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# ORB-PCA Based Feature Extraction Technique for Face Recognition

Vinay.A[a]*, Akshay Kumar C[b], Gaurav R Shenoy[b], K N Balasubramanaya Murthy[a], S Natarajan[b]

[a]*PES University, 100 Feet Ring Road, BSK III Stage, Bengaluru-560085*
[b]*PES Institute of Technology, 100 Feet Ring Road, BSK III Stage, Bengaluru-560085*

**Abstract**

Face Recognition is one of the most prevalent fields in the domain of Computer Vision and the problems pertaining to it are very challenging. The potency of FR systems in biometric authentication systems is slowed down by their processing speed constraints, which substantially limits their computational capabilities and furthermore, the prevalent SURF and SIFT feature descriptors are computationally complex and demand very high level hardware requirements for processing. Off late, ORB, a cost effective feature descriptor, has been effective for such systems. Hence, in this paper, we propose a novel technique that utilizes ORB, and in turn, incorporate PCA as a post-processing step to reduce the dimensionality of the descriptors and hence improve ORB's authentication performance over the widespread methods such as SIFT-PCA and SURF-PCA.


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*Keywords:* Recognition; GPU; ORB; PCA; SIFT; SURF.

## Introduction and Related Work

Face recognition (FR)[10] is one among the most popular fields that has found innumerable applications in

* Vinay A. Tel.+9180-2672-2108; fax:+9180-2672-0886.
*E-mail address:* a.vinay@pes.edu


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authentication systems. In spite of its extensive usage, it is perforated with numerous issues due to which its recognition accuracy deteriorates in certain unconstrained scenarios [11]. FR involves determining the unique characteristics of a face which are known as feature descriptors. The performance of an authentication system based on FR significantly depends on the choice of the feature detector. Many popular extraction techniques such as Scale Invariant Feature Transform (SIFT)[5], Speeded UP Robust Features (SURF) [3] (see [9] for a comprehensive survey of the evolution of the prevalent feature extraction mechanisms) are available but these are not always efficient in scenarios involving biometric authentication systems and other real time scenarios that are very computationally ineffective. Therefore, in this paper, we propose a feasible technique called ORB-PCA, which is based on the ORB (Oriented Fast and Rotated Brief) [1] feature descriptor and to overcome the computational disadvantages of ORB by using the PCA (Principal Component Analysis) [16] method to carry out dimensionality reduction [19] and reduce the cost and time of computation.

ORB[1] is a contemporary inclusion to a series of feature detection and extraction techniques (SURF [3] SIFT [5]) that was put forward by Rublee et al.ORB employs the improved methodologies of BRIEF [6](RBRIEF [1]) and FAST [7] (OFAST [13]) descriptors. These two were chosen because of their performance and low cost [1] and certain desirable characteristics such as their invariance to illumination, blur, affine and so on [1][6][7]. ORB overcomes the critical imperfections such as that of FAST's lack of orientation component and BRIEF's lack of rotation invariance. Therefore, ORB is rotation invariant and is proven to be faster than SIFT [1]. Moreover, it is free from licensing restrictions compared to the patented SIFT [5] and SURF [3] mechanisms.

Dimensionality reduction maps the data existing in the high-dimensional space to a lower dimensional space. This transformation may be linear or non-linear. Among the linear dimensionality reduction techniques, Principal Component Analysis is predominant. PCA gives the directions with maximum variance of the data [17][12].The objective of PCA is to retain the existing information after reducing the dimensions of the descriptors. It has proved to be considerably efficient [19]. The dimensionality reduction of the data is achieved by projecting the data onto the subspace spanned by the most significant eigenvectors (corresponding to largest Eigen values).

In our approach, we intent to enhance the performance of the ORB in computationally cost ineffective systems by using the dimensionality reduction aspects of PCA [19].Only the significant number of principal components are retained and information embedded in the descriptors is preserved. Thus PCA was chosen as a feasible option to serve in boosting the performance and computational effectiveness of ORB through dimensionality reduction.

