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Adaptive PCA-SIFT Matching Approach for Face Recognition Application

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Abstract—**This paper presents a novel human face identification approach. This approach consists of three parts: de-noised face database, Adaptive Principle Component Analysis based on Wavelet Transform (APCAWT), and the Scale Invariant Feature Transform approach, (SIFT). The main idea is to extend SIFT features by using a APCAWT on compressed and de-noised ORL database, JPG file format is used for compressing and double wavelet filters (Bior 1.1 and Haar both are at level 10 of decomposition) is used for de-noising process. For feature extraction the eigenface of PCAWT entered to SIFT algorithm, and thus only the SIFT features that belong to clusters, where correct matches may be expected are compared according to a specific threshold. Experiments are done to evaluate the performance of our proposed de-noising filter and the performance of PCAWT, and then evaluated the whole APCAWT- SIFT approach. We found the use of the APCAWT reduced the size of face image that entered to SIFT, this lead to increase the number of keypoints in face image and allowed to get good matching result.**

Index Terms—**PCA-SIFT, APCAWT-SIFT, Eigenface, double wavelet filter, Wavelet transform, keypoints.**

I. INTRODUCTION

IDENTIFYING of a face in human identification system is still problem in real world since the detecting of the important features in human face can be trusty used for security measures such as monitoring systems and human identification systems in airports, visa processing, ID card verification, driver license, and police office for criminal faces matching.

The SIFT algorithm, proposed in [1], is the most widely used in computer vision applications due to the fact that SIFT features are very peculiar, and fixed to scale, illumination changes and rotation. The main disadvantage of SIFT is that the computational complexity of the algorithm was increased quickly with the number of keypoints, especially at the matching step this is because the high dimensionality of the SIFT feature descriptor. In order to overcome this drawback, different modifications of SIFT algorithm have been proposed. Ke and Sukthankar [2] applied PCA to the SIFT descriptor. The PCA-SIFT reduced the dimensionality of SIFT feature descriptor from 128 to 36, so that the PCA-SIFT minimized the size of the SIFT feature descriptor length and speeded up the feature matching by factor 3 compared to the original SIFT method.

In this Paper we overcome SIFT drawbacks by changing the PCA eigenfaces entered to SIFT. This is done by producing adaptive PCA in wavelet domain rather than the mathematical computation and representation of PCA that entered to SIFT, and we called it APCAWT-SIFT. Our aim is to solve the problem of the bottleneck in matching process in PCA-SIFT and to increase the maximum number of SIFT matching keypoints.

Section 2 describes the related works; Section 3 contains the proposed matching approach. Sections 4 illustrate the experiments and results. The final conclusions are discussed in section 5.

II. RELATED WORK

SIFT is firstly developed by D. Lowe in 1999 [3], the main idea of SIFT is to extract features from images to achieve reliable matching between different parts of the same object. The extracted features are invariant to scale and orientation, and are very distinctive of the image. In 2006, A. Mohamed [4] proposed SIFT for face recognition process and compared with well-established face recognition algorithms, namely Eigenfaces and Fisher faces. The results show the superiority of SIFT over these two methods, specially using smaller training sets.

In 2007 A. Vedaldi [5] describes an implementation of the SIFT detector and descriptor using Matlab which is compatible with D. Lowe's implementation in the years 2001 [6] and in 2004 [3] respectively, and is distributed along with the source code.

In 2008, F. Alhwarin et al. [7], proposed an improvement on the original SIFT algorithm by producing more reliable feature matching for the object recognition purposes. This is done by splitting the features extracted from both the test and the model object image into several sub groups before they are matched. They also proposed in [8] a new method for fast SIFT feature matching and the experimental results show that the feature matching can be speeded up by 1250 times with respect to exhaustive search without lose of accuracy.

In 2012, D. Al Azzawy [9] studied and analyzed the

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performance of five different approaches for gender classification based on PCA, PCA-SIFT, Eigenface-SIFT, Volume- SIFT and modified Volume-SIFT methods all these methods are used as input to Support Vector Machine (SVM), his modified approach produced good result since it was efficient when the number of training samples increased to 220 image.

