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Abstract

Face Recognition is one of the most thriving and cutting-edge fields of research that stands unwaveringly as the most critically challenging problems in the domain of Computer Vision. In the design of an efficient FR system, the potency of the feature descriptor dictates the proficiency of the recognition performance. The effective employment of FR systems in handheld and mobile devices is hindered by their lack of GPU acceleration, which considerably limits their computational capabilities and furthermore, the prevalent SURF and SIFT feature descriptors are computationally expensive and hence are not viable for low-powered devices. To that end, ORB, a cost effective feature descriptor, has been effective for such devices. Hence, in this paper, we propose a novel technique that utilizes ORB, and in turn, address a few of its crucial inadequacies by incorporating RANSAC as a post-processing step to remove redundant key-points and noise (in the form of outliers) and hence improve ORB's efficacy to proffer a robust system for facial image recognition, that has improved accuracy than the prevalent state-of-the-art methods such as SIFT-RANSAC and SURF-RANSAC.

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1. Introduction and Related Work

Face recognition (FR) [26] is one most prolific forms of Biometrics that has found extensive applications in innumerable commercial and law-enforcement scenarios. In spite of its ubiquitous presence, it is riddled with a surplus of issues due to which its recognition accuracy undergoes a sharp decline in certain unconstrained scenarios [27]. The performance of an FR system predominantly relies on the choice of the feature detector and many popular extraction techniques are available such as SIFT [13], SURF [7] (see [25] for a comprehensive

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survey of the evolution of the prevalent feature extraction mechanisms) but these are not always viable in scenarios involving low-powered devices that lack GPU acceleration, as they are very computationally demanding. Therefore, in this paper, we propose a novel cost effective mechanism called ORB-RANSAC, which is based on the ORB (Oriented Fast and Rotated Brief) [1] feature detector, where we attempt to overcome a few of the critical disadvantages of ORB by using the RANSAC (Random Sample Consensus) [10] method to carry out dimensionality reduction and de-noising to augment recognition performance and accuracy.

ORB[1] is the recent addition to a legacy of feature detection and extraction techniques (starting with SURF [7]) that was proposed by Rublee et al. [1] in an effort to provide a cost effective alternative to the highly robust, but computationally expensive SIFT [13] feature extractor. ORB builds on the BRIEF [14] and FAST [17] descriptors. It was developed by adding an orientation component to the FAST descriptor (using the corner orientation based Intensity Centroid [33] method) called *oFAST*, along with the incorporation of a steered version of BRIEF according to the orientation of key-points known as *rBRIEF*, in order to ensure invariance of the in-plane rotation [1]. Thus, ORB is rotation invariant and resistant to noise and is proven to be two orders of magnitude faster than SIFT [1]. It can aid in real-time applications to enable low power devices without GPU acceleration to perform panorama stitching and patch tracking. Furthermore, it is free from licensing restrictions, unlike the prevalent SIFT [13] and SURF [7] mechanisms.

In our approach, we aim to improve the accuracy of the ORB approach by using RANSAC [10], a highly potent technique for robust fitting of models in the presence of outliers that was pioneered by Fischer et al. in 1981. It has demonstrated high efficiency in outlier removal i.e. eliminating mismatched pairs of points [10][30][31]. RANSAC operates by classifying a given set of points in a model, as either inlier or outlier and thus reduces the redundant key-point matches. This classification is conducted on the basis of a given threshold and excludes the points that fall outside the threshold as outliers, and therefore in the context of FR, it can be beneficial in the following ways: (1) it can improve key-point detection as only the relevant key-points will be considered during the matching process and the unnecessary points do not clutter the process, (2) by removing the redundant key-points, it can reduce the high number of errors that are produced due to mismatched pairs [10][30][31], (3) it has been successful in a few seminal works [30][31] in filtering out incorrectly mapped points that are yielded by the imprecision of the SIFT [13] model and hence there is promise of extending this philosophy to other feature detectors (ORB, in our case). Therefore, owing to the aforementioned characteristics, RANSAC was chosen as a viable candidate for our deliberations to serve in providing an appropriate amount of performance boost to ORB through dimensionality reduction and de-noising.