In order to obtain results close to the real-time scenarios we demonstrate our experiments on the *LFPW*[15] database which is very challenging and is rarely used in FR due to extensive variations between the test images. The increase in the recognition accuracy compared to SIFT-PCA[21] and SURF-PCA[21] can be inferred from the results.

The rest of the paper is organized as follows: section 1 gives an overview of the proposed methodology, section 2 details the experimental setup, Section 3 describes the experimentation results along with the pertinent evaluation metrics and section 4 proffers a discussion of the proposed approach and outlines future work.

## 1. Overview of Proposed Methodology

This section presents an overview of the various steps involved in our technique.

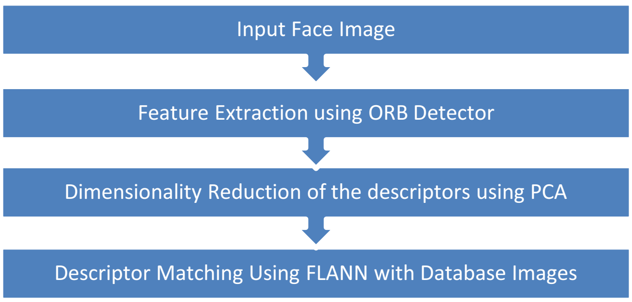


**Fig.1.Framework of the Proposed Methodology**

Feature extraction is performed on the query image and the database images using ORB detector [1]. It is then accompanied by dimensionality reduction (retaining the existing information) using the PCA [4] methodology. Finally, the descriptors of both the input face and database images are matched using FLANN (Fast Library for Approximate Nearest Neighbour Search)[8] to determine whether they belong to the same face.

## 2. ORB-PCA-FLANN

In this section we put forth the technical aspects of the methodology. There are mathematical conceptions about all the steps pertaining to our proposed technique which is required for better understanding and they also serve as a proof to account for the improved accuracy.

### *2.1 ORB (Oriented FAST Rotated BRIEF) Detector*

It operates by adding an accurate orientation component to FAST by utilizing an Intensity Centroid Cloud mechanism and renders BRIEF rotation invariant by constructing a variant called steered BRIEF and subsequently evolves it into the r-BRIEF offspring, which is adequately rotation invariant [1][2].
The Orientation component is added to FAST by using the Intensity Centroid approach (IC) [13] that employs a robust measure of corner orientation. The moments of a patch that are utilized to find the centroid are represented as follows [13]:

$$m_{pq} = \sum_{x,y} x^p y^q \, I(x,y) \tag{1}$$

where $m_{pq}$ represents the $(p+q)^{th}$ order moment of an image whose intensity $I(x,y)$ varies as a function of $x$ and $y$ image coordinates.
By considering the moments in Eqn.1, the centroid is obtained as follows:

$$C = \left(\frac{m_{10}}{m_{00}}, \frac{m_{01}}{m_{00}}\right) \tag{2}$$

A vector is constructed from the centre to the centroid $\overrightarrow{OC}$ and then accordingly the orientation of the patch becomes [1]:

$$\theta = atan2(m_{01}, m_{10}) \tag{3}$$

where atan2 represents the quadrant-aware version of arctan. Considering [1] the importance of the illumination parameter of the corner[13] is not taken into account because the angle measures remain the same irrespective of the type of the corner. The rotational invariance can be enhanced by ensuring that the moments are computed with respect to x and y that remain within the circular region of radius r [1]. An optimum choice for the patch size is r, in a manner that ensures that the run of x, y is from [−r, r]. Typically with Hessian measures, as the value of |C| approaches zero, it tends to become unstable but this does not happen with FAST corners, which is favourable for the proficiency of the system [1][13].

Secondly, ORB involves the addition of a rotation aware component called r-BRIEF which is an evolved version of the steered BRIEF descriptor coupled with a pertinent learning step is also outlined in [1] to find the less correlated binary features.

