidean distance: $d(A,B) = \sqrt{\sum_{i=1}^{D}(a_i - b_i)^2}$ (2)

3.3 Eigenface

Eigen's face employs the appearance-based method in computer vision to identify the face of humans. It understands the diversity in the educational variation of photos of the face, which is afterward used to alter and organize photos [22]. Eigenfaces are the important section for the distribution of faces. The goal of the Principal part investigation (PCA) is to make a global error in the preliminary group of pictures and illustrate this diversity using some variables [23]. This is a dimensionality reduction process that focuses on getting rid of the required amount of important facial data segments [22]. An eigenvector is one such vector that does not change its way under the associated direct variation and Eigen's features are the combination of eigenvectors that chooses one element from facial picture space [23]. The covariance matrix C is computed, and by using the following equations (3) [24], the eigenvectors e_i and eigenvalues λ_i are found out in equation (2):

$$C = \frac{1}{M}\sum_{n=1}^{M} \varphi_n \varphi_n^T = AA^T \quad (3)$$

$$Ce_i = \lambda_i e_i \quad (4)$$

If v_i and μ_i are eigenvectors and eigenvalues of matrix A^TA [24] that is shown in equation (5), then:

$$A^TAv_i = \mu_i v_i \quad (5)$$

After multiplying both sides together of equation (3) with A, we get the value of equation (6)

$$AA^TAv_i = A\mu_i v_i \quad (6)$$

Applying $C = AA^T$ in equation (6), equation (7) will be,
$$c(Av_i) = \mu_i(Av_i) \quad (7)$$

The preparation set is altered hooked on a vector P [24], diminished by the mean worth Ψ and expected by a grid of eigenvectors which are shown in equation (8),

$$\omega = E^T(P - \Psi) \tag{8}$$

It is evident that after subtracting the collected images into training and testing parts, the covariant value was computed. Subsequently, eigenvalue and eigenvector were also calculated before doing projection. Furthermore, all of the required works that had been done were saved in a specific folder after getting the expected outcomes of projection. All of the necessary descriptions are added in Fig. 4 to better understand the overall process.

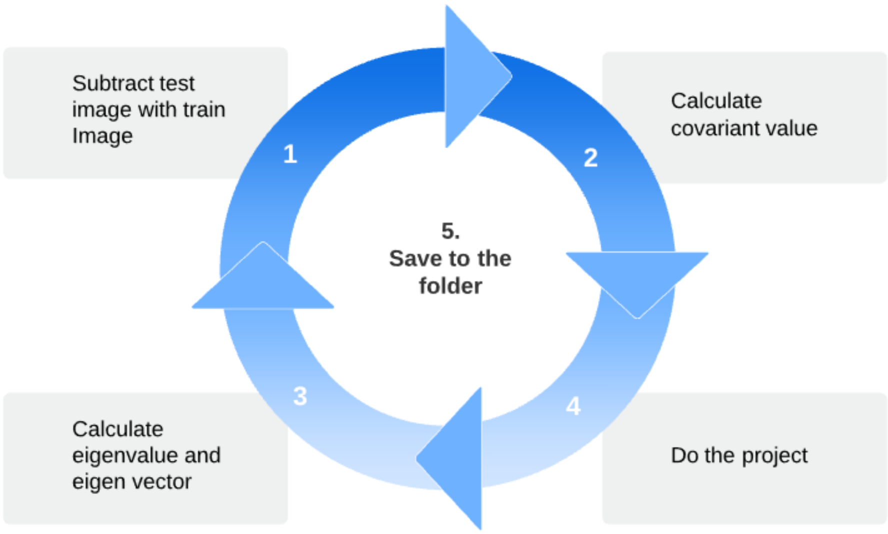

Fig. 4. The Required Steps of Eigenface Technique.

3.4 Speed Up Robust Features (SURF):

SURF [25] is a standard pivotal part that involves a storyline and a descriptor of intriguing details. The radar finds that the intrigue focuses on the picture, and the descriptor defines the highlights of the emphasis of the conspiracy and constructs the element vectors of the focus of the intrigue [26].

1) Interest Point Detection: The SURF indicator was found based on the Hessian matrix. Assumed a fact X (x, y) in an image I, the Hessian matrix H(X , σ) at X at scale σ is distinct in this manner [26] and [27]. The equation (9) is given below.

$$H(X, \sigma) = \begin{bmatrix} L_{xx}(X,\sigma) & L_{xy}(X,\sigma) \\ L_{xy}(X,\sigma) & L_{yy}(X,\sigma) \end{bmatrix} \tag{9}$$

Where $L_{xx}(X,\sigma)$ is the convolution of the Gaussian second order derivative $\frac{\partial^2}{\partial x^2} g(\sigma)$ through the image I at point X, and likewise for $L_{xy}(X,\sigma)$ and $L_{yy}(X,\sigma)$.