In 2013, Tong Liu et al. [10] proposed a face recognition system based on SIFT feature and its distribution on feature space. The proposed method gave a higher face recognition rate than other methods included matching and total feature based methods in three famous databases.

This research is the first work that takes in its account the matching of keypoints between the de-noised face image and its corresponding eigenface as a contribution to enhance the faces matching process. This matching approach can be used for human face identification purposes.

Our approach was compared with the performance of PCA-SIFT.

III. The Proposed Matching Approach

The proposed system has the following block diagram as shown in figure (1):

A. *The proposed de-noised faces database*

Image de-noising based on averaging of two wavelets transformed images algorithm is as follows:

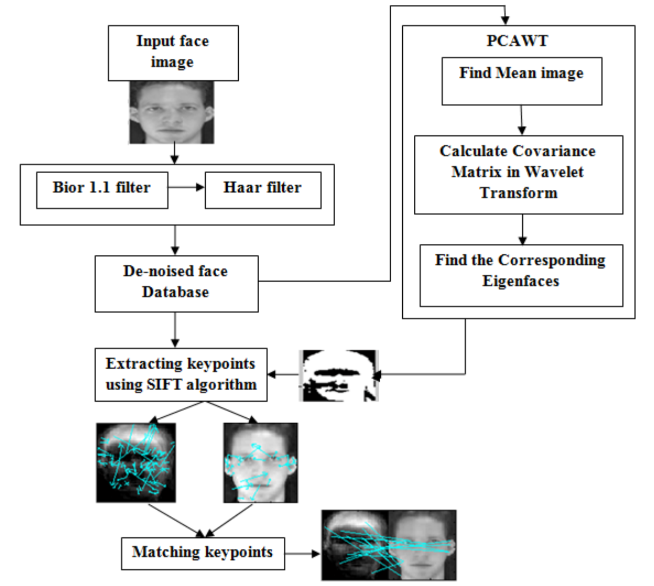

Fig. 1. The adaptive approach block diagram

Step1: Load face images database (suppose all face images are noisy images by default).

Step2: Perform multiscale decomposition of the noisy image with the help of bior1.1 wavelet filter.

Step3: Calculate the wavelet coefficients of noisy image for 10 different levels.

Step4: Select only those coefficients more than the threshold and shrink those less than the threshold to 0.

Step5: combine the wavelet coefficients with the same spatial location across adjacent scales as a vector; this means the row vector formed by concatenating the transposed column matrix of wavelet coefficients.

Step6: Invert the multiscale decomposition to reconstruct the de-noised image.

Step7: Repeat the steps 1 to 6 for the Haar wavelet filter and reconstruct the image.

Step8: Convert the de-noised face images database from PGM to JPG format.

Step 9: Compute PSNR

Step 10: Compute MSE

B. *The Proposed PCAWT*

The proposed idea of applying the wavelet transform in the implementation of Eigenface is done by the using of a single-level two-dimensional wavelet decomposition in the implementation of the covariance matrix [11, 12], as an alternative of conventional ideas of converting the intensity of the face image data into the spectral domain, followed by applying the Eigenface as in [13, 14]. The proposed idea is called as Principles components Analysis based Wavelet Transform (PCAWT).

The covariance matrix can be computed by using the WT as follows: WT the two datasets, multiply one resulting transform by the complex conjugate of the other, and inverse transform the product [15].

Here are the steps to computing these Eigenfaces:

Step1: Obtain face images I_1, I_2... I_M (training faces).

Step2: Represent every image Ii as a vector x_i.