We believe that PCA can also be applied to ORB [1][2], once the space is reduced (by cutting down redundancy) using RANSAC [10], but we defer this to future work and focus the crux of our efforts in this paper on establishing the effectiveness of RANSAC with the ORB detector. In our deliberations, we endeavour to make ORB more efficient by removing outliers by using RANSAC as a post-processing step, after applying descriptor matching using the FLANN (Fast Library for Approximate Nearest Neighbour Search) [19] algorithm.

RANSAC [10] works well with a certain probability, but this increases as the number of iterations increase. The classical RANSAC requires us to ensure that the probability of selecting inliers in the selection of data is high, in which case the requisite for more number of iterations may be slightly lenient. But both of these are cumbersome, as the iterative process in RANSAC is time consuming and the “maximization of inliers” condition is also not optimal [12].

Although RANSAC is highly accurate, even in the presence of large number of outliers, it lacks an upper bound on the computation time i.e. iterations and if we limit the iterations, in certain scenarios, it does not

reach an optimal solution. Furthermore, in case of contaminated sets, where the numbers of inliers is less than 50%, its performance tends to decline. This led to the formation of an improved version, the Optimal RANSAC [15], which can overcome both these disadvantages and is effective even in scenarios where the number of inliers is less than 5%. In this paper, we utilize the classical RANSAC method and perform our experimentations within the threshold of such errors and defer the task of FR recognition in the case of the aforementioned unconstrained scenarios and the application of Optimal-RANSAC [15][16] to future work.

Additionally, for the face authentication scenarios, we incorporate an informed assumption that at least one large face exists in the given complex background and essentially skip the face detection step. This assumption holds merit, as it has been demonstrated to produce favorable results in [24].

We will demonstrate using extensive mathematical arguments and exhaustive experimentations on the one of the most challenging database LFPW, that the proposed ORB-RANSAC approach is adequately proficient and cost-effective and can render improved recognition accuracy than the state-of-the-art SIFT-RANSAC and SURF- RANSAC methodologies.

The rest of the paper is organized as follows: section 2 describes the proposed methodology, section 3 details the experimental setup , Section 4 elucidates the experimentation results and section 5 proffers a discussion of the proposed approach and outlines future work.

2. Proposed Methodology

The section elaborates on the various sequences of steps along with the requisite background information of the techniques employed in our approach.

The ORB-RANSAC methodology is illustrated in Fig. 1.

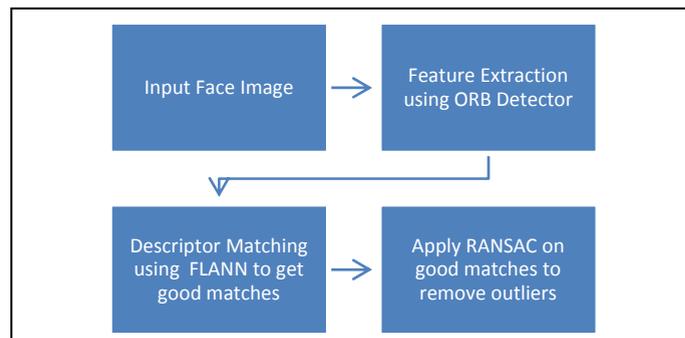


Fig.1.Framework of the Proposed Methodology

The feature extraction process is carried out on both the query (input face) and gallery (database) images using the ORB detector [1], The descriptors of both the query and gallery images are matched using FLANN (Fast Library for Approximate Nearest Neighbour Search) [19] to conclusively determine the good matches which is subsequently followed by outlier removal technique using the RANSAC [10] methodology.

