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An Efficient Scheme for Optimization of Recognition Algorithms

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A B S T R A C T

In this paper, the multimodal analysis is applied in image fusion and its effectiveness on the face recognition algorithms is discussed. Firstly, the implementation of multimodal analysis in image fusion based on the wavelet decomposition is presented and the methods of merging the wavelet coefficients of single modes and generating multimode are posed. Then, the practical results of the experiments performed on two image databases are presented. Finally, the multimode is functionally compared with the single modes. The distinction of the presented method in comparison with other methods based on the multimodal analysis is that in this method, merging the single modes and constructing the multimode is performed in the feature extraction stage. It leads to more accurate results.

Keywords: Recognition algorithm; Multimodal analysis; Wavelet.

1. Introduction

The images fusion using multimodal analysis is the mixing and combining the information obtained from multiple images with this assumption that the images have the same scene. The outcome of images fusion is a new image that is more suitable for human or machine vision or other subjects in image processing such as segmentation, feature extraction and object recognition. The multimodal analysis in images fusion can be applied in many fields, for example, remote sensing, medical imaging, machine vision and face recognition [1,2,3,4].

It is possible that some images of one scene have different information, although have the same scene. For example, it can be supposed that the images are taken by different sensors [5]. If these different information can be merged for obtaining a new and optimized image, then it gives a synthetic image and the used concept is called “images fusion based on multimodal analysis”.

For images fusion, this paper applies a method based on the wavelet decomposition, namely, a multiresolution approach. This method is described in the next sections.

2. Implementing multimodal analysis in images fusion based on the wavelet decomposition

The wavelet decomposition is an effective and powerful method for implementing multimodal analysis in images fusion. Fig.1 shows a generic block-diagram for this method.

It is seen that three stages are in this process:

1. Applying the wavelet transform to each of single modes and obtaining the wavelet coefficients.

2. Using an appropriate algorithm for merging the wavelet coefficients of single modes and obtaining one mode.

3. Applying the inverse wavelet transform to the wavelet coefficients of the previous stage and finally, obtaining the synthetic image.

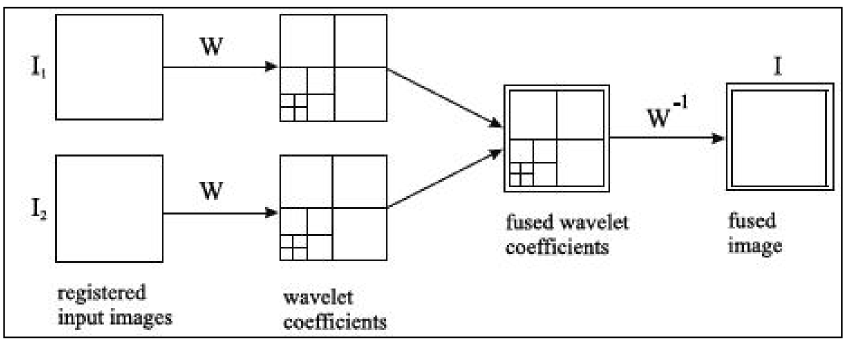

Fig. 1. Block-diagram for images fusion based on the wavelet decomposition.

The important stage in images fusion algorithm based on the wavelet decomposition is to merge the coefficients, i.e. selecting an appropriate method for merging. The most common methods for merging the wavelet coefficients are the "averaging method", "selecting maximum value" and "selecting minimum value" [6,7]. In the averaging method, the mean value of different modes wavelet coefficients at each point is considered as the final mode wavelet coefficient at this point. In the selecting maximum (minimum) method, the maximum (minimum) value of coefficients at each point is selected as the final mode wavelet coefficient. For example, in the selecting maximum method:

$$\begin{aligned} A^k(r,c) &= \max\left\{\left|A_1{}^k(r,c)\right|,\left|A_2{}^k(r,c)\right|,\ldots,\left|A_n{}^k(r,c)\right|\right\} \\ D^k(r,c) &= \max\left\{\left|D_1{}^k(r,c)\right|,\left|D_2{}^k(r,c)\right|,\ldots,\left|D_n{}^k(r,c)\right|\right\} \end{aligned} \qquad (1)$$

in which:

A_i^k : the approximation coefficients of the i*th* single mode at k*th* level of the wavelet decomposition,

D_i^k : the details coefficients of the i*th* single mode at k*th* level of the wavelet decomposition,

$\text{index } j, j:1,\ldots,k$: levels of the wavelet decomposition,

(r,c) : a generic point in the wavelet coefficients.

3. Why the wavelet method

For several reasons, the wavelet method has been preferred for implementing multimodal analysis in images fusion:

1. This method is a multiscale or multiresolution method that can highly cover the different image resolutions.

2. The discrete wavelet transform (DWT) can afford the image to be decomposed to the coefficients of different wavelets.

3. The coefficients obtained of different images (of the same scene) can be nicely merged together and make the new coefficients, so that, the information of the images is gathered greatly.

