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ScienceDirect

Procedia Computer Science 133 (2018) 913–923

Procedia Computer Science

www.elsevier.com/locate/procedia

International Conference on Robotics and Smart Manufacturing (RoSMa2018)

An Efficient ORB based Face Recognition framework for Human-Robot Interaction

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Abstract

In Human-Robot Interaction (HRI) , quick and efficient FR techniques are often required in service robots. In a real time scenario, it is absolute that face image patterns observed by robots depends often on variations such as pose, light conditions, location of the robots (view point), etc. In addition to these constraints, the service robots are expected to be quick enough for FR so that they can be deployed in applications such as counting people, security and surveillance, directing humans, etc. In this paper, ORB, a computational expensive and quick feature extraction technique is used, which has been a panacea for the above mentioned constraints. One of the dimensionality reduction techniques called PCA (a tool which reduces high dimensional data to lower dimension while keeping most of the data) with its sublime advantages of reduction of storage and time is often used. But, in the FR system , the linear uncorrelated components of PCA doesn't consider the non-linear factors such as occlusion and in such cases PCA fails to find the good representative direction. Kernel PCA (KPCA) which uses kernel methods considers even the non-linear factors and is proven to be more suitable than PCA, thus producing better results. By considering all these factors, our paper proposes a novel technique ORB-KPCA for FR along with Threshold Based Filtering (TBF). The proposed technique is proven to be efficient in both time and space by experimenting on three benchmark datasets (ORL, Faces96, Grimace).

Keywords: Face Recognition; ORB; Kernel PCA; SIFT; SURF; HRI.

1. Introduction

Today we all are witnessing the importance of HRI in the field of biometrics (involving Artificial Intelligence (AI) and robotics) that has immense influence on innumerous commercial and security applications.

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10.1016/j.procs.2018.07.095

Most of the task's are being automated by deploying intelligent robots such as greeting robots, surveillance robots, bomb disposal robots , etc. Security is one of the dominant factor for the reputation of any institution or a corporation for ensuring the reliability of the sensitive information and there is an urgent need to safeguard the same. The well known fact that humans often tend to make mistakes being biased in several situations has urged the use of intelligent robots in various industries. These intelligent robots are often used in voter verification, banking with ATM's, etc. Our paper deals with the novel FR framework (ORB-KPCA-TBF) making the robot interaction with humans quicker, accurate and robust towards unrestrained scenarios such as changes in scale, in-plane rotations, pose and background. The proposed technique is proven to be of practical usage in terms of cost, speed and storage.

2. Background and Related Work

In FR, key-point detection and description along with feature vector matching are the two customarily used stages and are the stalwart of the entire system as they directly contribute to overall efficiency, performance and accuracy. Therefore, at-most importance is given to these stages and we see tremendous amount of research being done to meet the requirement of the efficient system. An in-depth explanation about feature detection and descriptors can be seen in [18].

We see a lot of well-versed key-point detector and descriptor methodologies for FR systems such as SIFT(Scale Invariant Feature Transform) [4] [5], a proficient algorithm developed by David Lowe[6][7] that performs key-point detection along with feature vector (descriptor) calculation and also pervasively used in the computer vision domains as in motion analysis, object recognition, image restoration, image-understanding systems, visual mapping and so on and yet is preferred for its robustness against fluctuations in scale, translation, in-plane rotation, background noise and so on. Similarly, SURF (Speeded-Up Robust Features) [1] [2] [3] which was developed by Herbert Bay has proven to be a computationally less expensive substitute to SIFT. SURF has some of the notable features like robustness to scale and in-plane-rotation, peculiarity etc. It is also quick in computation as it is based on multi scale face-theory involving a fast Hessian matrix. Though the above mentioned descriptors have created a foundation in FR systems they didn't meet the expectations of accuracy, precision and efficiency in real time scenarios and were computationally expensive. Later, the recent addition to the legacy of FR system, ORB (Oriented Fast and Rotated Brief) [8] was proposed by Rublee et al to provide the best substitute for the lack of accuracy (of SURF) and computational expense (of SIFT) and was built by reforming the BRIEF [9] and FAST [10] key-point feature descriptors. ORB was enhanced by introducing an Orientation component to the FAST (called oFAST [8]) descriptor along with the fusion of a steered version of BRIEF descriptor (called rBRIEF [8]) in order to assure robustness against in-plane rotation [1]. ORB [8] is proven to have much greater efficiency when it comes to unprocessed matching potential and reliability of image matching applications. While often a GPU acceleration for quick computation is a concern, ORB overcomes this problem by enabling low power gadgets without GPU acceleration. Adding to the advantages of ORB the limitation of licensing constraint as observed in SIFT and SURF have been overcome.

