Sparse Representation Approach for Variation-Robust Face Recognition Using Discrete Wavelet Transform

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ABSTRACT

Face recognition has become one of the most challenging tasks in the pattern recognition field and it is very important for many applications such as: video surveillance, forensic applications criminal investigations, and in many other fields it is also very useful. In this paper we are using sparse representation approach based on discrete wavelet transform (DWT) to achieve more robustness to variation in lighting, directions and expressions, because sparse representation does not exterminate obstacles posed by several practical issues, such as lighting, pose, and especially facial expressions, which tend to distort almost all the features and can thus compromise the accuracy of sparse representation. The result of new proposed approach is compared with sparse representation approach to show that the proposed approach is more robust to illumination, direction and expression variations than sparse representation.

Keywords: *Face recognition, L1-minimization, sparse representation, discrete wavelet transform (DWT).*

1. Introduction

Automatic face Recognition is a form of biometric identification [7]. It has one of the challenging tasks in the pattern recognition field. The recognition of faces is one of the very important roles for many applications such as: video surveillance, retrieval of an identity from a database for criminal investigations and forensic applications, secure electronic banking, mobile phones, credit cards, secure access to buildings.

The identification problems in pattern recognition can be describe as an unknown face will be enter to the system, then the system will be determined identity from a database of known faces, whereas in verification problems, the system needs to confirm or reject the requested identity of the input face.

Sparse representation, also known as compressed sensing [4][5], has been applied recently to image-based face recognition and with sparse representation we can represent each face by a set of features, which sufficiently characterize each face individual. With the prior knowledge that faces of the same individual are similar to each other, a test face can be considered as being well approximated by linearly combining the number of faces that have same individual in the training set.

With all the promising advantages, the use of sparse representation for face recognition does not exterminate obstacles posed by several practical issues[12], such as lighting, pose, and especially facial expressions, which tend to distort almost all the features and can thus compromise the sparsely of the representation. To achieve robustness to lighting, variation directions and expressions, we are using sparse representation based on Discrete Wavelet Transformation (DWT).

This paper is organized as follows. Section 1 is this introduction. Section 2 discusses a few related works from the literature. Discussion of sparse representation for face matching is provided in Section 3.In section 4, discrete wavelet transform is explained. The details of the proposed sparse representation approach are provided in Section 5. Section 6provides the details of the conducted experiments along with results .The paper concludes with a brief summary of results and proposal of future research directions.

2. Related work

Face recognition research has been concentrated primarily on developing algorithms to deal with challenges posed by variations in acquisition conditions like illumination conditions and head pose with respect to the camera [8] [11].Tremendous success in dealing with these problems is one of the primary factors that have generated interest new methods in face matching that include sparse representation technique[6].

There are many problems to develop the face recognition in computer science such as high dimensionality, meaning, large in data size for face

images and the large number of identities to classify. The above two problems are combine and solved as a pattern recognition problem by carefully partitioning a high-dimensional data space into thousands of domains, each domain represents the possible appearance of an individual's face images.
Very recently, an interesting work was reported by Mr. John Wright, Dr. Allen Y. Yang, Dr. S. Shankar Sastry, and Dr. Yi Ma. [2][3], where they used sparse representation (SR) approach for robust FR. Training face images are used as the dictionary to represent an input testing image as a sparse linear combination of them using L1-norm minimization. The classification based on sparse representation (SRC) of face images is evaluating which class of training samples could result in the minimum reconstruction error of testing image with the sparse coding coefficients. And they test their SRC algorithm using several conventional holistic face features, namely, Eigenfaces, Laplacianfaces, and Fisherfaces, and compare their performance with two unconventional features: randomfaces and downsampled images then compare their algorithm with three classical algorithms, namely, NN, NS and SVM on Extended Yale B Database. And still we have recognition problem when face recognition has to be performed under various real-world conditions [3].
Also D Murugan, Dr. S Arumugam, K Rajalakshmi and Manish T[7]show in their work that exploiting discrete wavelet transform is applied on image to dimensionality reduction. The approximation coefficients in discrete wavelet transform is extracted and it is used to compute the face recognition accuracy instead of using all the coefficients.
Pillai et al. [13] use a similar approach to select and recognize individuals from iris images. One practical drawback of sparsity-based biometric recognition is the need for several images per subject in the gallery [3][13].