2.1 ORB (Oriented FAST Rotated BRIEF) Detector

The ORB method operates by improving upon the popular FAST detector [17] and BRIEF descriptor [14]

approaches. 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][14][17]. ORB overcomes some of the crucial inadequacies of the aforementioned existing mechanisms such as FAST's lack of orientation component and BRIEF's lack of rotation invariance. 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 modified FAST key-point orientation is termed *oFAST* and is implemented by initially detecting FAST points in a given image and since the parameter FAST considers is the intensity threshold between the center pixel and the pixels in the circular ring about the center (FAST-9 with a circular radius of 9 is opted here as it is found to be favourable due to the performance boost it can offer). [1]. FAST lacks the capability to render a measure of corner-ness but is amply responsive along its edges and hence Harris Corner measure [32] can be employed to appropriately order the FAST key-points [1]. To accomplish this, let us suppose we have a target of N key-points, then we need to set the threshold sufficiently low in such a way that we obtain more than N key-points, which can subsequently be ordered in accordance with the Hessian Measure [32] and finally we can select the top N points [1]. Furthermore, since FAST does not yield features that are multi-scale, a scale pyramid of the image is utilized in order to produce FAST features that are adequately filtered using the Harris measure at each level in the pyramid [1].

Intensity Centroid technique (IC) [33] is employed in order to make FAST robust against orientations. The IC makes an assumption that the intensity of the corner is offset from its centre and subsequently uses this vector in order to add an orientation [1]. The moments of a patch that are used to compute the centroid are represented as follows [33]:

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

By employing the moments in Eqn.1, the centroid can be obtained as follows:

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

Now, a vector can be constructed from *O* (centre of the corner) to \overrightarrow{OC} (centroid) and then accordingly the orientation of the patch becomes [1]:

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

In the aforementioned equation atan2 is the four-quadrant inverse tangent of the arguments and additionally, although [33] also asserts the importance of the illumination parameter of the corner, based on the favourable results [1] an intelligent assumption can be made to not take this into account as the angle measures remain the same irrelevant of what the type of the corner is.

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.

Consider the illustration of conventional BRIEF operation, before adding an orientation component 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][14]:

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

where $p(x)$ denotes the p 's at a given point x .

Hence, the feature can be written as a vector of n binary tests as follows:

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

In our experimentations, the Gaussian distribution around the centre of the patch is considered. The length of the vector n is chosen to be 256. This configuration is shown to produce reasonable results [1][34].

Furthermore, a necessary pre-requisite is the smoothing of the image before experimentations are carried out. The implementation followed by [1] employs a method involving an integral image with each test point being a 5×5 sub-window of a 31×31 pixel patch. In our approach, this smoothing is also performed up to a sufficient degree by the RANSAC [10] method through its de-noising capabilities by removing noise in the form of outliers and is more concise than the aforementioned method as RANSAC has been demonstrated to be remarkably effective in filtering out incorrectly mapped points that arise from the imprecision in the extraction model itself (ORB in this case) [1][30][31]. 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).

Steering BRIEF is outlined in the subsequent paragraphs:

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

$$S = \begin{pmatrix} x_1, \dots, x_n \\ y_1, \dots, y_n \end{pmatrix} \quad (6)$$

By using Θ (patch orientation) and R_Θ (corresponding rotation matrix), a steered version S_Θ of S can be written as follows [1]:

$$S_\Theta = R_\Theta S \quad (7)$$

Henceforth, the steered BRIEF operator can be represented as [1][14]:

$$g_n(p, \Theta) := f_n(P) | (x_i, y_i) \in S_\Theta \quad (8)$$

The angle is discretized such that every angle is a multiple of $\frac{2\pi}{30}$ (12 degrees). A lookup table of pre-computed brief is constructed. The accurate set of points S_Θ will be used to compute its descriptor as long as key-point orientation Θ is constant across all the directions.

Furthermore, by the approach taken by Rublee et al. [1] for calculating the variance and correlation of oriented

BRIEF features and choosing the appropriate learning method for de-correlation the BRIEF features under rotational invariance (to render r-BRIEF), we obtain a robust performance in nearest neighbour applications (corroborated by FLANN) [1].