Dimensionality Reduction is a data reduction technique used to reduce the dimensions of the data while keeping most of the information. Each image has a huge number of pixels due to which detection and matching for each pixel becomes computationally expensive and requires a lot of storage. Hence, dimensionality reduction is incorporated in Face Recognition.

A linear dimensionality reduction technique such as PCA [15] considers an image as a linear combination of transparent basis images but doesn't consider factors which are non-linear such as occlusion [17], that is, the data can't be well represented in linear space. In contrast to Linear PCA[15] , KPCA[16][17] allows us to generalize Linear PCA to non-linear dimensionality reduction and have potential to capture part of higher order statistics which is essential for encoding the structure of the image.

FLANN (Fast-Library for Approximate Nearest-Neighbor Search) is used for feature matching. FLANN is known to perform fast approximate nearest neighbor searches very well in high dimensional spaces.

Though RANSAC [20] can be well used (for filtering out false matches) with certain probability, the number of iterations also increases as the probability of selection of good matches of larger dataset increases. Also the process is time consuming as RANSAC uses the iterative approach and the "maximization of in-liners" constraint is not so efficient . Hence it lacks boundary conditions on the computation time and thus does not yield an optimal solution. In real time streaming data scenarios where speed (of computation) and efficiency is of at-most concern RANSAC fails due to its increased computational time.

In this paper, we present two novel techniques namely (1) ORB-KPCA which is based on ORB (Oriented-Fast and Rotated-Brief) [8] feature descriptor to overcome computational disadvantages of ORB by using a non-linear dimensionality reduction technique called Kernel Principal Component Analysis (KPCA) [16] [17] and (2) Threshold Based Filter (TBF) which is used on number of matches in the two images to ensure the correct filtering of good matches, and has proven to be quick enough and more accurate than that of RANSAC [20].

3. Proposed Framework

This Section elaborates the various methodologies incorporated in our approach. The presented pipeline is illustrated in Fig. 1.

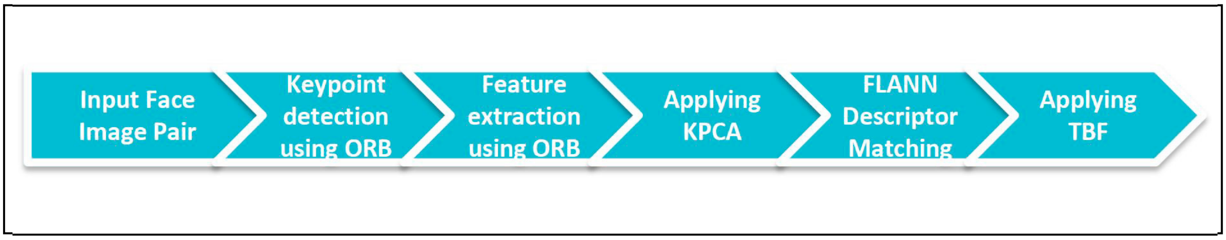

Fig. 1. Block Diagram of Proposed System

Keypoint detection and Feature extraction is done on both the test and gallery images (for m:n matching) and further KPCA [16] [17] is applied to the extracted feature descriptors of pair of input images. The FLANN [14] matcher is used conclusively to match the descriptors computed after KPCA was applied. Since FLANN also includes bad matches (giving matches for two different face images), the proposed Threshold Based Filtering Method is used to identify only the good matches. Later the match is classified as TP (true-positive), TN (true-negative), FP (false-positive) or FN (false-negative).

