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Multi-modal medical image fusion based in Multiscale Alternative approach to cross bilateral filter

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Informations	Abstract
Keywords : Image fusion, multi-scale image decomposition • Visual saliency, cross bilateral filter, weight maps *Correspondence : dida.hedifa@univ-ouargla.dz	Image fusion is a process of combining additional information from source images into a single image. We are interested in this paper in the medical field where image fusion is a great advance in medical imaging because it helps the doctor to make his diagnosis. The aim of this paper is to propose a multi-scale method based on the cross bilateral filter, visual saliency detection, and weight map construction for image fusion. In the proposed image fusion approach, the cross bilateral filter is applied to one source image to obtain a base layer by considering another image for the guiding purpose. Whereas, the detail layers are computed by finding the difference between source image and the base layers and used for visual saliency extraction and weight maps construction. Later, base layers are averaged to get the final base layer. Finally, final base and detail layers are combined to obtain the fused image. The proposed method has been tested on a set of gray scale and color medical images. The results show that the proposed method can be competitive or even outperform the methods in comparison in terms of subjective and objective evaluations.

1. Introduction

Image fusion is an important branch of information science, [1] which has been widely used in many fields, such as bioinformatics, medical image processing, and military target visualization. Image fusion is the art of combining multiple images from different sensors to enhance the overall information content as compared to the limited data found in a single-sensor image [2]. The key problem of image fusion is how to extract salient features from the source images and how to combine them to generate the fused image.

In the field of medical imaging, [3] many imaging methods are used, among them, positron emission tomography (PET), single-photon emission tomography (SPECT), computer tomography (CT), and magnetic resonance imaging (MRI) are used to capture complementary information. The previously mentioned imaging methods differ according to the information they provide, for example, a CT scan provides information about the bone structure while an MRI provides information about soft tissues. Therefore, the combination of the two types of imaging methods provides more information regarding disease cases and increases the ability to diagnose.

Several Multiscale fusion algorithms have been proposed, included the Laplacian Pyramid [4], Wavelet transform [5], Curvelet transform [6], Contourlet Transform [7], Nonsubsampled Contourlet Transform [8]. Although these methods are widely used in integrating images in various applications, most of them fail to maintain a certain quality of the source images.

Bavirisetti et al. Proposed the cross bilateral filter (CBF) based algorithm that relies on analyzing, fusion, and then reconstructing images. This method is referred to as "Alternative approach to CBFF" or (ACBFF), more about this algorithm can be found in [2]. Despite the good results, it still needs to be developed in order to obtain a good fusion of images and to reduce the anomalies that hinder the diagnostic process in the medical field in particular. In this paper we present a new algorithm Multiscale Alternative approach to CBFF (MACBFF). In this algorithm the single-scale decomposition of user images in ACBFF has been replaced by multiscale image decomposition and an extension of this method is proposed for fusion of medical images in color.

This paper is structured as follows. In Section 2, we give a brief introduction to CGF for multi-scale decomposition. In Section 3, the proposed image fusion method is introduced in detail. The experimental results,

visual and quantitative evaluation are presented in Section 4. Finally, Section 5 draws the conclusion.

2. Decomposition and reconstruction by the CBF

The multi-scale decomposition allows the representation of edge information at different resolutions. Simultaneous use of CBF can help transfer edge structures at different scales. The main requirement of a merge algorithm is to transfer information from one image to another. Therefore, multiscale CBF operating in structure transfer mode can support this at different resolutions, thus improving performance [9].

A. Cross bilateral filter

The cross bilateral filter (CBF) performs the smoothing by considering the statistical properties of the neighborhood of a pixel[10]. It calculates the output as a linear time invariant (LTI) filter. However, it uses another image for guidance purposes. This additional image can be the entry or its translated version. You can also choose a completely different image for this purpose. Like other edge-preserving filters, CBF can also preserve edge information during the decomposition process, which helps to avoid artifacts[10]. Besides the edge preservation property, CBF also has another property called structure transfer property. If the guide image is the same as the input, then an edge preserving smoothing will be performed, while the structural behavior remains the same. On the other hand, when the guide image differs from the input, the smoothing process is regulated by the guide image structures. So when we apply CBF on images, the edge structures can be transferred.