2.2 Descriptor Matching Using FLANN

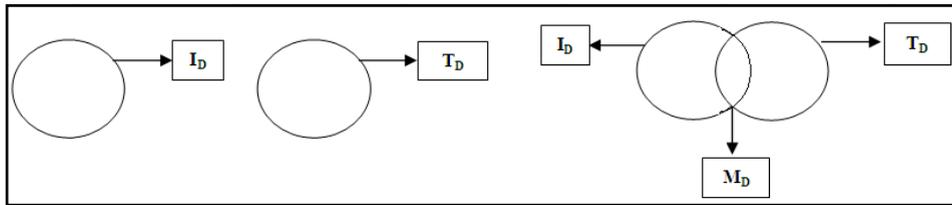


Fig.2 Descriptor Matching using FLANN

In order to carry out descriptor matching, we initially assume that I represents the Query Image and T represents the Gallery image, then $I_k = \{I_{k1}, I_{k2}, I_{k3}, \dots, I_{kn}\}$ where I_{ki} is a set of key-points of Test Images (I) and similarly, $T_k = \{T_{k1}, T_{k2}, T_{k3}, \dots, T_{kn}\}$ is a set of key-points of Template images (T).

Let us suppose that $I_D = \{I_{D1}, I_{D2}, I_{D3}, \dots, I_{Dmn}\}$, where I_D represents a set of descriptors (feature vectors) of image I and $T_D = \{T_{D1}, T_{D2}, T_{D3}, \dots, T_{Dmn}\}$, where T_D is a set of descriptors of image T. Then, we have $M_D = \{M_{D11}, M_{D12}, M_{D13}, \dots, M_{Dmn}\}$, where M_D is the set of matched descriptors, as represented in Fig 2.

The feature vectors thus extracted from the query and gallery face images are compared to conclusively determine whether there is a match by using FLANN [19] (Fast Library for Approximate Nearest Neighbour Search) matching algorithm.

2.3 Random Sample Consensus (RANSAC)

RANSAC [10] is a highly robust estimation technique that fits any given model by removing outliers in the given data set. It functions by computing model parameters principally based on the random voting principle and is capable of efficiently computing even in the presence of significant number of outliers (more than 50%) and can also robustly deal with multiple structure data [10][35]. An illustration of line fitting performed by RANSAC, where the outliers (denoted in red) do not influence the end result is depicted in Fig.3.

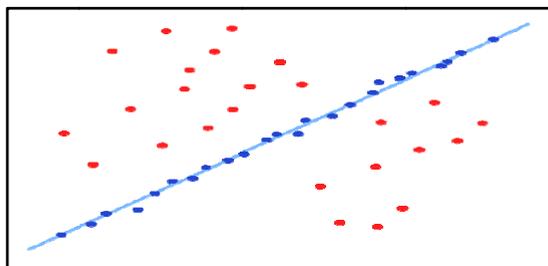


Fig.3. Line Fitting in RANSAC [10]

The distance threshold t is the first crucial parameter to consider for RANSAC and is typically determined by making the following assumption based on statistical theory: the distribution of an effective point under the given transformation model in accordance to the distance is known and accordingly we calculate the distance threshold t in such a manner that the probability of the effective point in the point set is α . If we further suppose that the distribution satisfies the zero mean and variance σ of the Gaussian distribution, the value of t can be

effectively computed [10][30]. In such a scenario, the square distance between the points is d^2 , which is the squared sum of the Gaussian variant, which meets the χ_m^2 (chi-square distribution) and essentially has m degrees of freedom. Subsequently, on the basis of the integral property of the Chi-square distribution the probability of the random variable that obeys the Chi-Square Distribution will be lower than the integral upper limit and is represented as follows [10][30]:

$$F_m(k^2) = \int_0^{k^2} \chi_m^2(\xi) d\xi < k^2 \quad (9)$$

Additionally, the distance threshold can be computed as follows [30]:

$$t^2 = F_m^{-1}(\alpha)\sigma^2 \quad (10)$$

Consequently, we can aptly classify the point set into effective and invalid points as depicted by Equations 11 and 12 respectively [10][30]:

$$\text{Effective point: } d^2 < t^2 \quad (11)$$

$$\text{Invalid point: } d^2 \geq t^2 \quad (12)$$

Subsequently, the second crucial parameter for RANSAC is the choice of the number of iterations (N) [30]. The value that is chosen for N needs to be sufficiently high to ascertain that the probability p (typically set to 0.99) is such that at least one of the random samples set does not contain an outlier. If we suppose that u represent the probability that any given data point is an inlier and accordingly, $v = 1 - u$ is the probability of observing an outlier. Then, N iterations of the minimum of points that are denoted is needed and we have [10][30]:

$$1 - p = (1 - u^m)^N \quad (13)$$

Consequently, we obtain:

$$N = \frac{\log(1-p)}{\log[1-(1-v)^m]} \quad (14)$$

The choice of aforementioned crucial parameters decides the proficiency of RANSAC in any given scenario.

3. Experimental Setup

The proposed approach has been tested and compared exhaustively on the LFPW dataset. The proposed technique is tested on each database multiple times to establish the consistency of the results.

The datasets were segregated into gallery and probe sets. The gallery set consisted of five images per subject and rest of the images was used for the probe set.

4. Experimentations and Results

Based on the number of good matches obtained as a result after the application of FLANN, two thresholds are set in order to be regarded as a match or mismatch. The thresholds for recognition is obtained by taking the ratio of inliers which are returned by RANSAC algorithm to the total number of good matches returned by

FLANN. It is obvious that for a fixed number of good matches the ratio of inliers to the total number of good matches will be higher if it is a match. Hence by the same logic and exhaustive experimentations, two thresholds were set for two bounds of good matches. The test image is classified as a match if it exceeds the threshold of that bound of good matches. The following table depicts the thresholds set for all the three approaches along with bounds of good matches.

Table1. Thresholds and bounds of good matches.

TECHNIQUE	GOODMATCHES	THRESHOLD
SIFT-RANSAC	< 20	0.5
	>20	0.35
SURF-RANSAC	< 20	0.45
	>20	0.4
ORB -RANSAC	< 20	0.
	>20	0.4

Table2. Comparison results of SIFT-RANSAC, SURF-RANSAC, ORB-RANSAC.

PARAMETERS/TECHNIQUE	SIFT-RANSAC	SURF-RANSAC	ORB-RANSAC
Average time per image in sec	0.9276	0.6854	0.3962
Accuracy in %	69.72	65.27	75.08

From table2 it is evident that proposed approach outperforms the other two mentioned techniques both in terms of the time consumption and accuracy. An illustration of the experimental result of proposed technique for one of the face set of a celebrity from *LFPW* [26] is given in Fig.4 in comparison with the other techniques.



Fig.4.a.SIFT-RANSAC technique.



Fig.4.b.SURF-RANSAC technique.



Fig.4.c.ORB-RANSAC technique.

5. Discussion and Future Work

We have presented a novel approach for Face Recognition based on the cost-effective ORB detector and RANSAC mechanism and established the compatibility of RANSAC with the ORB detector. We have demonstrated using pertinent mathematical arguments and exhaustive experimentations over multiple benchmark databases, a pronounced increase in accuracy with significantly lower computational expense over the existing state-of-the-art mechanisms such as SIFT-RANSAC and SURF-RANSAC by employing RANSAC to remove redundant key-points and noise in the form of outliers. We believe that, in addition to the traditional applications, the proposed method will be particularly effective for hand-held devices with low GPU as it is quick and efficient and involves relatively less computational expense than the prevalent methodologies.

Future work is currently being steered towards further expediting the recognition performance of the proposed system by incorporating the PCA [29] technique to perform dimensionality reduction in conjunction with a novel extension of RANSAC (we will comprehensively compare and choose the most effective recent extension among Modified RANSAC [12], Optimal RANSAC [15] and the Improved RANSAC [35]) to perform outlier removal to ensure that the key-point matching process is as streamlined as possible. Efforts are also being expended towards gauging the performance of the system by conducting experiments with specific hand-held devices in order to ascertain consistent proficiency.

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