Wavelet Based Image De-noising to Enhance the Face Recognition Rate

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Abstract

In this paper a comparison between face recognition rate with noise and face recognition rate without noise is presented. In our work we assume that all the images in the ORL faces database are noisy images. We applied the wavelet based image de-noising methods to this database and created new databases, then the face recognition rate are calculated to them. Three experiments are given in our paper. **In the first** experiment different wavelet methods with different level of decomposition (up to ten decompositions) are used for de-noising the ORL database and the comparison is done when Principal Components Analysis (PCA) is applied to evaluate the verification rate. **In the second** experiment de-noising different sets of ORL database with methods that have best performance in levels (1, 2, 3, and 10) is done (as a result from experiment 1). **In the third** experiment we implement the proposed Haar10 method on PCA, Linear Discriminate Analysis **(**LDA), Kernel PCA, Fisher Analysis (FA) face recognition methods and the recognition rates are evaluated for both the noisy and de-noisy databases.

Keywords: *Image de-noising, Wavelet decomposition, Noisy and de-noisy face recognition rate, False accept rate (FAR), verification rate at 0.1% rate, Face recognition rate.*

1. Introduction

Quality of a biometric sample affects the performance of the recognition algorithm. In literature, several research papers exist on analyzing the effects of quality on the performance of different biometric modalities such as iris and fingerprint. Environmental corruption such as noise, blur, adverse illumination and compression rates (in JPEG and other compression techniques) influence the performance of state-of-art recognition algorithms [1, 3].

An excellent overview of pattern recognition in wavelet domain can be found in [5]. It would also be worthwhile to mention at this point that the most papers use wavelets as part of the face recognition system.

The work presented in [6] is along those lines of thought. Sabharwal and Curtis [7] used Daubechies 2 wavelet filter coefficients as input into PCA. The experiments were performed on a small number of images and the number of wavelet decomposition was increased in each experiment (up to three decompositions). The observed recognition rate increased mostly around 2 %.

Garcia et al. [8] performed one standard wavelet decomposition on each image from the FERET database. This gave four bands, each of which was decomposed further (not only the approximation band). In this way there are 15 detail bands and one approximation.

Similar idea can be found in [9] as well. However, in this paper several wavelets are tested (Daubechies, Spline, Lemarie), and finally Daubechies 4 is chosen to be used in a PCA-based face recognition system. The HH subband after three decompositions was used as input to PCA and recognition rate increase of ≈ 5%.

Xiong and Huang [10] performed one of the first explorations using features directly in the JPEG2000 domain.

Chien and Wu [11] used two wavelet decompositions to calculate the approximation band, later to be used in face recognition. Their method performed slightly better than standard PCA. Similarly, in [12] Li and Liu showed that using all the DWT coefficients after decomposition as input to PCA yields superior recognition rates compared with standard PCA.

Two decompositions with Daubechies 8 wavelet were used by Zhang et al. [13] with the resulting approximation band being used as input into a neural network based classifier. By using Daubechies 4 wavelet and PCA and ICA,Ekenel and Sankur [14] tried to find the subbands that are least sensitive to changing facial expressions and illumination conditions. PCA and ICA were combined with L1,

L2 and COS metrics in a standard nearest neighbor scenario.
Earlier studies confirm that the information in low spatial frequency bands plays a dominant role in face recognition. Nastar et al. [15] investigated the relationship between variations in facial appearance and their deformation spectrum. They found that facial expressions and small occlusions affect the intensity manifold locally.

Noise will be inevitably introduced in the image acquisition process and de-noising is an essential step to improve the image quality [2, 4]. The problem in face recognition system is the recognition of noisy face image; the questions that should be answered in this research are: will image de-noising improve the recognition rate for face images? And which image de-noising method is appropriate for face image noise removal? To answer these questions, a wavelet based image de-noising is used for noise removal to all images in the ORL database and the Principal Components Analysis is implemented on both the original ORL database and on the de-noising one, then the recognition rate is measured for both noisy and de-noising databases.

Image de-noising can be used with face recognition methods to improve the face recognition rate. The aim of this research is to compare the recognition rate of noisy faces (default ORL database) and the recognition rate of the de-noising faces (new database after noise removal).