3.1 Key-point Extraction

3.1.1 ORB (Oriented-Fast and Rotated BRIEF)

3.1.1.1 ORB feature descriptors

The ORB [8] descriptors as mentioned has proven to be one of the quickest and most efficient feature descriptors covering all the attributes of SIFT [4] [5] and SURF [1] [2] [3]. ORB [8] is proven to have much greater efficiency when it comes to unprocessed matching ability and overall performance. We now see in sections 3.*1.1.2* and 3.*1.1.3* the modification to the components of ORB (FAST and BRIEF).

3.1.1.2 oFAST:FAST Keypoint Orientation

The upgraded version of FAST key-point orientation is termed as oFAST [8].FAST takes one's about the center in a circular ring and the intensity threshold between the center pixels as a parameter. Hence, FAST-9 having better performance than the FAST is opted here. Though FAST is considerably responsive down its edges, it doesn't have the potential to generate a measure of corner-ness and hence a Harris corner measure [12] is opted to order the key-points. Also since multi-scale features are crucial for FR but cannot be produced by FAST, a scale of pyramid of the image is employed which produces FAST attributes (filtered using Harris) at each level in the pyramid.

The FAST [10] is less robust to rotation, hence Intensity Centroid (IC) [13] technique is employed to improve on it. The Intensity Centroid vector (IC) is used to chalk up an orientation from the assumption that the IC considers a corner's intensity is offset from its center. The patch moments is defined as:

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

The centroid can be obtained by utilizing the moments of Eqn. (1) as follows:

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

Now a vector is constructed from the corner's center, O, to its centroid, (vector OC) and consequently the orientation of the patch becomes [1]:

$$\theta = \mathrm{atan2}(\mathrm{m}_{01}, \mathrm{m}_{10}) \tag{3}$$

In the previously mentioned equation (3), $a\tan 2$ is the quadrant-aware edition of the arctan. Although Rosin declares taking into account the illumination parameter of the corner [13] a smart decision is made by ignoring this as irrespective of the corner type, the angle measures are consistent [8].

3.1.1.3 rBRIEF:Rotation -Aware Brief

The r-BRIEF is an enhanced version of the steered BRIEF descriptor merged with the learning step to find less correlated binary tests. Since the robustness to in-plane rotation [8] is absent in the traditional BRIEF, a more efficient method is deployed by steering the BRIEF following to the orientation of the key points.

Now let us define a 2 x n matrix considering n sets of binary tests placed at (x_i, y_i),

$$S = \begin{pmatrix} x_1,\ldots, & x_n \\ y_1,\ldots, & y_n \end{pmatrix} \tag{4}$$

We then construct the "steered" version S_θ of S by corresponding rotation matrix R_θ and using of patch orientation θ

$$S_\theta = R_\theta S, \tag{5}$$

Finally we get the steered BRIEF operator as:

$$g_n(p,\theta) := f_n(p) \mid (x_i, y_i) \in S_\theta \tag{6}$$

We further do the angle discretization by increments of $2\pi/30$ (12 degrees) and by including a look-up table of the BRIEF patterns which are already computed. The accurate set of S_θ is used to compute its descriptor unless the key-point orientation θ is changed in various directions.

3.1.2 Experimentation and Analysis of ORB vs SIFT vs SURF

From our theoretical knowledge (3.1.1) we know that ORB [8] seems to have the most practical applications as it is built by improvising the FAST [10] and BRIEF [9] descriptors making it much more robust to in-plane rotations and inclusion of orientation component. We prove it practically by testing it with one of the well-known benchmark dataset, ORL [14]. The ORL dataset consists of 40 folders each containing 10 differently scaled, posed and rotated images of same face, making it total of 400 images. We split the dataset into test and train containing 5 images each for all folders accounting to 200 testing and 200 training images, resulting in 40,000 cases (200 x 200). We tabulate the average time taken for calculating descriptors (key-point detection and computation) per image pair (two images used for matching) along with average number of key-points that are detected in each of the images. We found that the speed and Efficiency of the ORB descriptors was unbeatable by SURF and SIFT descriptors. SIFT turned out to be the most stable (in terms of average key-points detected) but at the cost of efficiency (10 times slower than ORB) and though SURF was also fast, it came to be approximately 3 times slower than ORB. Hence the order of speed has come up as: ORB>SURF>SIFT and the order of average key-points detected as: SIFT>SURF>ORB.