2) Interest Point Description: The point of focus in a picture is a point in its neighborhood that is special. A two-step strategy is usually used to diagnose and clarify this point: A. Feature Detectors: where an algorithm that uses an image as input is a feature detector (extractor) and outputs a set of regions ('local features'). B. Descriptor function: where a descriptor is computed to a detector-specified picture field. Descriptors are built by removing rectangular areas about the attention facts. The frames are separation in 4x4 sub-regions [26], [27]. The shape is described by a vector in equation (10) and shown in Fig. 5.

$$V = \left[\sum d_x, \sum d_y, \sum |d_x|, \sum |d_y|\right] \quad (10)$$

In face recognition, SURF characteristics can be derived from photographs through SURF detectors and descriptors utilizing SIFT functionality. Interest points are first removed from each face picture during pre-processing, such as normalization and histogram equalization. This results in the acquisition of between 30-100 interest points per photo. The SURF feature vectors [28] of the range of interest points are then determined to characterize the picture and these feature vectors are normalized to 1. These characteristics are person-specific since each person's picture varies in the amount and position of points selected by the SURF detector and the characteristics measured by the SURF descriptor around these points.

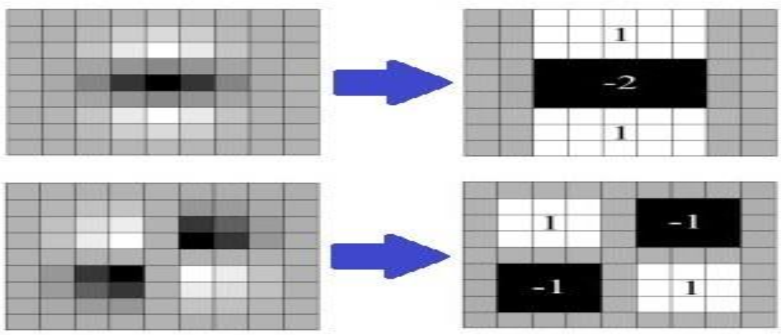

Fig. 5. Gaussian second-order partial derivatives and pattern.

4 Experimental Results and Discussion

4.1 Expected Outcomes After Using Eigenface

Some images from the training database are displayed in Fig. 6 and Fig. 7, where all 190 eigenvalues are demonstrated. Every eigenvalue belongs to one eigenvector and shows us to what extent images from the training database differ from the average image in the same path. It is observed that only 10% of the vectors have considerable eigenvalues, whereas the remaining vectors consist of eigenvalues almost close to 0. Eigenvectors consisting of insignificant eigenvalues are needless to consider because they do not contain critical image data.

Fig. 6. Training Images.

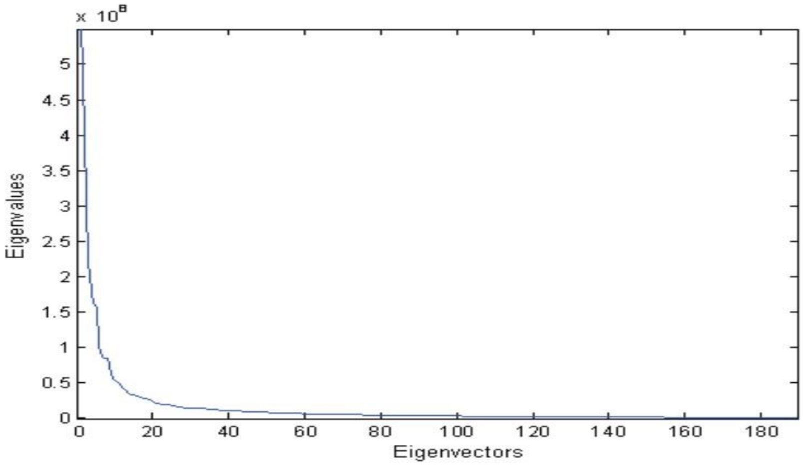

Fig. 7. Eigenvalues.

In Fig. 8, the first three eigenfaces are displayed as outputs and these images are quite similar to the input values which had been taken from the explained dataset.

Fig. 8. Graphical Representation of Eigenfaces.

The calculated results are displayed based on the different number of principle elements. Among all of the displayed results, the highest results (approximately 98.5%) for both Manhattan and Euclidean distances were for 190 eigenvectors. In comparison, the lowest outcomes were observed for 6 eigenvectors which were about 86.5% and 76.7% respectively. The distance of Manhattan was considerably higher than the Euclidean distance except for the calculated findings of 20 eigenvectors, which were almost 0.9% higher, after considering all listed eigenvectors. A sufficient explanation has been added in Fig. 9.