Suppose that A and B are two different images, $G_{\sigma_s}(K-I)$ is the kernel space of A and $G_{\sigma_s}(B_K - B_I)$ is the kernel range calculated on the image B then the mathematical equation of the CBF is given by[9]:

$$A_{CBF}[B, A]_K = \frac{1}{W_K} \sum_{I \in S} G_{\sigma_s}(K-I) G_{\sigma_r}(B_K - B_I) A_I \quad (1)$$

Where

$$W_K = \sum_{I \in S} G_{\sigma_s}(K-I) G_{\sigma_s}(B_K - B_I) \quad (2)$$

$$G_{\sigma_s}(K-I) = \frac{1}{2\pi\sigma^2} \exp\left(-\frac{K-I^2}{2\sigma^2}\right) \quad (3)$$

G_{σ_s} is the Gaussian spatial kernel and G_{σ_r} is the Gaussian kernel of the scale. The parameters σ_s and σ_r are spatial and range parameters, which control the smoothing respectively.

The multiscale decomposition of the image I can be performed using CBF. Suppose that b^{n-1} , G^{n-1} are the base layer and the guide images at level $(n-1)$, σ_s and σ_r are the spatial and range parameters and r is the filter window size, then the base layer b^n can be calculated by performing a CBF of the image b^{n-1} considering G^{n-1} as the guide image. The d^n detail images can be calculated by taking the difference between the previous base layer

b^{n-1} and the current base layer b^n . These expressions are given by [*]:

$$b^n = CBF(b^{n-1}, G^{n-1}, \sigma_s, \sigma_r, r) \quad (4)$$

$$d^n = b^{n-1} - b^n \quad (5)$$

Where:

$$b^0 = I \quad (6)$$

The input image I can be reconstructed from base layer b^n and detail layers d^k , $k = (1, \dots, n)$ as follows [**]:

$$I = \sum_{k=1}^n d^k + b^n \quad (7)$$

This multiscale decomposition and reconstruction process is illustrated by algorithm 1 and figure 1.

Algorithm 1: Decomposition and reconstruction of an image by the CBF.

Inputs: Image to filter I, guidance image G^0 , σ_s , σ_r , r and the number of levels n

Outputs: Reconstructed image I and base layers and details (b^k, d^k)

1. $b^0 = I$
2. For $k = 1, 2, 3, \dots, n$ do
 - $b^k = CBF(b^{k-1}, G^{k-1}, \sigma_s, \sigma_r, r)$
 - $d^k = b^{k-1} - b^k$
- End for
3. $I = \sum_{k=1}^n d^k + b^n$

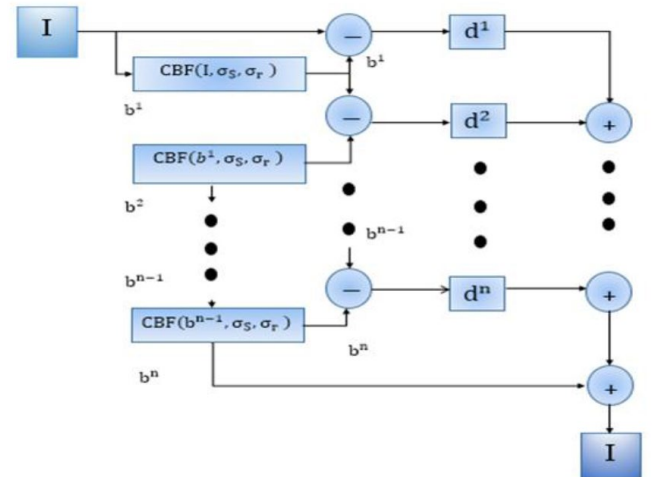


Fig. 1. Functional diagram of the multi-scale image decomposition and reconstruction of an I image by the CBF.

3. Proposed image fusion method

The proposed method MACBFF requires the following steps to perform the merge:

Multi-scale decomposition of source images using CBF.

- Generation of visual saliencies of each input image at different levels.
- Calculation of weight maps corresponding to detail layers.
- Combine detail layers using weight maps
- Generation of the final fused image.