In order to ensure efficient Rotation of the BRIEF [6] operator, a bit string description of an image patch is constructed from a set of binary intensity tests [1]. To better illustrate the operation of conventional BRIEF, before an orientation component is added to it by ORB, let us suppose that there is a smoothed image patch $p$.Then a binary test τ on it is represented as follows [1][6]:

$$\tau(p; x, y) := \begin{cases} 1 & : p(x) < p(y) \\ 0 & : p(x) \geq p(y) \end{cases} \tag{4}$$

where p(x) denotes the intensity of the patch $p$at a given point x.

Subsequently, the feature which is a function of the patch considered can then be represented as a vector of $n$ binary tests as follows:

$$f_n(p) := \sum_{1\leq i\leq n} 2^{i-1}\tau(p; x_i, y_i) \tag{5}$$

In our deliberations, we utilize the Gaussian distribution around the centre of the patch along with the choice of vector length n as 256 (shown to produce reasonable results in [1][14]).The combination of the two, we believe is the reason for the additional performance boost proffered by our proposed method. Since, one of the crucial contributions of ORB is the in-plane rotation invariance that it confers on BRIEF, as the classical BRIEF undergoes a sharp decline in the presence of in-plane rotation exceeding a few degrees. The first step in their approach was to steer BRIEF in accordance to the orientation of the key-points (this step is dubbed steered-BRIEF).

The steering of BRIEF is carried out as follows:

Let us consider that for any given feature set of $n$ binary tests at a particular location$(x_i, y_i)$, a 2 × n matrix can be represented as follows [1]:

$$S = \begin{pmatrix} x_1,\ldots,x_n \\ y_1,\ldots\ldots y_n \end{pmatrix} \tag{6}$$

Subsequently, by utilizing $\Theta$ (patch orientation) and $R_\Theta$ (corresponding rotation matrix), a steered version $S_\Theta$of S can be obtained as follows [1]:

$$S_\Theta = R_\theta S \tag{7}$$

Consequently, the steered BRIEF operator can be written as [1][6]:

$$g_n(p, \Theta) := f_n(P) \mid (x_i y_i) \in S_\Theta \tag{8}$$

We discretize the angle to increments of $\frac{2\pi}{30}$ (12 degrees) and construct a lookup table of pre-computed BRIEF patterns. As long as the key-point orientation $\Theta$ is consistent across views, the correct set of points $S_\Theta$ will be used to compute its descriptor

Furthermore, by utilizing the approach outlined by Rublee et al. [1] for analysing the variance and correlation of oriented BRIEF features and opting the learning method for de-correlation the BRIEF features under rotational invariance (to render r-BRIEF), we obtain robust performance in nearest neighbour applications (corroborated by FLANN) [1].

### 2.2 PCA (Principal Component Analysis)

Principal component analysis is a statistical procedure applied to reduce the dimensions of the data. PCA operates by transforming a given set of input data of higher dimensions into lower dimensional data. Here, the input to the PCA is the ORB descriptors of both, the query face and the database. The eigenvectors of the correlation matrix are found and only those with the significantly higher Eigen values are considered. It is described as a transformation of a given set of N input vectors with the same length K (=32 for ORB descriptor) in the N-dimensional vector x=$[x_1, x_2, \ldots\ldots, x_N]^T$ into a vector y given by [22]

$$y = A(x - m_x) \tag{9}$$

Each row of x consists of K values belonging to one input. The vector $m_x$in Eq (9) is the mean vector and is mathematically given as[22]

$$m_x = E\{x\} = \frac{1}{K}\sum_{k=1}^{K} x_k \tag{10}$$

Matrix A in Eq. (9) is determined from the covariance matrix $C_x$. Rows in the A matrix consist of eigenvectors of $C_x$ ordered according to corresponding Eigen values in descending order. The $C_x$ matrix is obtained by the relation given by [22]

$$C_x = E\{(x - m_x)(x - m_x)^T\} = \frac{1}{K}\sum_{k=1}^{K} x_k x_k^T - m_x m_x^T \tag{11}$$