2. A Framework of the de-noising face image for improving recognition rate

Our proposed work is to apply image de-noising process by wavelet transform to the ORL faces database, then implement the PCA on these database to evaluate the recognition rate for a specific face image before and after de-noising. Figure 1 shows that the Discrete Wavelet Transform is applied prior to dimensionality reduction. PCA is then applied with the above technique to find the face recognition accuracy rate and to compare the results of the de-noising method with PCA method.

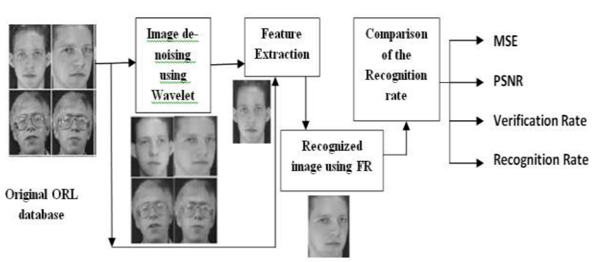

Fig.1 Proposed work block diagram

2.1 Wavelet-based image de-noising

Intuitively, de-noising a noisy face image improves the face recognition performance, provided the right sets of parameters are used [1].
The DWT provides a compact representation of a signal's frequency components with strong spatial support. DWT decomposes a signal into frequency subbands at different scales from which it can be perfectly reconstructed. 2D-signals such as images can be decomposed using many wavelet decomposition filters as shown in Figure 2 and Figure 3 in many different ways. The general wavelet-based procedure for de-noising the image is as follows [16]:
1. Choose a wavelet filter (e.g. Haar, Daubechies, symlet) and number of levels for the decomposition. Then compute the 2D-DWT of the noisy image.
2. Threshold the non-LL subbands.
3. Perform the inverse wavelet transform on the original approximation of LL-subband and the modified non-LL subbands.

2.2 Face Recognition algorithms

All face recognition algorithms consist of two major parts: (1) face detection and normalization and (2) face identification. Algorithms that consist of both parts are referred to as fully automatic algorithms and those that consist of only the second part are called partially automatic algorithms. Partially automatic algorithms are given a facial image and the coordinates of the center of the eyes. Fully automatic algorithms are only given facial images [17]. This subsection consists of description to the general work of PCA [4], LDA [19], KPCA [20] and KFA [21] that will be used in our work.

General work of face recognition algorithms

Step 1: Load images from a database. In our case, from the de-noised ORL databases.
Step 2: Partition data into training and test sets. In our case, the first 3 images of each ORL subject will serve as the training/gallery/target set and the remaining images will serve as test/evaluation/query images.
Step 3: Compute training and test feature vectors using the chosen method. In our case we use different algorithms for feature extraction (PCA, LDA, KPCA, and KFA) and, therefore, first compute the subspace using the training data from the ORL database.
Step 4: Compute matching scores between gallery / training / target feature vectors and test / query

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feature vectors. In our case we use the Mahalanobis cosine similarity for computing similarity matrix.
Step 5: Evaluate results: computing of the face recognition rate and the FAR at 0.1%.

3. Experiments and results

In our work three experiments are conducted as trying to verify the effect of wavelet de-noising process on the performance of face recognition system. Figure 2 shows the Graphical User Interface (GUI) of the wavelet de-noising methods used in our experiments. All experiments are applied to the existing face recognition system implemented in the PhD face recognition toolbox. The Toolbox description and user manual are in the referenced section [23, 24].

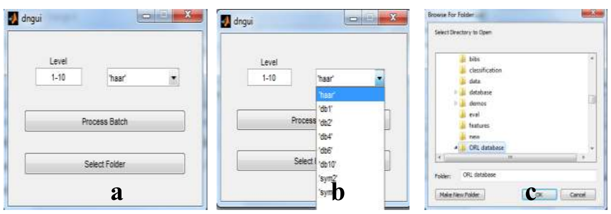


Fig.2 GUI of the wavelet de-noising algorithms

In our work we used ORL database because the demo scripts of the PhD toolbox were written for use with the ORL (AT&T) database. Our Faces Database, (formerly 'The ORL Database of Faces'), contains a set of face images taken between April 1992 and April 1994 in the lab. There are ten different images for each of 40 distinct subjects. Figure 3 illustrates some images of the database. For some subjects, the images were taken at different times, varying the lighting, facial expressions (open / closed eyes, smiling / not smiling) and facial details (glasses / no glasses). All the images were taken against a dark homogeneous background with the subjects in an upright, frontal position (with tolerance for some side movement).
The files are in PGM format, and the size of each image is 92x112 pixels, with 256 grey levels per pixel. The images are organized in 40 directories (one for each subject), which have names of the form sX, where X indicates the subject number (between 1 and 40). In each of these directories, there are ten different images of that subject, which have names of the formY.pgm, where Y is the image number for that subject (between 1 and 10). The database can be retrieved from http://www.cl.cam.ac.uk/research/dtg/attarchive/facedatabase.html.