Table 1. Comparing SIFT vs SURF vs ORB descriptors

Terms	Average time per Image pair (in sec)	Average key-points for training images	Average key-points for testing images
SIFT	0.0112	68	67
SURF	0.0044	42	42
ORB	0.0015	40	39

3.2 Dimensionality Reduction using PCA and KPCA:

3.2.1 Principal Component Analysis (PCA):

Principal component analysis (PCA) [15] is a widely used statistical procedure in Face Recognition that is applied to decrease the dimensions of the data. The input provided to the PCA is the feature descriptors corresponding to both the query and gallery image. The bunch of likely correlated variables get converted into linearly uncorrelated principal components by utilizing an orthogonal transformation. Here, the first principal component explains the largest possible variance, and each following component being orthogonal to the one preceding it, in turn explains the largest possible variance.

Traditional PCA works on zero-centered data, having,

$$\frac{1}{N}\sum_{i=1}^{N} x_i = 0 \tag{7}$$

We now diagonalize the covariance matrix given as,

$$C = \frac{1}{N}\sum_{i=1}^{N} x_i x_i^T \tag{8}$$

The Eigen decomposition of the covariance matrix C is given as,

$$\lambda v = Cv \tag{9}$$

Where λ is a scalar, termed the Eigen value corresponding to the Eigen Vector v

This can now be written as,

$$\lambda x_i^T v = x_i^T Cv \,, \forall\, i \in [1, N] \tag{10}$$

3.2.2 Kernel PCA

KPCA [16] [17] being a nonlinear dimensionality reduction technique extends the conventional principal component analysis (PCA) [15] to a feature space having high dimensions making use of the “kernel trick” which allows us to generalize Linear PCA to nonlinear dimensionality reduction . Making use of a kernel, the linear operations of PCA are carried out in a reproducing kernel Hilbert space. In a real time FR System, a large amount of storage is required to store key-points and descriptors. By using KPCA we can reduce the storage required. The input given to the KPCA is the descriptors corresponding to both the query and database image. While it may not be possible to linearly separate N points in $d < N$ dimensions, they can certainly be linearly separated in $d \geq N$ dimensions. That is, we depict the N points x_i , to an N-dimensional space as,

$$\Phi(x_i) \text{ where } \Phi : R^d \rightarrow R^N \tag{11}$$

Here, as Φ creates linearly independent vectors, there is no covariance on which Eigen decomposition has to specifically be performed which is done in Linear PCA. Instead, in KPCA, a non-trivial and arbitrary Φ function is used that is never calculated, which allows the possibility to use very-high dimensional Φ 's where we don't have to evaluate the data in that space. The Φ (x) - space is also called 'feature space' which is generally avoided. We now construct an N-by-N Kernel to represent the inner product space which would otherwise be intractable.

$$K = k(x, y) = (\Phi(x), \Phi(y)) = \Phi(x)^T \Phi(y) \tag{12}$$

The Kernel allows us to compose a version of the PCA mathematically where we never have to compute the eigenvectors and eigenvalues of the covariance matrix in the feature space. This kernel-formulation of PCA now computes the projection of the data onto those components.

The projection onto the k'th principle component V^k from a point in the feature space is,

$$V^{k^T} \Phi(x) = (\sum_{i=1}^{N} a_i^k \Phi(x_i))^T \Phi(x) \tag{13}$$

We solve the Eigen equation given below in (14) to calculate,

$$N \lambda a = Ka \tag{14}$$

Where, a is the eigenvector, λ is the eigenvalue of K , and N is the number of data points.