Euclidean and Manhattan distances have been calculated based on the different types of images of five persons to carry out the rate of recognition. After evaluating all of them, the highest predictable distance was noticed for both distances (Euclidean and Manhattan) where the recognition rate of the 5th person was around 98.5% and 98.8%, however, the lowest rate of prediction was discovered for 1st person (82.5%, 86.5%). Besides, Fig. 10 shows that both distances such as Euclidean and Manhattan provide similar results (only 94%) for the position of 4th.

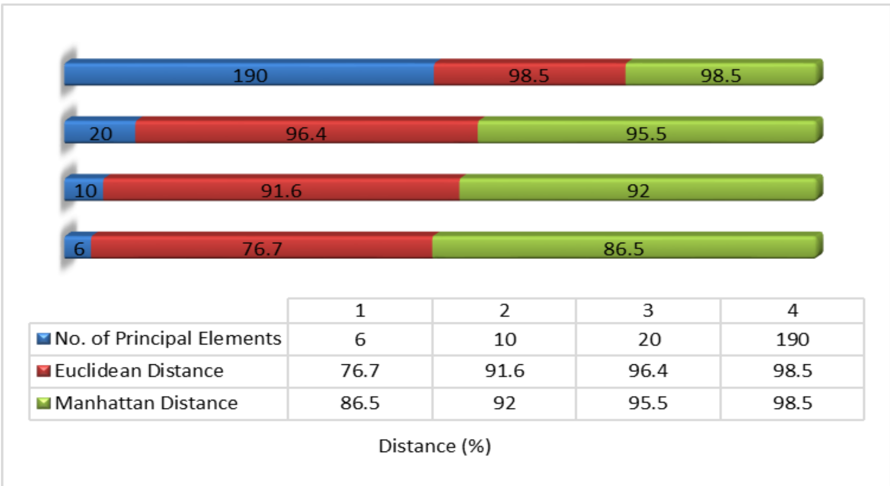

Fig. 9. The Examined Results of Face Recognition by Eigenface.

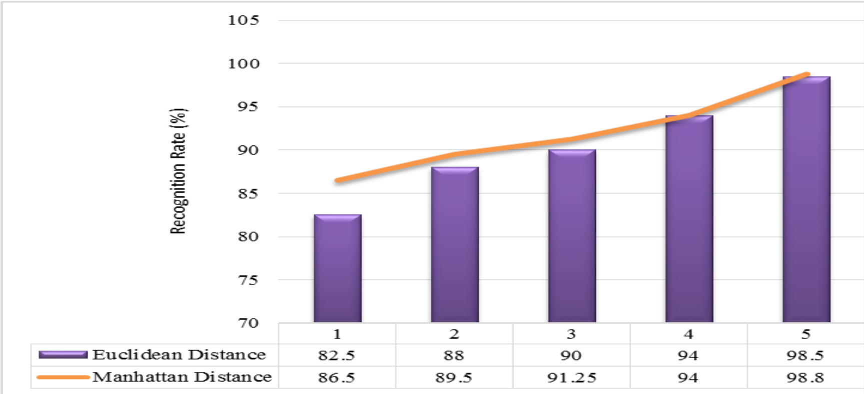

Fig. 10. The Examined Results of Per Person for Different Number of Images by Eigenface.

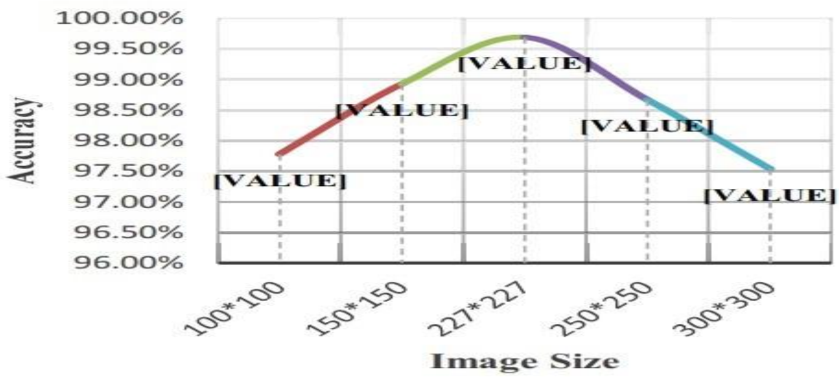

Fig. 11. Accuracy based on Image Size.

The corresponding Fig. 11 is illustrated based on various levels of image size. If the image size is low there is not enough data to process and if too high, it takes too much time to read and process the image data. So the ideal size is 227*227. For all of these images, the most predictable accuracy [37-38] which was just over 99.50% was depicted for 227*227 image size, on the other hand, the last result was witnessed for the size of 300*300 which accuracy was close to 97%.