In this paper we introduce new hybrid method based on sparse representation and discrete wavelet transformation (DWT). We are using DWT to analyze the input image and then construct sparse representation for further classification .Experimental results show how these techniques reduce error rate of face recognition.

3. Sparse representation

The use of sparse representation for face recognition was developed by Mr. John Wright, Dr. Allen Y. Yang, Dr. S. Shankar Sastry, and Dr. Yi Ma.[5].Given as input set of training samples from r different classes, the output is determine unknown test image belong to which class. We assume that face images of the same person under varying illumination and variation in direction lie on a low-dimensional linear subspace. The individual subspaces can be represented by matrices A_1, A_2,...,A_r , where each column in A_{ii}s a training sample from class i. Under this assumption, a test sample y from class j can be expressed as a linear combination of the columns of A_j . Therefore, if we let $A = [\ A_1\ A_2\ ...\ A_r]$, then for some vector x that has non-zero components corresponding to the columns of A_j, we have,

$$y = Ax \tag{1}$$

where $x = [0,\dots,0,\dots,\alpha_{i,1},\dots,\alpha_{i,ni},\dots,0,\dots,0]^T$ is a coefficient vector whose entries are zero except those corresponding to the i-th class [6].
The computational problem of sparse representation is to find the sparse solution x. This sparse solution x explains how to combine all training samples to obtain a global representation of test sample. To classify a new test sample y, we calculate all the partial reconstructions $y_i = Ax_i$ by considering the contribution of coefficients of x associated with each subject towards the reconstruction of y. Then we classify the new test sample y as the subject whose training samples best represents the test sample. For reference we include the algorithm1 given in [3] as follows:

Algorithm 1

- **Input**: *n* training samples divided into *r* classes, $A_1, A_2,...,A_r$ and a test image y.
- Set $A = [\ A_1 A_2\ ...\ A_r]$.
- Solve the L1 minimization problem : min $\| x \|_1$ subject to $y = Ax$
- **For** each subject i ,
  Compute the residuals: $r_i = \| y - Ax_i \|_2$ where x_i is obtained by setting the coefficients in x, corresponding to training samples not in class i, to zero.
- **End**
- **Output**: the class with the smallest residual identity(y) = arg min r_i(y).

The system architecture for face recognition using sparse representation is presented as shown in Figure 1:

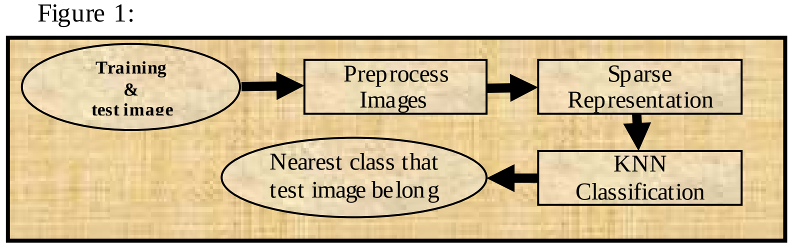

Figure 1Block diagram of sparse representation approach

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4. Discrete Wavelet Transform

Discrete wavelet transform (DWT) is a well-known signal analysis tool, widely used in feature extraction, compression, denoising and other applications.
The one dimensional wavelet decomposition is first applied along the rows of the images, and then their results are further decomposed along the columns. This results in four decomposed sub images L1, H1, V1, and D1. The analysis is original image of resolution NxN can first filtered along the rows and downsampled by 2 yielding two NxN/2 images that have high and low frequency contents, respectively. After this decomposition, the wavelet transform is applied to the columns of these NxN/2 resolution images. In the final stage of the decomposition we have four N/2xN/2 resolutions subband images. The decomposition can be continued further by performing same processing steps on the scaling component. In figure 2 we are show that DWT 1st level decomposition for original image[9].

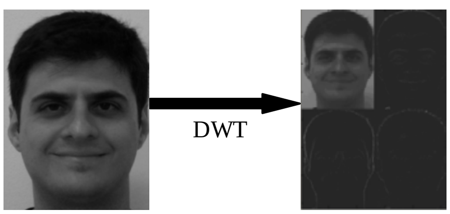

Figure 2 Sample one-level wavelet decomposed image

The discrete wavelet transform of a function f(x, y)of size M x N is:-

$$W_{\varphi}(j_0,m,n)=\frac{1}{\sqrt{MN}}\sum_{x=0}^{M-1}\sum_{y=0}^{N-1} f(x,y)\,\varphi_{j_0,m,n}(x,y) \quad (2)$$

$$w_{\Psi}^{t}(j,m,n)=\frac{1}{\sqrt{MN}}\sum_{x=0}^{M-1}\sum_{y=0}^{N-1} f(x,y)\,\Psi_{tj,m,n}(x,y) \quad (3)$$

W_{φ} (j_0,m,n) coefficients define an approximation of f(x,y)at scale j_0.$w_{\Psi}^{t}(j,m,n)$ coefficients add horizontal ,vertical and diagonal details for scale $j \le j0$.