To normalize a^k's , we require,

$$1 = (V^k)^T V^k \tag{15}$$

We centralize K to K' ,

$$K' = K - 1_N K - K 1_N + 1_N K 1_N \tag{16}$$

Where, 1_N is an N-by-N Matrix where each element of the matrix takes value $1/N$.

3.3 FLANN

FLANN is a library used for attaining fast approximate nearest neighbour searches working on dimensions of higher level. [14]. FLANN provides great flexibility as it has several algorithms to choose from. Depending on our requirement we can achieve best results for nearest neighbour search along with best framework for instinctively selecting the best parameters and algorithm based on the dataset. Also, it works faster than Brute Force Matcher. The descriptors of the test image and that of the gallery image were passed to the FLANN matcher. This provided a vector of good matches between the two images.

3.4 Threshold Based Filtering

A Threshold Based Filter (TBF) is used on the number of key points matched to determine if the two images belong to a same face after and is applied after the Lowes ratio. The filter consists of two layers, the first layer imposes a minimum value on number of total matches obtained from the FLANN matcher whereas the second layer imposes a threshold on the good matches. This is computed by rejecting poor matches based on the ratio between the first and second-best match. If both the cases are satisfied then the two images are classified as to be of the same face. It is seen that TBF performs better in filtering out good matches when compared to RANSAC.

4. Databases

To evaluate our framework we used benchmark databases namely ORL [20], Faces96 [21], Grimace [22] and Faces95 [28]. Each database consists of images of equal size. The ORL database had black and white images taken at different times by varying the illumination, facial expressions (smiling/not smiling, open/closed eyes) and facial details. The Faces96 database consists of images of varying inclination, illumination and size of face area. Grimace consists of sequence of images similar to Faces96 where the subject adjusts his/her head and makes grimaces.Fig2 illustrates a sample of images.

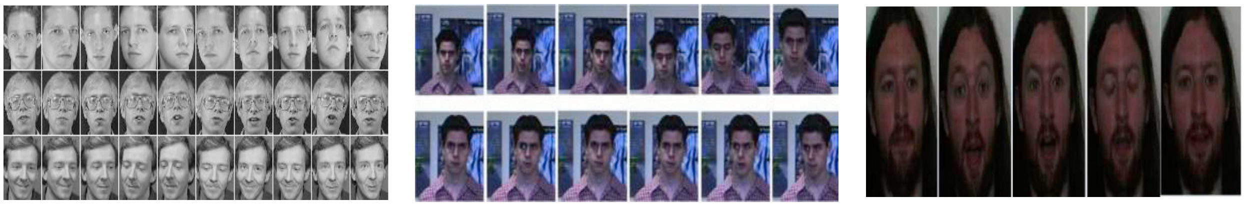

Fig. 2 (a) Sample of images from ORL database ; 2 (b) Sample of images from Face96 database; 2 (c) Sample of images from Grimace Database.

5. Algorithm

For each input image pair :

Extract keypoints using ORB.
Generate the ORB descriptors based on the keypoints of the image.
Apply KPCA on the ORB descriptor.
Apply FLANN Matching on the descriptor obtained after applying KPCA.
Use Threshold Based Filtering to determine if it should be classified as a match or not.

6. Results and Inferences

This section reports the experimental results obtained for the test cases on the technique used. Comparison of results obtained using on proposed technique with others have been tabulated in Tables 2 and 3. Both ORB-KPCA and ORB-KPCA-TBF techniques were broadly tested on each of the database mentioned in Section 4. Accuracy of the ORB-KPCA-TBF technique although lower than 90%, is still an acceptable improvement in accuracy of about 5% over the other techniques.

Illustrations of results of the proposed techniques on benchmark databases is given in Fig.3 and Fig.4. As seen from the Figures.4.(a) and 4.(b), it is observed that the TBF performs better in removing false matches when compared with other outlier removal techniques like Ransac. The results tabulated in Table 2 show that the proposed technique performs better than other methods when compared in terms of accuracy. It is seen that KPCA based methods perform better than PCA. Also, though ORB-KPCA-TBF takes slightly more time per image compared to ORB-KPCA, it has a fairly higher accuracy than the latter.

