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Morphological Wavelets for Multifocus Image Fusion

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Abstract: This paper presents a method for multifocus image fusion, based on multiresolution signal decomposition using morphological wavelets. The method is based on the algorithm proposed by De and Chanda. The main contribution of this paper is the way in which are chosen the signal detail of the fused image in the reconstruction step. A comparison of results obtained using the original and improved method is also presented.

Keywords: multifocus image fusion, morphological wavelet

1 Introduction

In the case of images representing very large depth scenes, the clarity of objects varies depending on their distance to the object on which the camera was focused. In these situations, multiple images are captured, focusing the camera on objects at different distances. After, the images are combined to obtain a clear picture with contoured edges regardless of the distance at which the objects are placed.

For multifocus image correction there are a large number of methods, based on pixel, block or region fusion which must define and evaluate a sharpness criterion for quantification of high frequency content.

Heijmans and Goutsias [1], [2] introduced in 2000 the morphological version of the linear Haar wavelet transform that uses the morphological dilation and erosion operators. De and Chanda [3] proposed in 2006 a morphological decomposition scheme which has a great advantage for the computing complexity: only operations with integer numbers are required.

2 Morphological Wavelets

The analysis $\left(\psi^{\uparrow},\omega^{\uparrow}\right)$ and synthesis $\left(\psi^{\downarrow},\omega^{\downarrow}\right)$ operators are defined by the following relations:

$$\psi^{\uparrow}(X)(B)=M=max\{X(r,c),X(r,c+1),X(r+1,c),X(r+1,c+1)\} \quad (1)$$

$$\omega^{\uparrow}(X)(B)=(y_v,y_h,y_d), \quad (2)$$

where y_v,y_h,y_d are the vertical, horizontal and diagonal signal details:

$$y_v=\begin{cases} M-X(r,c+1) & if \quad M-X(r,c+1)>0 \\ X(r,c+1)-M & otherwise \end{cases} \quad (3)$$

$$y_h=\begin{cases} M-X(r+1,c) & if \quad M-X(r+1,c)>0 \\ X(r+1,c)-M & otherwise \end{cases} \quad (4)$$

$$y_d=\begin{cases} M-X(r+1,c+1) & if \quad M-X(r+1,c+1)>0 \\ X(r+1,c+1)-M & otherwise \end{cases} \quad (5)$$

The signal reconstruction is made using the synthesis operator:

$$X'(u,v)=\hat{X}(u,v)\dot{+}\hat{Y}(u,v), \quad (6)$$
$$(u,v)\in\{(r,c),(r,c+1),(r+1,c),(r+1,c+1)\},$$

The $\dot{+}$ operator is the usual additive operator and

$$\hat{X}(r,c)=\hat{X}(r,c+1)=\hat{X}(r+1,c)=\hat{X}(r+1,c+1)=M, \quad (7)$$

$$\hat{Y}(r,c)=min(y_v,y_h,y_d,0), \quad (8)$$

$$\hat{Y}(r,c+1)=min(-y_v,0), \quad (9)$$

$$\hat{Y}(r+1,c)=min(-y_h,0), \quad (10)$$

$$\hat{Y}(r+1,c+1)=min(-y_d,0). \quad (11)$$

In the fusion step, the signal details with the greater absolute value are selected for reconstruction.

3 Multifocus image fusion algorithm

The algorithm proposed by De and Chanda is described below [3]:

1. ***Analysis step***. The analysis operators $\psi^{\uparrow}$ and $\omega^{\uparrow}$ are recursively applied (k times) to the input images $X_i, i=1\ldots n$. The multiresolution decomposition is obtained: $\overline{X}_i=\{X_i^k,Y_i^1,Y_i^2,\ldots Y_i^k\}$,

where X_i^k are the scales images on the kth level and $Y_i^j,\ j = 1\ldots k$ are the details on levels $1,2,\ldots k$ of the decomposition.

2. ***Fusion step***. $\{\overline{X}_i, i = 1,2,\ldots n\}$ are compared and combined to obtain $\overline{X} = \{X^k, Y^1, Y^2, \ldots Y^k\}$ where:

$$X^k(r,c) = max\{|X_1^k(r,c)|, |X_2^k(r,c)|, \ldots |X_n^k(r,c)|\}. \tag{12}$$

$$Y^j(r,c) = max\{|Y_1^j(r,c)|, |Y_2^j(r,c)|, \ldots |Y_n^j(r,c)|\}. \tag{13}$$

3. ***Synthesis step***. The fused image X^j for each level $j,\ j = k-1\ldots 0$ is obtained by applying the synthesis operators: $X^j(r,c) = \psi^{\downarrow}(X^{j+1}(r,c)) + \omega^{\downarrow}(Y^{j+1}(r,c))$

If the input matrices have values in range $[0,R]$ then the scaled images X_i^k have values in the same range $[0,R]$ and the values of details $Y_i^j,\ j = 1\ldots k$ are in the range $[-R,R]$.