4. After merging coefficients, the final synthetic image can be easily obtained through the inverse discrete wavelet transform (IDWT), so that, the information is retained in the merged coefficients too.

4. Experiments and results

In the previous sections, the multimodal analysis in images fusion was surveyed. What was performed was the wavelet decomposition of each image and then the merging coefficients of multiple images and finally obtaining the coefficients of the final image. The distinction of the presented method in comparison with other methods based on the multimodal analysis is that in this method, merging the single modes and constructing the multimode is performed in the "feature extraction" stage, namely, the multimodal analysis is used to merge the feature vectors (obtained of the wavelet coefficients of the single modes) and to obtain the synthetic feature vector (of the final mode) and finally, these synthetic feature vectors are used in the recognition algorithm. It causes the feature vectors and subsequently, the face recognition algorithm more accuracy and efficiency.

The single modes have been obtained of the wavelet decomposition of the face image using different wavelet transforms. For any face image, three single modes have been considered that obtained of applying the "Haar", "Daubechies" and "Biorthogonal" wavelet transforms to that image. Then, each of three methods mentioned in the section 2 has been used to merge the coefficients of the single modes and make the multimode coefficients.

In the performed experiments, single-mode cases have been compared with multimode case from the viewpoint of the results. Two face image databases have been used in experiments, ORL and Yalefaces.

4.1. The experiments performed on the ORL database

The first series of experiments has been performed using the "ORL" face images.

i. Single-mode case

In this case, the experiments have been performed on the single modes generated using the "Haar", "Daubechies" and "Biorthogonal" wavelet transforms. The results have been given in table 1.

Wavelet Name	FRR[1]	FAR[2]	Recognition Rate
Haar	10.3 %	12.1 %	77.6 %
Db1	9.2 %	9.7 %	81.1 %
Bior 1.1	7.9 %	12.3 %	79.8 %

Table 1: The recognition rates of the single-mode cases (ORL database)

ii. Two-modes case

Two modes have been used in this case. One of them has been generated using the "Haar" and another using the "Daubechies" wavelet transform. These are single modes and should be merged together and make the multimode. Three methods "averaging", "selecting maximum value" and "selecting minimum value" have been applied for the fusion. The results after merging have been given in table 2.

Merge and Combine Method	FRR	FAR	Recognition Rate
Average value	5.6 %	3.4 %	91.2 %
Max	3.6 %	3 %	93.4 %
Min	2.7 %	3.6 %	93.7 %

Table 2: The recognition rates of the two-modes case (ORL database)

iii. Three-modes case

Three modes have been used in this case. These modes have been generated using the "Haar", "Daubechies" and "Biorthogonal" wavelet transforms. The results of recognition process after merging these three single modes have been shown in table 3.

Merge and Combine Method	FRR	FAR	Recognition Rate
Average value	3.6 %	3.1 %	93.3 %
Max	2.7 %	3.5 %	94.8 %
Min	2.6 %	2.2 %	95.2 %

Table 3: The recognition rates of the three-modes case (ORL database)

4.2. The experiments performed on the Yalefaces database

The second series of experiments has been performed using the "Yalefaces" face images.

i. Single-mode case

The experiments of this case are performed like the 4.1.i subsection. Table 4 shows the results.

Wavelet Name	FRR	FAR	Recognition Rate
Haar	10.2 %	11.1 %	78.7 %
Db1	9.6 %	8.4 %	83.2 %
Bior 1.1	8.1 %	10.7 %	81.2 %

Table 4: The recognition rates of the single-mode cases (Yalefaces database)

ii. Two-modes case

This case and the 4.1.ii subsection are alike. The results have been given in table 5.

Merge and Combine Method	FRR	FAR	Recognition Rate

[1] False Rejection Rate

[2] False Acceptance Rate

Average value	4.2 %	3.1 %	92.7 %
Max	2.5 %	2.9 %	94.6 %
Min	2.5 %	2.7 %	94.8 %

Table 5: The recognition rates of the two-modes case (Yalefaces database)

iii. Three-modes case

The experiments are performed like the 4.1.iii subsection. Table 6 gives the results.

Merge and Combine Method	FRR	FAR	Recognition Rate
Average value	2.5 %	2.7 %	94.8 %
Max	1.9 %	2.6 %	95.5 %
Min	1.3 %	1.8 %	96.9 %

Table 6: The recognition rates of the three-modes case (Yalefaces database)

Conclusion

As the experiments showed, the presented method optimizes face recognition algorithms and improves their recognition rates. The distinction of the presented method in comparison with other methods based on the multimodal analysis is that in this method, merging the single modes and constructing the multimode is performed in the feature extraction stage. It causes the face recognition algorithms more accuracy and efficiency. Apropos, the results showed that using the method of "selecting minimum value" for merging the coefficients leads to more accuracy in comparison with two other methods. Also, it is a small difference between the obtained results of the ORL and Yalefaces databases that is owing to the difference between the resolutions of images of the ORL and Yalefaces databases that have been available.

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