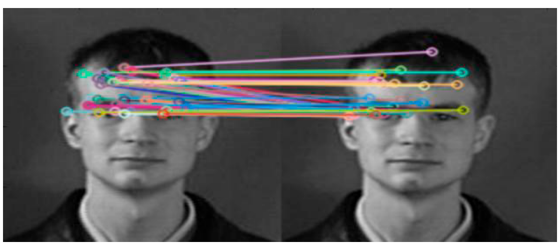

Fig 3.(a) ORB-KPCA without TBF.

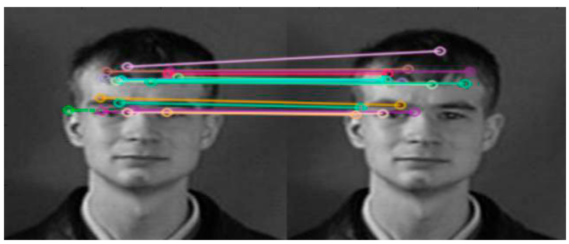

Fig 3.(b) ORB-KPCA-TBF.

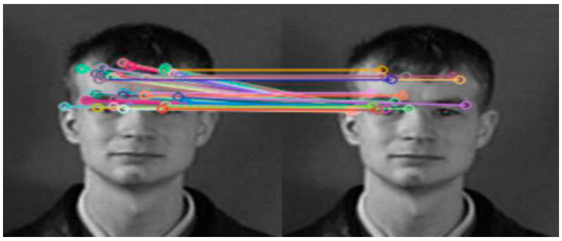

Fig 3.(c) ORB-PCA without TBF.

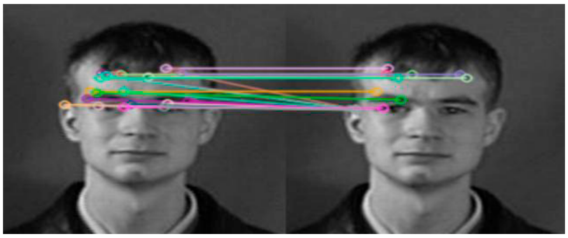

Fig 3.(d) ORB-PCA-TBF.

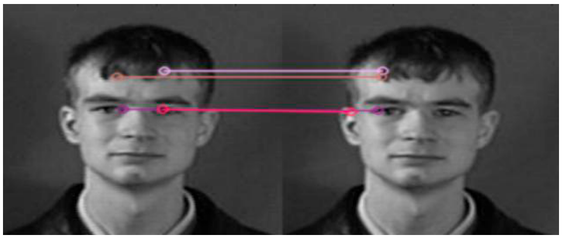

Fig 3.(e) Using RANSAC.

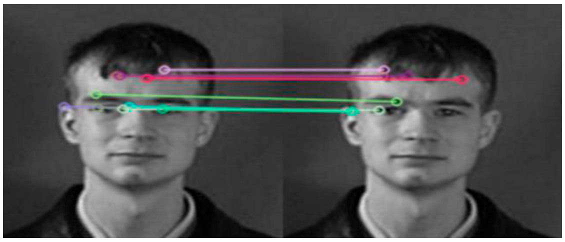

Fig 3.(f) Using TBF.

Fig 3. Comparison of Results obtained on images of the same face.

Table 2. Comparing results obtained on benchmark databases

Method	ORL (%)	Grimace (%)	Faces96 (%)	Average Time per image (in sec)
SURF-PCA	72.12	73.56	74.56	0.011
SURF-PCA-TBF	80	78.96	77.91	0.0126
SURF-KPCA	80.34	79.2	77.87	0.0117
SURF-KPCA-TBF	83.28	80.12	82.59	0.016
SIFT-PCA	67.12	69.56	66.66	0.0348
SIFT-PCA-TBF	69.2	77.3	78.96	0.0422
SIFT-KPCA	78.8	78.72	76.77	0.0416
SIFT-KPCA-TBF	81.36	82.12	80.52	0.0599
ORB-PCA	81.15	79.6	79.2	0.003210
ORB-PCA-TBF	81.015	84.46	80.36	0.004935
ORB-KPCA	82.3	81.3	80.25	0.004854
ORB-KPCA-TBF	**87.3**	**85.4**	**84.1**	**0.005085**

Fig 4. (a) ORB-KPCA-TBF on images of different faces.