The basic decomposition steps for images can be described in figure 3.

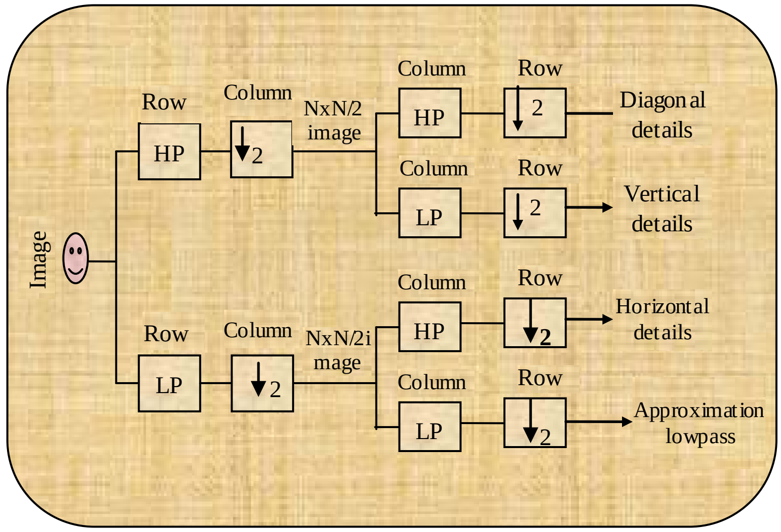

Figure 3Wavelet pyramid decomposition process

5. Proposed framework

The proposed algorithm is an adaptation in using sparse representation algorithm to overcome the problem of recognition under illumination, direction and facial expression variation [8][10]. We will see that the proposed algorithm solves these problems by perform three steps as follows:

1. Generate DWT for each image.
2. Generation of training matrix A .
3. Recognition via DWT and sparse representation then Classification.

We can be summarized the proposed approach with block diagram figure 4 as shown:

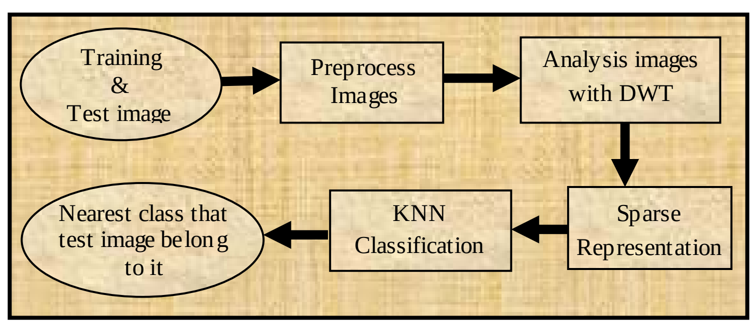

Figure 4Block diagram of proposed approach

5.1 Generate DWT for each image

In Discrete Wavelet Transform, the most apparent information in the signal appears in high amplitudes and the less apparent information appears in low amplitudes[1]. The advantage of wavelet transforms is enable high compression ratios with good quality of reconstruction. The Discrete Wavelet Transform (DWT), The Discrete Wavelet Transform (DWT), which is based on sub-band coding, is found to yield a fast computation of Wavelet Transform. The one dimensional wavelet decomposition is first applied along the rows of the images, and then the results are decomposed along the columns. This results in four decomposed sub imagesL1, H1, V1, and D1 for each image. These sub images represent different frequency localizations of the original image.

5.2 Generation of training matrix A

We define a new matrix A for the entire training set as the concatenation of the n training samples of all r object classes:
$A = [A_1\ A_2\ \dots\ A_r]$, where for i class $A_i = [v_{i,1}, v_{i,2}, \dots, v_{i,n}] € R^{mxn}$
And $v_{i,1}$ is define as L1, H1, V1, and D1approximation and details coefficients for image 1 in class i that result after apply DWT on image , this is for class i in matrix A. So we need multiple images per subject to populate training matrix A for the sparse recognition process to function effectively.
Training matrix A consists of columns, each of them is theL1, H1, V1, and D1approximation and details coefficients that results from apply DWT on each images.

