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Face recognition approach combining Discrete wavelet transform and Self-organizing maps

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***Abstract*— This paper proposes a face recognition approach built on interfacing Discrete wavelet transform (DWT) and Self-organizing maps (SOM) neural networks. The key design phases involve: i) A multiresolutional discrete wavelet analysis splitting original images into different scales and frequencies. In addition to approximation sub-image, mean of horizontal, vertical and diagonal sub-images of same scale is calculated engendering only detail one per level. ii) Images representation performed by applying spatial filtering to retrieve local statistics, namely: Entropy and Energy. Multidimensional feature vectors are constructed by combining all statistical sub-images features. iii) Images generalization achieved thanks to the unsupervised training and evaluation SOM algorithm. Experiments demonstrate that the proposed method exhibits satisfactory results with promising recognition accuracy rate.**

***Keywords*— Face recognition, discrete wavelet transform, self-organizing maps.**

I. Introduction

Nowadays, face recognition technology has several potential applications; among others access control and information security [1-3]. However, despite the raised issues and the manifold proposed solutions, the general face recognition problem still relevant considering its intrinsic complexity related to human face changing appearance. Indeed, occlusion (due to clothes, glasses ...), illumination and expression variations are unavoidable and out of control.

In this work, we introduce a face recognition approach combining discrete wavelet transform (DWT) and self-organizing maps (SOM).

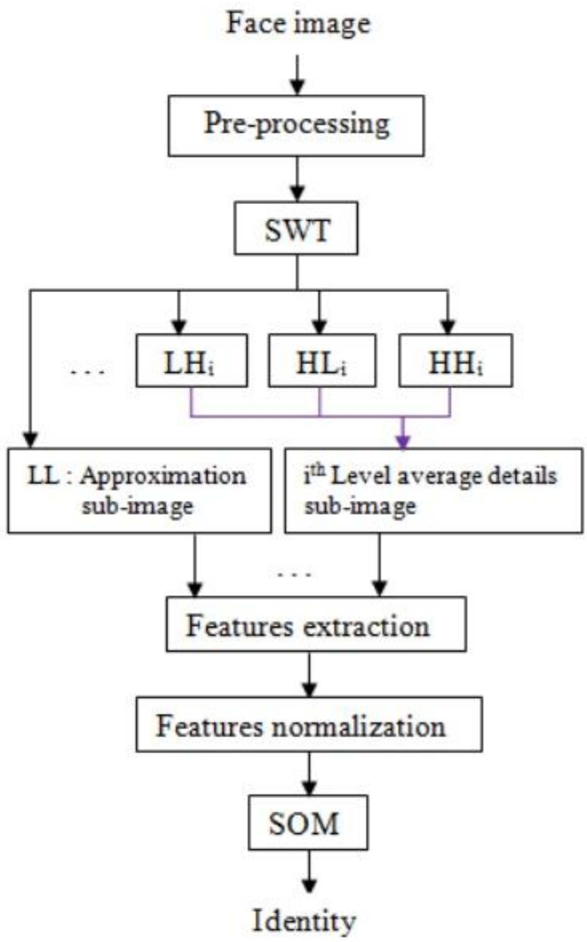
However, in spite of splitting information into different frequency channels, wavelet transforms miss local statistical knowledges. There exists a wide variety of textural features. In this study, we opted for Energy and Entropy data to report local statistics. Thus, for an automatic image representation, DWT was used along with local statistics.

The motivation of performing classification through SOM algorithm is argued by the unsupervised and nonparametric SOM characteristics, ensuring robust training and evaluation of the injected data.

The paper proceeds as follows: the proposed method is detailed in section 2. Data set and methodology are described in section 3. Experiments under FERET database are reported in section 4. Finally, conclusions and suggested future work are drawn in section 5.

II. The proposed method

Proposed approach flow is illustrated here below:



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A. Pre-processing

Before the recognition process, all colour images (of gallery and test sets) were converted to gray-level ones then normalized to ensure that data are impartially treated during the training step. Since we are processing grayscale images, we applied histogram equalization. This adjustment would better distribute intensities on the histogram. From each normalized image, only the face was localized and cropped through Viola Jone's object detection algorithm which allowed fast and accurate detection thanks to Adaboost features selection and cascade computational resource allocation.