Step3: Compute the average face $\psi = \frac{1}{M}\sum_{i=1}^{M} x_i$

Step4: Subtract the mean face $\varphi_i = x_i - \Psi_i$

Step5: Compute the covariance matrix

$$C = IWT(WT(\varphi)WT(\varphi^T)) = AA^T$$

using a single-level two-dimensional wavelet with Daubechies filters mode (db1, db2 , db6, db10).

a. [cA1,cH1,cV1,cD1]=dwt2(φ, 'Daubechies filter type')

b.[cA2,cH2,cV2,cD2]=dwt2(φ T,'Daubechiesfilter type')

c.C=Idwt2(cA1×cA2,cH1×cH2,cV1×cV2,cD1×cD2, 'Daubechies filter type')

Step6: Compute the eigenvectors u_i of AA^T:

a. Consider matrix AA^T as a M×M matrix.

b. Compute the eigenvectors v_i of AA^T such that:

$A^TAv_i \rightarrow \mu_i V_i \rightarrow AA^TAV_i = \mu_i A v_i \rightarrow Cu_i = \mu_i u_i$

Where $\mu_i = Av_i$

c. Compute the μ best eigenvectors of AA^T: $\mu_i = Av_i$

Step7: Keep only K eigenvectors.

C. *Adaptive PCAWT-SIFT*

In this paper, the work of SIFT is modified by replacing the output of PCA with the output of the PCAWT, so that, the same steps of SIFT in [9, 16] is used. The output of PCAWT-SIFT will give the corresponding vectors in wavelet domain.

Step 1: Input: New_X is eigenfaces matrix of X image of proposed PCAWT

Step 2: Initialization:

Octaves = 4; Intervals = 5;

$\sigma = 21/2$;

Scale_Size = 0.5;

Contrast_Threshold = 0.02;

Curvature_threshold = 10.0

Step 3: Begin:
Step 4: For Octave= 1 to Octaves
Step 5: For Interval = 1 to Intervals
Step6: $G(x, y, \delta) = \frac{1}{2\pi\delta^2} e^{-(x^2+y^2)/2\delta^2}$
Step 7: Find C = Convolution X with G; where G is a Gaussian filter and C is a blurred image.
Step 8: $\delta = \delta^{1/2}$
End for Interval
Step 9: Find Difference of Gaussian (DoG) between each two adjacent of Intervals of C.
Step 10: Find the Extrema (Maximum and Minimum value of DoG) for each point in the DoG.
Step 11: Pos = coordinates of Extrema when DOG is above Contrast_threshold
Step 12: Eliminates all points Pos that have value of DoG below Curvature_throshold
Step 13: Orient = the orientations of key-points (Pos)
Step 14: Scale = the scale of key-points (Pos)
Step 15: Desc = Extract feature descriptors for the key-points.
Where the descriptors are a grid of gradient orientation histograms and the sampling grid for the histograms is rotated to the main orientation of each keypoint
Step 16: Resize the X image by Scale_size ratio
End for Octave
Step 17: Output: Pos: vector (N×1) contains at coordinates of N key-points.
Step 18: Scale: vector (N×1) contains at scale of each point.
Step19: Orient: vector (N×1) contains at orientation of each point.
Step 20: Desc: matrix (N×128) matrix with rows containing the Feature descriptors corresponding to the N key-points.

IV. Experiments and Results

Our matching approach consist of three parts: de-noising process by double wavelet filter (Haar-Bior 1.1 filter), proposed PCAWT and the adaptive SIFT matching features. To evaluate the performance of the adaptive approach, the performance of first two parts are tested separately, then the result of the whole APCAWT-SIFT approach is evaluated as third part.

A. Evaluation of our proposed filter

The performance of our proposed filter is compared among other wavelet filters performance and the evaluation is done on the first image in AT&T ORL database as shown in figure(2) and under two criteria's measures include the Peak Signal to Noise ratio (PSNR) and the Mean square Error (MSE) As shown in Table(1). The higher value of PSNR ratio means the better de-noising, and the smaller value of MSE means the better de-noising.

Fig. 2. First image in ORL database s1\1.pgm.