The size of the covariance matrix is N x N since x is N-dimensional. The covariance between input vectors $x_i$, $x_j$ is given by [22]

$$C_x(i,j) = E\{(x_i - m_i)(x_j - m_j)\} \tag{12}$$

In addition, for PCA to work exactly, one should use standardized data so that the mean is zero and the unbiased estimate of variance is unity [20].PCA assumes that the data follows a *Gaussian distribution*.Although PCA seems to be effective in its applications in FR systems [20] it is constrained with the curse of dimensionality [18]. The number of components to retain can be determined by the relation[20]

$$\frac{\sum_{i=1}^{N} V_i}{\sum_{k=1}^{K} V_k} = \alpha \qquad where\ 0 < \alpha <= 1 \tag{13}$$

In the equation above, V represents the Eigen values, K represents the number of principal components retained and N stands for total number of Eigen values. In the experiments that we carried out,$\alpha = 0.95$ gave good accuracy which can be witnessed in the next section.

*2.3 Descriptor Matching Using FLANN*

FLANN stands for Fast Library for Approximate Nearest Neighbours[8]. A plethora of algorithms is optimized for fast nearest neighbour search for large datasets with high dimensional features. Also, it works more faster than Brute Force Matcher. The descriptors of query image, $\overrightarrow{D_q}$ and descriptors of every database image, $\overrightarrow{D_{d_i}}$ are passed through the FLANN matching algorithm [8] that gives a vector of good matches, $\overrightarrow{G_{(q,\ d_i)}}$ between the key-points of the query image and the key-points of the images in the database. A proper threshold on the number of key-points matched should be set to conclude that two images belong to a same face.

## 3. Experimental Analysis

This section reports the experimental results of the test cases of the technique used in comparison of SIFT-PCA, SURF-PCA, ORB and ORB-PCA. The results were obtained for 1000 cases and the database used for the evaluation of the metrics is *LFPW* [15]. As stated earlier, this dataset has images with varying illuminations, colours, rotations, translations and quality of the face region of interest and hence, is the case very closer to the real time scenarios. Each image is of $250 \times 250$ dimension. As the size of the dataset increases, the execution time also increases since the computations involved increases. The accuracy of the technique, though not very high, but, is much greater than the other techniques. Also, the time consumed by the technique is much lower when compared to SIFT-PCA and SURF-PCA .The improvement in the time consumed is minimal but the accuracy is greatly improved in ORB-PCA compared to ORB.

**Table1. Comparison results of SIFT-PCA, SURF-PCA, ORB and ORB-PCA.**

| Techniques | SIFT-PCA | SURF-PCA | ORB | ORB-PCA |
|---|---|---|---|---|
| **Average time per image in sec** | 0.957 | 0.674 | 0.356 | 0.332 |
| **Specificity/ TNR** | 51.613 | 55.674 | 53.488 | 74.186 |
| **Precision/ PPV** | 69.118 | 54.463 | 73.134 | 80.862 |
| **Accuracy/ ACC** | 69.469 | 61.361 | 69.770 | 78.879 |
| **Recall** | 83.186 | 68.736 | 80.065 | 82.425 |
| **F1 Score** | 75.502 | 60.772 | 76.443 | 81.636 |
| **FAR** | 0.484 | 0.443 | 0.465 | 0.258 |
| **FRR** | 0.168 | 0.313 | 0.199 | 0.176 |
| **HTER** | 0.326 | 0.378 | 0.332 | 0.217 |
| **TER** | 0.494 | 0.691 | 0.532 | 0.393 |

An illustration of the experimental result of proposed technique for one of the face set of a celebrity from *LFPW* [15] is given in Fig.2. in comparison with the other techniques. This technique was implemented using Open CV C++. The different colours of the key points are obtained by the Open CV functions and do not have any significance. It can be inferred that ORB-PCA has dominating characteristic results as compared to the other techniques mentioned. The reason being that the ORB-PCA has been distinctively able to match the key points after the Dimensionality Reduction of the descriptors, as there would be removal of the redundant description about the image which serves very little in the matching step.