5.3Recognition via DWT and sparse representation

The identity is determined independently for each image as follows. First the DWT of all training samples S_i and test sample z is obtained. Then based on the DWT of given test sample y and the DWT of training matrix A, the sparse coefficient vector x is obtained by solving (1). Final classification is performed by the K-nearest neighbor (KNN) or nearest subspace (NS) classifier which determines the class present in A that best represents the test sample using the recovered x. Representation error for the i-th class is computed by reconstructing test sample using the samples belonging to that class only as follows.

$$r_i(y) = \min \| y - Ax_i \|_2$$

where $x_i = [0, 0, \dots, 0, x_{i;1}, \dots, x_{i;ni}, ,.0, \dots, 0]^T € R_n$.
Clearly, NN seeks the best representation in terms of just a single training image, while NS seeks the best representation in terms of all the training images of each subject [3].

The modified algorithm 1 is summarized as Algorithm 2.

<u>Algorithm 2</u>

- **Input**: *n* training samples partitioned into *r* classes, $S_1, S_2, \dots, S_r$ and a test sample *z*.
- **For** each subject i ,
  Generate DWT A_i for each subject i
- **End**
- Generate DWT y of test sample *z*.
- Set matrix A based on DWT of images
  $$A = [A_1 A_2 \dots A_r].$$
- Solve the L1 minimization problem
  $$\min \| x \|_1 \quad \text{subject to } y = Ax$$
- **For**
- Compute the residuals: $R_i = \|y - Ax_i\|_2$, where x_i is obtained by setting the coefficients in *x*, corresponding to training samples not in class *i*, to zero
- **End**
- **Output:** identity (z) = argmin $[R_i]$.

6. Experiments

In this section, we quantitatively verify the performance of Algorithm 1 and Algorithm 2 using public face databases namely, FEI Face Database. There are 14 images for each of 200 individuals, a total of 2800 images. All images are colorful and taken against a white homogenous background in an upright frontal position with profile rotation of up to about 180 degrees. Scale might vary about 10% and the original size of each image is 640x480 pixels. Figure 5 shows some examples of image variations from the FEI face database.

Figure 5 Examples of image variations from the FEI face database.

Two experiments has been done to test and compare recognition rate in two approaches first approach using sparse representation via face recognition, second using sparse representation base on DWT. First test under different illumination we done on 30 full frontal face images manually registered to evaluate experiments on a controlled environment, and 10 images for test is shown in figure 6


Figure 6 Sample images that tested

We compute recognition rate for different illumination as shown in table 1.

Table 1 Face recognition techniques accuracy in %

Brightness dark→light	Recognition Rate %	
	SRC approach	Proposed approach
-95	10	10
-90	10	10
-85	10	10
-80	10	10
-75	10	10
-70	10	20
-65	50	100
-60	100	100
-55	100	100
-50	100	100
-45→45	100	100
50	100	100
55	100	100
60	90	100
65	90	100
70	80	100
75	50	100
80	20	100
85	10	100
90	10	90
95	10	30

Figure 7plots the recognition performance of SRC and SRC based on DWT, under various illumination. We see the wavelet transform is sensitive to strong lighting conditions.

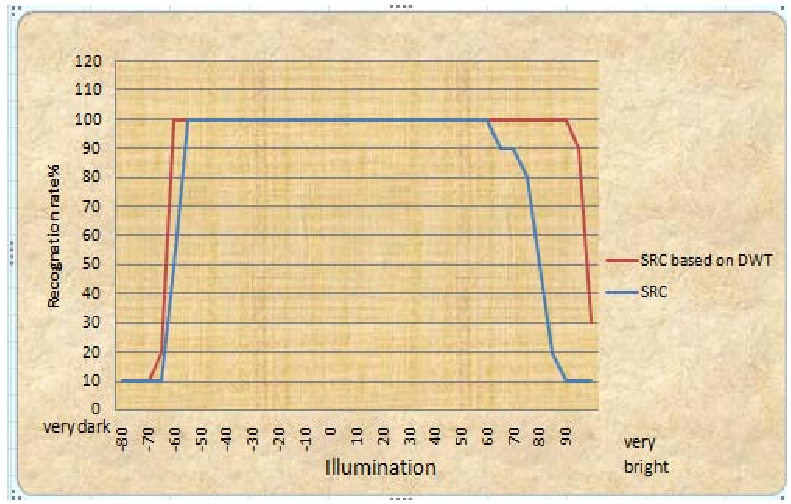

Figure 7Recognition rate for different illuminations.