B. Discrete wavelet transform

Based on a given mother wavelet, 2-level DWT was performed on pre-processed images decomposing each of them into 1 approximate and 2*3 detailed (horizontal, vertical and diagonal) sub-images.

C. Features extraction

In spite of splitting information into different frequency channels, wavelet transforms miss local statistical knowledges. Indeed, we opted for Energy and Entropy data to report local statistics.

Furthermore, to reduce extracted features dimension, mean of horizontal, vertical and diagonal sub-images was calculated resulting into one detail sub-image. Actually, one approximate and one detail sub-images are obtained using DWT.

Based on these elements, spatial filtering operations were carried out on wavelet coefficients by sliding a fixed-size window through approximate and average details non overlapping sub-blocks. The retrieved features are:

- Entropy which is a statistical measure of randomness that can be used to characterize the texture of the input image:

$$\text{Entropy} = -\sum_i x_i^2 \log(x_i^2)$$

- Energy which is also a statistical feature used for representing textural information, computed as follows:

$$\text{Energy} = \frac{1}{N}\sum_i |x_i|^2$$

Where x_i represents a wavelet coefficient and N is sub-block dimensionality. Supposing M the dimensionality of the whole image, d $(=M/N)$ correspond to local statistics per feature count. Consequently, the achieved feature vector FV is dx4 sized:

$$FV = \{\text{Entropy}_{\text{app}}; \text{Entropy}_{\text{det}}; \text{Energy}_{\text{app}}; \text{Energy}_{\text{det}}\}$$

With;
- $\text{Entropy}_{\text{app}}$: approximate sub-blocks entropy
- $\text{Entropy}_{\text{det}}$: average details sub-blocks entropy
- $\text{Energy}_{\text{app}}$: approximate sub-blocks entropy
- $\text{Energy}_{\text{det}}$: average details sub-blocks entropy

D. Features normalization

Since we are handling several features data types, we standardized features vectors to fit into [0 1] range before setting them as input to SOM network. In fact, before machine learning, it is a good, if not compulsory, practice to scale features in order to normalize independent data range.

E. Self-organizing map

Features vectors are used as input to the Self-organizing map neural network (SOM). SOM was initialized using random process and trained in batch mode. The training process was run on two phases as argued in [12], namely a rough training phase to adjust the topological order of features vectors and a fine tune one carried on the first phase achieved map to provide an accurate quantification of the input space.

After SOM training, each test image is projected in the resulting map by determining the Euclidean distance between test image feature vector and map weight vectors. Finally, the SOM classification decision corresponds to the best matching prototype label.

III. Data set and Methodology

To proof the efficiency of the proposed method, namely the DWT-SOM algorithm, we have run several experiments on the well-known color FERET database. In fact, FERET Database contains a total of 11338 facial images of 1208 subjects, affording a wide variety across gender, ethnicity and age. It comprises 13 subsets, each of them representing images of the same pose. The carried experiments interested (*fa*) gallery images and (*fb*) probes subsets, where (*fa*) designates the regular frontal pose images subset, and (*fb*) the alternative frontal images subset, token shortly after the corresponding (*fa*) ones. In the recognition process, (*fa*) gallery set was used for training and (*fb*) probe set for testing.

Initially, training and testing images are in '.ppm' file format and of 512 by 768 pixels. During the pre-processing stage, they were converted to grayscale images ('.pgm' file format), normalized according to the histogram equalization approach and finally, belonging faces cropped to a size of 256*256.

2-level DWT was applied to each of them using the Daubechies wavelet family. As a result of the transform, 1 approximate and 2*3 detailed (horizontal, vertical and diagonal) sub-images were obtained. As mentioned before, each 3 detailed sub-images of the same level average was computed. Finally, we obtained 1 approximate sub-image 64*64 sized and 2 average details ones 64*64 and 128*128 seized.

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Features were extracted from each sub-image by sliding along a varying size window. Since we opted for Entropy and Energy local statistics, we recovered features vectors (FVs), with already mentioned features.