The maximum value of $X_i^k, i = 1\ldots n$ corresponds to the brightest pixel. For $Y_i^j, i = 1\ldots n,\ j = 1\ldots k$ the greatest absolute value corresponds to contrast changes that appear on edges, lines or region boundaries.

In the fusion step of the algorithm above, the maximum absolute value is selected for each position of the morphological wavelet decompositions. Using this strategy, in the reconstruction step, for some positions, the synthesis operator is applied (8-11) to values y_v, y_h, y_d selected from different sources.

The proposed optimization is to select the three components y_v, y_h, y_d of the detail signal from the same source, corresponding to the greater value of:

$$\|Y_i^j(r,c)\| = (Y_{i(h)}^j(r,c))^2 + (Y_{i(v)}^j(r,c))^2 + (Y_{i(d)}^j(r,c))^2.$$

In the following section a comparison of the results obtained using the original and modified fusion algorithm is presented.

4 Fusion results evaluation

The results of the fusion procedure were evaluated using the similarity between 2 images in terms of the Roberts gradient operator [3]:

$$S(G,G') = 1 - \frac{\sqrt{\sum \left(G(r,c) - G'(r,c)\right)^2}}{\sqrt{\sum \left(G(r,c)\right)^2} + \sqrt{\sum \left(G'(r,c)\right)^2}} \qquad (14)$$

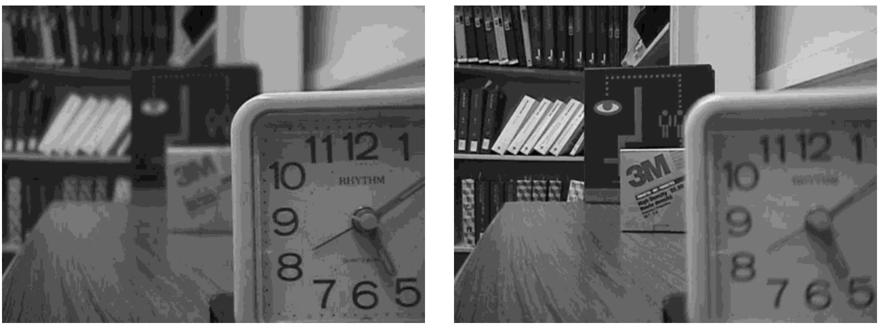
where $G(r,c) = max\{G_1(r,c), \ldots G_n(r,c)\}$ for all the positions (r,c) in the gradients $G_i, i = 1 \ldots n$ of the input images $X_i, i = 1 \ldots n$ and G' is the gradient of the fused image X'. $G(r,c)$ is the magnitude of Roberts operator defined bellow, for each position:

$$G(r,c) = \frac{1}{2}\left\{\left|X(r,c) - X(r+1,c+1)\right| + \left|X(r,c+1) - X(r+1,c)\right|\right\} \qquad (15)$$

The quality of the fused image is better when the similarity value is closest to 1.

The fusion method was tested on a set of multifocus images available on Internet (www.ece.lehigh.edu/SPCRL/IF/disk.htm). In the figures below are depicted the input images (fig. 1) and the fusion process results (fig. 2).

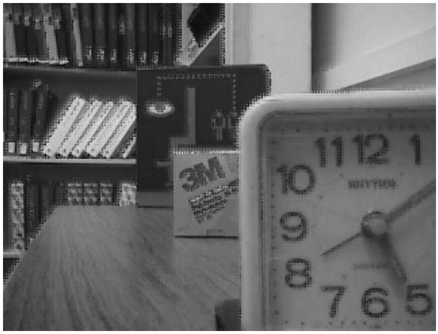
The similarity values computed using (14) for the fused images are summarized in the table below. The evaluation includes also the results obtained for two other methods: pixel level fusion based on gradient maximization and a fusion algorithm using a bilateral gradient based sharpness criteria [4].



a. disk1.png b. disk2.png

Figure 1. Input multifocus images

(a). fused_de_1.png



(b). fused_de_2.png

(c). fused_modif_1.png

(d). fused_modif_2.png

Figure 2. Image fusion results

Fusion method	**Similarity**
Morphological wavelet, decomposition on 1 level (fig.2.a)	0.741
Morphological wavelet, decomposition on 2 levels (fig.2.b)	0.617
Modified morphological wavelet, decomposition on 1 level (fig. 2.c)	**0.825**
Modified morphological wavelet, decomposition on 2 levels (fig. 2.d)	0.650
Pixel level fusion based on gradient maximization	0.780
Sharpness criteria based on bilateral gradient	0.768

It is noted that the fusion result is better in case of the modified fusion algorithm than in other applied methods. We note also that the results are superior if a single level of wavelet decomposition is applied. This is due to the fact that by applying higher levels of decomposition, the restored image contains blocks of pixels, visible even for the two level decompositions. The fusion algorithms were tested using an image processing application developed in C++ language for the Windows operating system.

5 Conclusion

Preserving the advantage of reduced computational costs the proposed method leads to a better similarity than the original algorithm of De and Chanda [3]. The research will continue with the analysis and implementation of other image fusion methods.

References

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