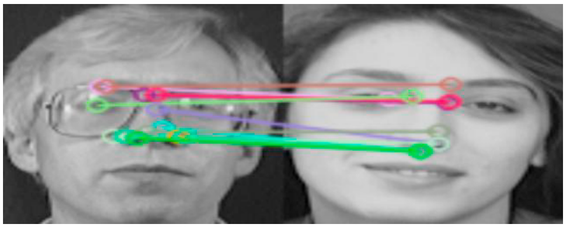

Fig 4. (b) ORB-KPCA without TBF on images of different faces.

Table 3. Comparison of Proposed Techniques with some standard techniques

Method	Average Accuracy (%)
APCAWT-SIFT [24]	82.17
ORB [25]	73.42
Improved SIFT Matching [26]	75.77
PCA-SIFT [27]	68.24
LBP frontalface [29]	73.62
Proposed technique	**87.3**

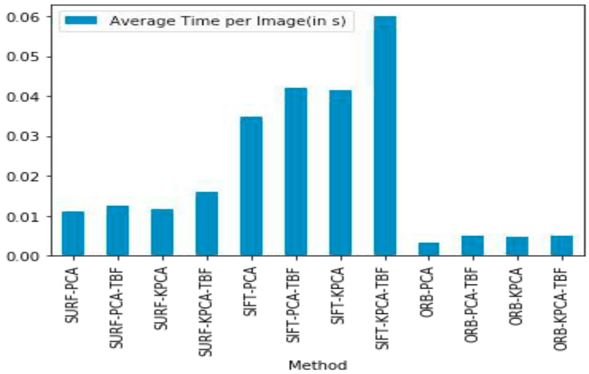

Fig 5. Comparison of average time taken of proposed technique with other standard techniques

A comparison of accuracy of the proposed technique with that of some standard techniques used for face recognition when tested on the benchmark datasets is shown in Table.3. The proposed technique is seen to have higher average accuracy. Fig.5 shows a comparison of the average time taken by the proposed technique with that of other standard techniques. It is observed that the proposed technique ORB-KPCA-TBF is more efficient in terms of time taken. ORB-based techniques are seen to be more efficient in terms of matching time when compared to SIFT and SURF based techniques.

7. Conclusion and Future Work

In Human-Robot Interaction (HRI) , quick and efficient FR techniques are often required in service robots. We have introduced a novel approach for Face Recognition which is based on the cost-effective ORB-descriptor, Kernel PCA which is a non-linear dimensionality reduction technique and threshold based filtering to remove false matches. In the design of the FR system, it is important to carry out analysis on datasets varying in illumination, rotations and translations. Hence, our experimentation has been conducted on the benchmark datasets: ORL, Faces96 and Grimace which conveys that the ORB-KPCA-TBF method outperformed other methods in terms of not only efficiency, but also accuracy as seen in the results. Some of the other dimensionality reduction techniques that are often used in FR such as PCA, LDA, LPP, NPE have their own limitations such as computational expensiveness of PCA, lack of processing speed of LDA and low recognition rate of LPP and NPE with increase in face images [23]. The proposed method which uses KPCA outperforms the above mentioned techniques in terms of accuracy and computational cost. The other novel technique (TBF) proposed is proven to perform better than RANSAC in filtering out the false matches and is computationally efficient yielding an optimal solution.

Thus, considering the novel approach in the proposed technique, there was an improvement in accuracy of about 5% when compared with other techniques, while also being computationally more efficient than others. In real time applications such as HRI in service robots, where speed and storage are of at-most concern, the proposed technique is a suitable solution. Future work is being focused towards improving further the accuracy of the FR system by implementing other detector/descriptor and dimensionality reduction technique combinations on benchmark databases.

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