B. Multi-scale image decomposition

Consider two source images I_1 and I_2 of the same size. These two images are decomposed by CBF to a base layer B containing large scale variations and detail layer D containing small scale variations as follows [3]:

$$B_1^k = \begin{cases} I_1 & \text{si } k = 0 \\ CBF(B_1^{k-1}, B_2^{k-1}, \sigma_s, \sigma_r, r) & \text{si } k = 1, \dots, n \end{cases} \quad (8)$$

$$B_2^k = \begin{cases} I_2 & \text{si } k = 0 \\ CBF(B_2^{k-1}, B_1^{k-1}, \sigma_s, \sigma_r, r) & \text{si } k = 1, \dots, n \end{cases} \quad (9)$$

Where B_1^k, B_2^k are base layers of two source images at k level which depend on their previous level base layers B_1^{k-1}, B_2^{k-1} respectively. The detail layers D_1^k, D_2^k are obtained by finding the difference between the previous and current level base layers:

$$D_1^k = B_1^{k-1} - B_1^k, k = 1, \dots, n \quad (10)$$

$$D_2^k = B_1^{k-1} - B_2^k, k = 1, \dots, n \quad (11)$$

C. Generation of visual salience maps

Visually salience maps of source images are calculated by taking the absolute value of the detail layers D_1^k, D_2^k as follows:

$$S_1^k = |D_1^k| \quad (12)$$

$$S_2^k = |D_2^k| \quad (13)$$

D. Calculation of the weight map:

We need to integrate all the targeted regions into a single fused image. Weight maps representing complementary information based on salience information can automatically integrate detail layer. The weight maps W_1^k and W_2^k are calculated by normalizing the extracted saliency maps as follows:

$$W_1^k = \frac{S_1^k}{\sum_{i=1}^2 S_i^k}, k = 1, 2, \dots, n \quad (14)$$

$$W_2^k = \frac{S_2^k}{\sum_{i=1}^2 S_i^k}, k = 1, 2, \dots, n \quad (15)$$

E. Detail layer fusion

The detail layers are built into each k scale using the W_1^k and W_2^k weight maps using a linear combination:

$$D_F^k = W_1^k D_1^k + W_2^k D_2^k \quad (16)$$

The final detail layer D_F is obtained by combining fused detail layers obtained at each scale. This fused detail image D_F provides most of the visual information of the fused image:

$$D_F = \sum_{k=1}^n D_F^k \quad (17)$$

F. Base layer Fusion

The final base layer B_F is generated by taking the average of the base layers at the final scale n as:

$$B_F = \frac{1}{2}(B_1^n + B_2^n) \quad (18)$$

G. Reconstruction of the fused image

The fused image is obtained by combining the base layer B_F and the detail layer D_F :

$$F = B_F + D_F \quad (19)$$

Figure II.2 presents and summarizes the functional diagram of the MACBFF method and Algorithm II.3 summarizes the necessary steps of image fusion by the MACBFF method.