4.2 Displayed results of SURF after using different levels of dimensions

Our test results were compared with the SIFT approaches with this proposed method. Here, the feature vectors of a dimension are indicated by 64 and 128 and dbl refers to the appropriate size of the given image that was doubled before extracting the feature. After generating the combined outputs of SURF (64 and 128 dimensions) and SIFT approaches (128 dimensions), approximately 0.55 threshold values were observed for the first three consecutive features and around 0.5 threshold results were achieved for the last three features of SURF and SIFT techniques. The obtainable outcomes have been clearly shown in the following Fig. 12.

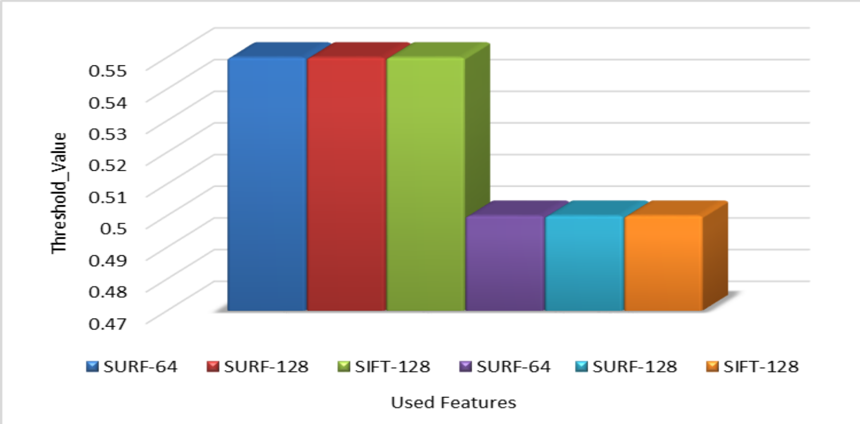

Fig. 12. Different ratio of thresholds.

The identification rates on all types of attributes are given in Fig. 13. It is clear that the identification rate of both SURF-64 and SIFT-128 are the same.

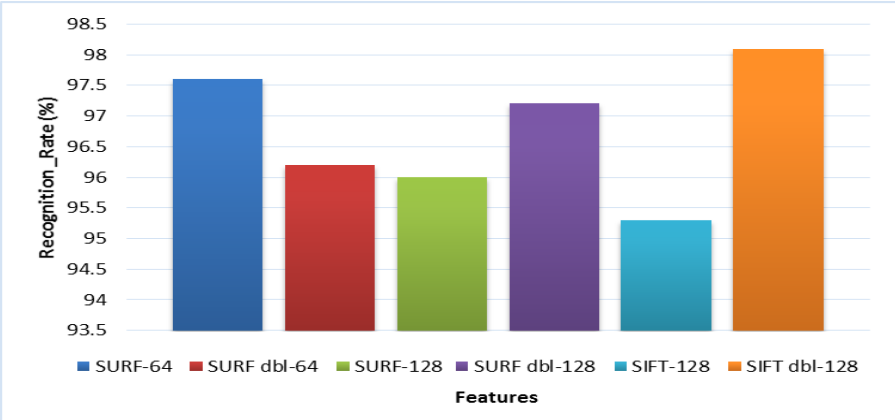

Fig. 13. The comparison of recognition rate between SURF and SIFT features.

The 128-dimensional SURF (SURF-128) attribute vectors are a bit better than SURF-64 and SIFT-128. In the case of N-dimensional attribute sets, the comparison for identification exceeds non-doubled attribute sets, but it is weaker for attribute sets "doubled" with 53 dimensions than "non-doubled" with 64 dimensions. The SURF profiling algorithm was created to be applied to high-dimensional data. On this particular dataset that cannot explain with more than 64 dimensions. This is because it will give rise to higher interest points for a doubled image in contrast to the non-doubled image, which means 128 dimensions will give higher discrimination data as opposed to 64 dimensions in the match.

5 Conclusion

Modern technology is all about performance and speed [29-30] [39]. Today is the scientific and technical era. For the present culture, new technology is a great blessing [31-34]. In every aspect of our lives, we see the application of new technologies [35-36]. Without science and technology, we cannot conceive about our daily life. This research focuses on different face recognition methods. To identify human faces, the eigenface technique is used here. Besides, the SURF process is also demonstrated. Compared to other approaches and even among the techniques, the accuracy rate of the ways is seen. It can be seen from the comparison that each approach has its value, which is dependent on the state of the data. Plans all demonstrate positive progress in the identification of individual features in any given status.

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