In our work we implemented all the de-noising wavelet methods shown in Fig 2-b on this database to generate new de-noised databases (one database for each wavelet de-noising method), then applied the face recognition tool box on them to compare the original results with the de-noising results.

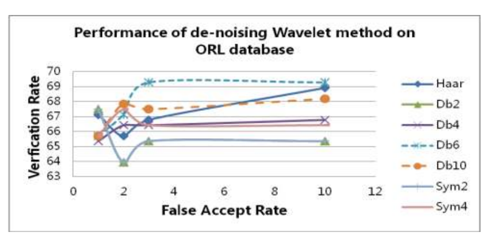
Fig.3: Face samples from the ORL face database.

Experiment 1: Recognized of de-noising image by PCA

Different wavelet de-noising methods represented by (Haar , db2, db4, db6, db10, sym2, sym4) at different levels (1, 2, 3 and 10 decomposition levels) are implemented on PCA face recognition method in this experiment to show the variations in verification rate at 0.1% FAR and results. We find that the performance of PCA on the original ORL database is equal to **66.07%** and we compare this result with the performance of PCA after implementing the de-noising wavelet methods. Table 1 shows the result of the proposed de-noised databases.

Table 1: the verification rate at 0.1% FAR after the de-noising process is implemented on ORL database at level L=1, 2, 3 and 10.

L	Haar	Db2	Db4	Db6	Db10	Sym2	Sym4
1	**67.14%**	**67.50%**	65.36%	65.70%	65.70%	**67.50%**	65.70%
2	65.70%	63.93%	**66.43%**	**67.14%**	**67.86%**	63.93%	**67.50%**
3	**66.79%**	65.36%	**66.43%**	**69.29%**	**67.50%**	65.36%	**66.43%**
10	**68.93%**	65.36%	**66.79%**	**69.29%**	**68.20%**	65.36%	**66.43%**



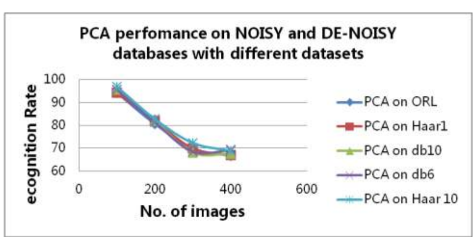
From the result above we find that the verification rate increased in a little variant in level 1 of decomposition using Haar, db2 and Sym2, but the verification rate decreased at level 2 for these methods, in contrast to the other four methods where the verification rate increased. Level 3 has nearly the same result as level 1 with a little decreasing in the percentage rate but it is still higher than the verification rate of origin PCA (66.07). At level 10 only db2 and Sym4 fail to enhance the verification rate in contrast to the other methods that shown increasing reach to more than 2.5% - 3% in both Haar and db6 (at level 3 and level 10) of wavelet.

Experiment 2: Recognizing different de-noising data set by PCA

In this experiment a comparison among different de-noising methods with different number of training image range from 100 to 400 images is done. Table 2 shows the verification rate at 0.1% FAR for the origin PCA implemented on ORL database and PCA implemented after wavelet image de-noising method (1D Haar wavelet, 2D daubchies10, 3D daubchies6, 10D Haar) is applied separately on the ORL database.

Table 2: verification rate at (0.1%) FAR when implementing Haar 10 de-noising wavelet using different dataset on PCA

No. of images	PCA on ORL DB	PCA on Haar1 DB	PCA on db10 DB	PCA on db6 DB	PCA on Haar 10 DB
100	94.29%	94.29%	95.70%	95.70%	**97.14%**
200	80.70%	82.14%	82.14%	81.43%	**82.86%**
300	70%	70%	68.10%	68.57%	**72.38%**
400	66.79%	67.14%	67.68%	**69.29%**	68.93%



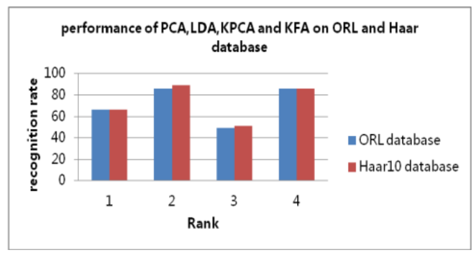
From this experiment we find that wavelet Haar at level 10 has the highest verification rate when the number of images is 100, 200, 300 and the daubchies 6 has the highest rate when 400 images are used for the recognition.