FVs were normalized in the [01] range before being transferred to the SOM network in order to ensure classification in an unsupervised approach.

SOM was trained in batch mode through the retrieved sub-blocks. The training process was run into two phases as argued in [12], specifically, a rough training phase to adjust the topological order of features vectors and a fine tune one carried on the first phase achieved map to provide an accurate quantification of the input space. In line with this, 100 updates were performed in the first phase, while 400 times in the second one. The initial weights of all neurons were set to the greatest eigenvectors of the training data, and the neighborhood widths of the neurons converged exponentially to 1 with the increase of training time.

IV. Experiments

A. Experiment 1:

First, the performance of the proposed method was evaluated considering 200 training images and 200 testing ones and Daubechies 2 as mother one. Sliding window size was varied. Resulting accuracies are summarized in Table 1:

TABLE I
COMPARATIVE PERFORMANCE OF THE DWT-SOM ALGORITHM WITH VARIANT SLIDING WINDOW SIZE

Sliding window size	Accuracy (%)
4 x 4	76.5
8 x 8	75
16 x 16	66.5
32 x 32	44

We note that the best DWT-SOM algorithm performance was reached for a sliding window 4x4 sized. Intuitively, the smaller the sub-block, the more performing the system. Moreover, there isn't a great difference between 4x4 and 8x8 sub-blocks sizes with regard to accuracy rates. Thus, to reduce execution time while achieving a promising accuracy rate, we can opt for 8x8 sub-blocks size.

B. Experiment 2:

Second, fixing the sliding window size to 4x4 (since it provides the best accuracy) we investigated the impact of Daubechies mother wavelet family on DWT-SOM algorithm performance. Resulting accuracies are summarized in Table 2:

TABLE II
COMPARATIVE PERFORMANCE OF THE DWT-SOM ALGORITHM WITH VARIANT DAUBECHIES MOTHER WAVELET

Mother wavelet	Accuracy (%)
db1	78
db2	76.5
db4	75
db6	77.5
db8	80.5
db10	78
db45	75

We can remark that the best DWT-SOM algorithm performance was reached for Daubechies 8 mother wavelet. However, all accomplished accuracies, relatively to varying Daubechies mother wavelets, are approximately of the same range.

C. Experiment 3:

In order to investigate the classification performance of the proposed approach, we reported cumulative match scores for ranks up to 10 representing the percentage of probes that are of a particular rank *k* (k = 1, ..., 10) or less. Considering 200 training images and 200 testing ones, the Daubechies 8 wavelet was set as mother one. Sub-blocks were 4x4 sized. He

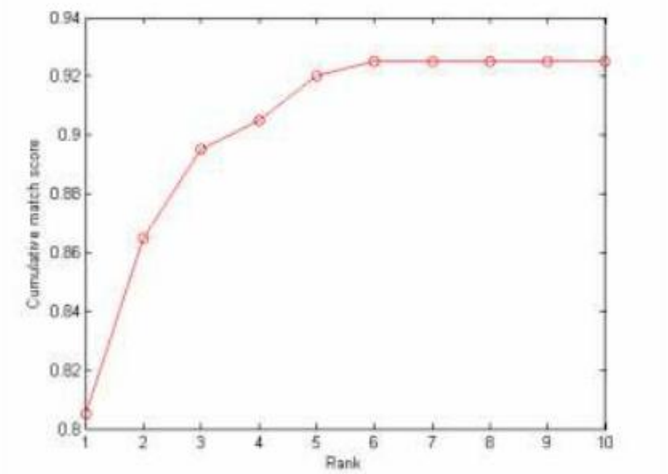

Fig. 1 Performance of the proposed approach

We can see that the correct answer was rank 1 for at least 80% of the probes, reaching more than 90% of them ranked 10 or less.

V. Conclusion

In this paper, we set up an automatic face recognition system based on discrete wavelets transform and self-

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organizing maps neural network. The obtained results proved this system efficiency thanks to promising classification accuracy rates.

As future work, we intend to investigate wavelets properties, namely: decomposition level and coefficients sets to be kept. In fact, this topic has been rarely discussed in the literature.

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