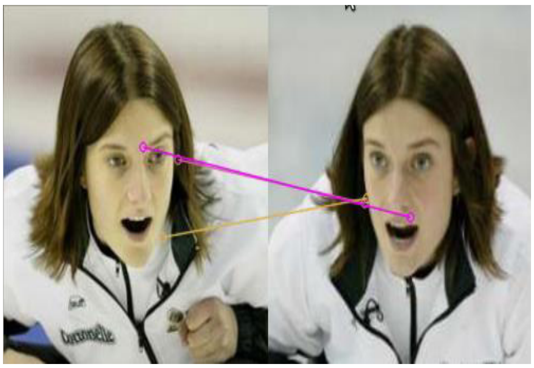

**Fig.2.a.SIFT-PCA technique.**

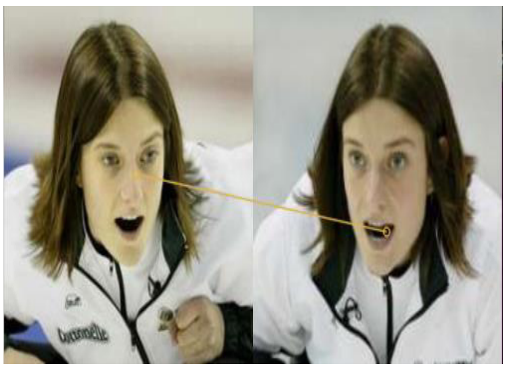

**Fig.2.b.SURF-PCA technique.**

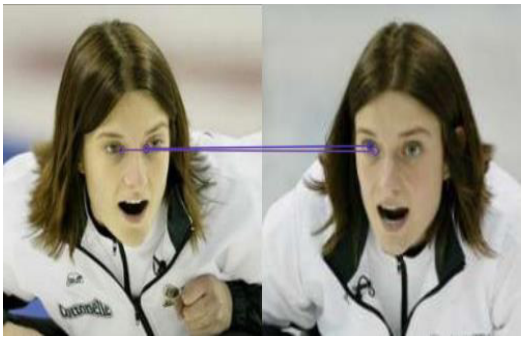

**Fig.2.c.ORB technique.**

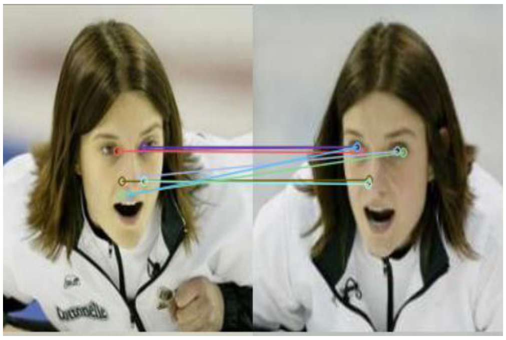

**Fig.2.d.ORB-PCA technique.**

## 4. Conclusion and Future Work

This technique thus proposed claims an incremental success in accuracy of over 10% and moreover, the technique proved to be faster than the other prevalent techniques that are mentioned in the paper. In today's scenario, most of the FR systems fail to satisfy when they are working on real time applications. This is because, the design of the FR system and its experimental analysis are carried out on the datasets that seldom vary with respect to the environmental/geometrical factors like illumination effect, occlusion, colour variations, translation effects and rotational effects. So, to overcome such challenges, the technique was analysed on the most complicated database so as to mark its success level in the real time scenarios.

In the future, FR systems can be designed to overcome all the factors mentioned above so that they yield higher accuracy and lesser time consuming. For this to happen, the images have to be normalized with respect o all the factors mentioned above. Other variants of SIFT, SURF and ORB can be tried on these normalised images such that they are adaptive to the variations in the dynamic images.

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