Experiment 3: Evaluate recognition rate using different face recognition method

In this experiment we test the performance of Haar 10 wavelet de-noising on different face recognition method (PCA, LDA, KPCA, FA). We use (PhD-tool) face recognition tool box in matlab to compare the recognition rate for the face recognition methods on original ORL database and the recognition rate for the face recognition methods on the new proposed de-noising database Haar 10 wavelet. The result in Table 3 shows the recognition rate on the original database and the proposed one.

Table 3: recognition rate for PCA, LDA, KPCA, and KFA with noisy and de-noising database

recognition rate	PCA	LDA	KPCA	FA
ORL database (with noise)	66.07%	86.07%	49.29%	85.70%
proposed database (without noise)	66.43%	89.29%	51.07%	86.07%



4. Discussion

In our work we implement three experiments. From the first experiment we find that the verification rate at (0.1%) FAR increases for some methods when we implement PCA with level 1 decomposition wavelet de-noising on ORL database, but there are a big variations in this rate at level 2 of decomposition for all methods that are used, and the methods which increased at level 1 was decreased at level 2 and vice versa, and in level 3 all wavelet methods are improving to the verification rate except db2 and sym2, see Table 1. This is because we do not notice any observable improvement on the rate at level 5 of decomposition. We discard the result of this level and only the result of level 10 is mentioned in this paper since it produces good improvement for both the verification rate at (0.1%) FAR and the recognition rate. For all wavelet de-noising methods from level 1 up to level 10 of decomposition, both the MSE and PSNR are measured to all face images in the original ORL database and the proposed de-noising one, by clicking on any image in the list of face images that have extension .pgm as illustrated in Figure 4 ,where the image on the left side is the face in the original ORL database and the face on the right side is the de-noising one by Haar10 wavelet with MSE=49.4861 and PSNR=31.186.

Fig.4 An example of implementing Haar 10 wavelet

The result of experiment 1 supports our work to use Haar at level 10 of decomposition in experiment 3 in spite of that it produces 68.93% verification rate at 0.1% FAR which is less than 96.29% that db6 gives at level 10. Since we find db6 has the same verification rate from level 3 up to level 10 decompositions. So we select Haar 10 wavelet because it makes improvement on these rates gradually. In experiment 2, we take the best performance of each wavelet de-noising methods at each (1, 2, 3 and 10) level of decomposition, so that we select Haar 10 wavelet to de-noise the ORL database and produce four new de-noising face image databases, then implement PCA face recognition method on these databases with different data sets (100, 200, 300 and 400) of face images. We do these four tests for each database, and get the results of 20 tests implemented by PCA (4 tests with 4 datasets are done by PCA ORL database, PCA on Haar 1, PCA on db10 at level 2 , PCA on db6 at level 3 and PCA on Haar at level 10), see Table 2.

In spite of db6 at level 3 gives the highest verification rate at 0.1% FAR which is equal to 69.29%, it is not improving the recognition rate at any level of decomposition. For this reason we take Haar 10 in experiment 3, since it is the only wavelet de-noising method that produces improvement for both the verification rate at (0.1%) FAR, and rank one recognition rates, see Table 1 and Table 3.

In experiment 3, we use Haar 10 de-noising wavelet database with different face recognition method represented by (PCA, LDA, KPCA, and FA) and find it produces (2.5%-3%) improvement over the recognition rate when ORL database is used with these face recognition methods. Figure 5 shows some images de-noised by Haar 10 wavelet process.

Fig. 5 Faces after de-noising by Haar 10 wavelet

5. Conclusions

From our work we proved that the image de-noising process has a powerful affect on face recognition rate. We find that the using of wavelet de-noising at higher level for decomposition will discard many metrics that are not important in the face image and focus on the important one like the eyes, nose, mouth, poses, etc., which improves the feature extraction process and leads to good recognition rate. As we see, the using of Haar Wavelet at level 10 produces good improvement on both verification rate at 1% FAR and the recognition rate.

For future work we can use many other wavelet de-noising methods and test them with more levels of decompositions by the same or different face recognition methods.

Acknowledgments

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