TABLE I
PSNR AND MSE FOR WAVELET FILTERS AT LEVEL 10 OF DECOMPOSITION

Wavelet filter	PSNR	MSE
Haar	31.186	49.4861
db10	30.8399	53.5903
Sym2	31.0957	50.5259
Sym4m	31.186	49.4861
Bior1.1	30.5269	57.5957
My proposed work	32.5226	36.3768

B. Evaluation of our proposed PCAWT

Table (2) shows a comparison between our method and two other mathematical methods represented by Standard PCA and PCA using Mahalanobis cosine similarity or simply Mahcos distance, when all of them are implemented on the same sample of 200 face image in the original ORL database and in the our de-noised database respectively.

TABLE II
A COMPARISON IN ACCURACY RATIO BETWEEN OUR PCAWT METHOD AND TWO MATHEMATICAL PCA METHODS USING 200 IMAGES IN ORL AND PROPOSED DATABASES RESPECTIVELY

Method Used	Database Used	Accuracy Ratio
Standard PCA	AT&T ORL DB Proposed de-noised DB	77% 84.5%
PCA + Mahcos [17-18]	AT&T ORL DB Proposed de-noised DB	79.29% 84.29%
My proposed PCAWT	AT&T ORL DB Proposed de-noised DB	85% 86%

C. Evaluation of APCAWT-SIFT matching approach

For keypoints detecting and keypoints matching, and to get more efficiency, we found it is good to compute a dot products between unit vectors rather than Euclidean distances. The ratio of angles is a close approximation to the ratio of Euclidean distances for small angles. In our paper we select distance ratio =0.9 as a matching threshold, this ratio only keep matches in a way that the ratio of the angles of the vector from the first nearest neighbor to the second nearest neighbor is less than the distance ratio.

Selecting a threshold larger than this ratio will lead to get more keypoints that is not necessary, because our aim is identify face images with the fewest possible number of features matching , and threshold lesser than this threshold will lead to false matching.

Keypoints detection

In our work, we used the same sample of face images in ORL database and the proposed de-noised database. ORL

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face database entered to PCA and the de-noised database entered to PCAWT. The comparison is done to evaluate the results when both methods entered to SIFT. Figure (3) and figure (4) shows the difference in the process of keypoints extraction and how the keys are shown for both eigenfaces in PCA-SIFT and APCAWT-SIFT respectively.

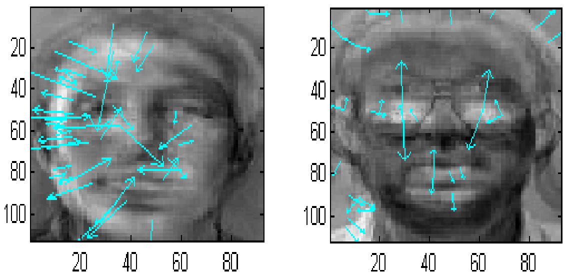

Fig. 3. Keypoint detecting by PCA-SIFT using a sample of face image in ORL database

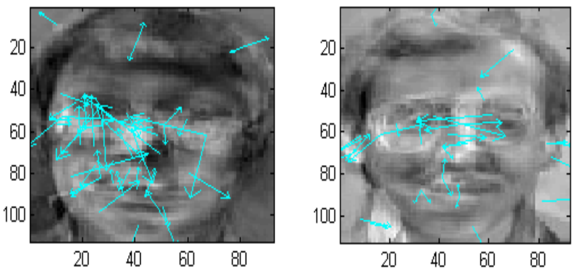

Fig. 4. Keypoint detecting by APCAWT-SIFT using the same sample of face image in the de-noised database.

Keypoints matching

The performance of our proposed approach was compared with the performance of PCA-SIFT. For APCAWT-SIFT, we done the matching between jpg face image and its corresponding eigenface image, we select the first image (1.jpg) of subjects (sX) where *X=1,2,3,…40* with its corresponding eigenface, we used the first subject from the first fifth class (sY\1.jpg) where Y=1,2,…5 and the first subject of last class (s40\1.jpg) and for PCA-SIFT the same samples from original ORL database (sX\1.pgm) is used and matched with its corresponding eigenface image. Table (3) shows the result of comparison in keypoints matching between PCA-SIFT and APCAWT-SIFT. Figure (5), shows the result indicated in the table for image s1\1.jpg using PCA-SIFT, and figure (6), show the result indicated in the table (3) for the same face image using APCAWT-SIFT.