The SRC based on DWT algorithm can recognize face up to 65 to dark and 90 to light but in SRC we found the recognize face up to 60 to dark and 65 to light So the proposed algorithm an high efficient algorithm to robustness for variation illumination .
Second test we apply two approaches on all FEI Database under different condition such as degree in illumination, expression and variation direction consists of 600 images for training and 300 for test as show in samples figure 8.


Figure 8 Sample from test FEI database

For the first approach SRC we found recognition rate 89% , the proposed and second approach is recognize by 89.66 %. Table 2 shows the result for recognition rate %.we see the nearest result because this database working with few changes in lighting so we don't see high efficiency of the proposed approach.

Table 2Recognition rates for SRC and Proposed Method.

Recognition method	Recognition rate %
SRC algorithm	89%
Proposed algorithm	89.66%

7. Conclusion

We have presented an efficient framework for face recognition based on sparse representation and DWT. Our system achieves robustness to variation in lighting, directions and expressions. An average recognition rate of 89 % is achieved under all prescribed variations. SR approach proved to be an efficient method for face recognition. Experimental results show an increase in face recognition rate when using DWT. Using level2 decomposition DWT rendered the method more robust to face image variations. The method robustness is particularly remarked for variations in lighting conditions.

We believe that face recognition under varying directions and expressions is still an interesting area of research, and we anticipate that there will be many further advances in this area. Other important directions of research should be in tackling large image base size and accuracy of classifiers. In the future work we plan to test the proposed algorithms on facial expression recognition.

References

[1] Gomathi E." Face Recognition Fusion Algorithm Based on Wavelet Transform and Fast Discrete Curvelet Transform". European Journal of Scientific Research. 2012;74(3):450-455.

[2] Wagner A, Member S, Wright J. Toward a Practical Face Recognition System : Robust Alignment and Illumination by Sparse Representation. Analysis. 2012;34(2):372-386.

[3] Wright J, Member S, Yang AY, et al. Robust Face Recognition via Sparse Representation. IEEE. 2009;31(2):210-227.

[4] Qinfeng Shi, Hanxi Li, and ChunhuaShen. Rapid face recognition using hashing.InProc.IEEE Conf. Computer Vision and Pattern Recognition, San Francisco, USA, 2010.

[5] A. Y. Yang, J. Wright, Y. Ma, and S. S. Sastry. Feature selection in face recognition: A sparse representation perspective. Tech. Report, 2007.

[6] Aggarwal G, Biswas S, Flynn PJ, et al. A Sparse Representation Approach to Face Matching across Plastic Surgery ∗.Organization.

[7] D Murugan, T "performance evaluation of face recognition using Gabor Filter, log Gabor filter and discrete wavelet transform". International journal of computer science and information technology 2010:1(2):125-133.

[8] Marsico MD, Nappi M, Riccio D. FARO : face Recognition Against Occlusions and Expression Variations. 2010;40(1):121-132

[9] Lee H-soo, Kim D. Tensor-Based AAM with Continuous Variation Estimation: Application to Variation-Robust Face Recognition.Analysis. 2009;31(6):1102-1116

[10] Xu Z, Chen H, Zhu S-chun, Luo J, Member S. A Hierarchical Compositional Model for Face Representation and ketching. Analysis. 2008; 30(6) : 955-969.

[11] Niese R, Al-hamadi A, Aziz F, et al. Robust Facial Expression Recognition Based on 3-d Supported Feature Extraction and SVM Classification. IEEE. 2008.

[12] Plumbley BMD, Blumensath T, Daudet L,Davies ME. Sparse Representations in Audio and Music : From Coding to Source Separation. Proceedings of the IEEE. 2009.

[13] J. K. Pillai, V. M. Patel, and R. Chellappa.Sparsity inspired selection and recognition of iris images. In Proceedings of the 3rd IEEE international conference on Biometrics: The- ory, applications and systems, pages 184–189, 2009. 115