TABLE III
A COMPARISON IN KEYPOINTS MATCHING BETWEEN PCA-SIFT AND PCAWT-SIFT

Image Name	Matching keypoints in PCA-SIFT	Matching keypoints in adaptive PCAWT-SIFT
S1\1.pgm	4	16
S2\1.pgm	10	13
S3\1.pgm	10	17
S4\1.pgm	13	14
S5\1.pgm	4	10
S40\1.pgm	7	10

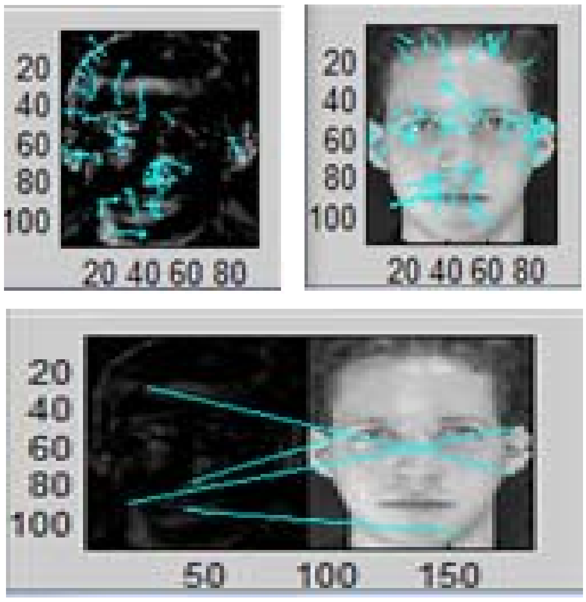

Fig. 5. Test image 1.pgm using PCA-SIFT, 46 keypoints in eigenface, 58 keypoints found in test image, found 4 matches.

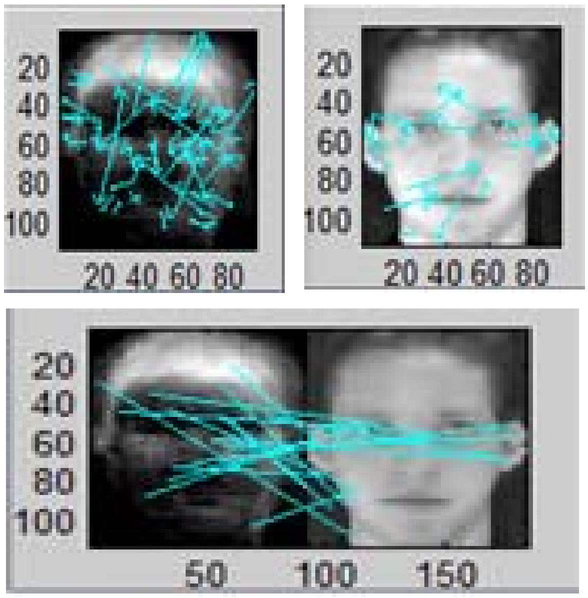

Fig. 6. Test image 1.jpg using APCAWT-SIFT, 64 keypoints in eigenface, 29 keypoints found in test image, Found 16matches.

V. Conclusions

Our approach produced processing to face images with high accuracy performance; this can be trusty used for security measures such as monitoring systems and human face identification systems in airports, visa processing, ID card verification, driver license, and police office.

We found the using of wavelet de-noising reduced the size of the input face image especially with the using of JPG images.

In this paper, two steps of wavelet transform are implemented, the first step is used for pre-processing the face image using de-noising process, and the second step is used for computing the covariance matrix of our PCAWT approach. These two steps lead to increase the number of keypoints using SIFT and allowed to get better performance than the traditional PCA-SIFT.

For matching process, we used distance ratio equal to 0.9, this ratio proved to be the best threshold for APCAWT-

SIFT and contributed in improving the keypoint matching and detecting accuracy. Since, in our matching approach, we rejected all matches in which the distance greater than 0.9.

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