Algorithm 2 Image fusion using the MACBFF method

Inputs: source images I_1 & I_2 , σ_s, σ_r, r and n

Outputs: Fused image F

1. $B_1^0 = I_1, B_2^0 = I_2$

2. **For** $k = 1, 2, 3, \dots, n$ **do**

$$B_1^k = CBF(B_1^{k-1}, B_2^{k-1}, \sigma_s, \sigma_r, r)$$

$$B_2^k = CBF(B_2^{k-1}, B_1^{k-1}, \sigma_s, \sigma_r, r)$$

$$D_1^k = B_1^{k-1} - B_1^k$$

$$D_2^k = B_1^{k-1} - B_2^k$$

$$S_1^k = |D_1^k|$$

$$S_2^k = |D_2^k|$$

$$W_1^k = \frac{S_1^k}{\sum_{i=1}^2 S_i^k}$$

$$W_2^k = \frac{S_2^k}{\sum_{i=1}^2 S_i^k}$$

$$D_F^k = W_1^k D_1^k + W_2^k D_2^k$$

End for

$$3. D_F = \sum_{k=1}^n D_F^k$$

$$4. B_F = \frac{1}{2} (B_1^n + B_2^n)$$

$$5. F = B_F + D_F$$

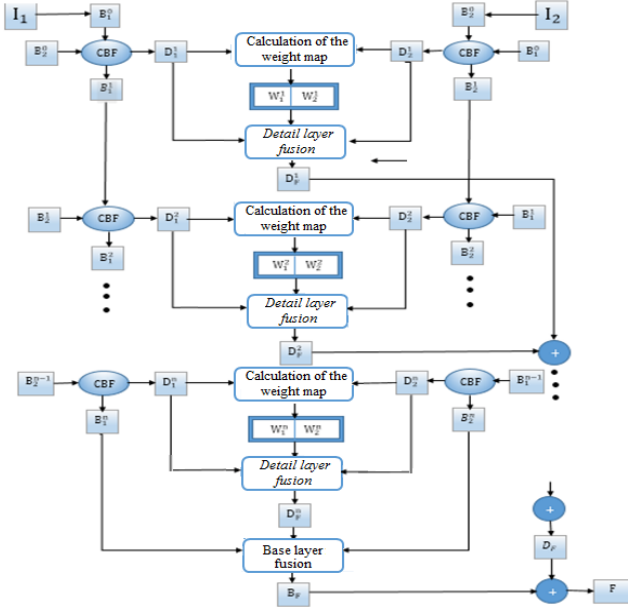


Fig. 2. . Functional diagram of the ACBFF method.

H. Extension of the CBFF method to color medical images

For medical images, there are two types of images; MRI and CT images are grayscale images while PET and SPECT images are color images. The principle of the proposed MACBFF is presented in figure 3, and have the following steps:

- Convert the three bands of the RGB space of the medical image to the YUV space.
- Where Y is the luminance, U and V are the blue and red complements.
- Apply the CBFF method between the Y intensity component of the color medical image (PET or SPECT) and the intensity of the grayscale image (MRI or CT) to obtain the fused Y intensity component.
- Switching from YUV color space to RGB color space to obtain a color fused image.

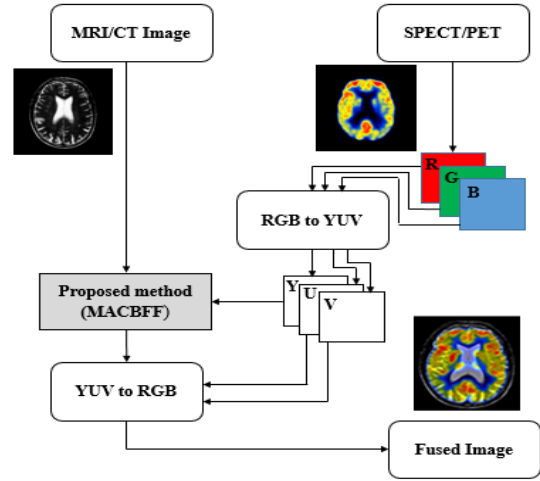
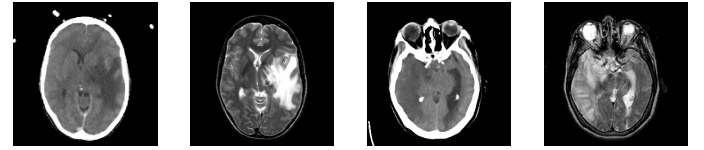


Fig. 3. Methodology used to fuse MRI/CT and SPECT/PET medical images.

4. Experiments and analysis

I. Image Resources

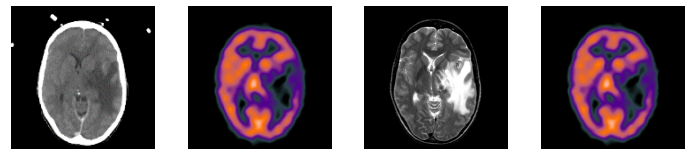
We have chosen two pairs of medical images in gray level (CT / MRI) which are represented in (figure 4.), and three pairs of medical images in color / gray level (CT/SPECT), (MRI/SPECT and (MRI/PET) which are shown in (Figure 4) , and which are available at the web <http://www.med.harvard.edu/AANLIB/home.html> [10]



(a) CT/ MRI-1 Image pair

(b) CT/MRI-2 Image pair

Fig. 4. Image pairs used for the MACBFF in in gray level.



(a) CT/ SPECT Image pair

(b) MRI/ SPECT Image pair



(c) MRI/ PET Image pair

Fig. 5. Image pairs used for the MACBFF in in gray/ color level.

J. Objective performance evaluation

To evaluate the performance of the proposed fusion method, several objective criteria are used:

- Average Pixel Intensity (API) measures an index of contrast.
- Standard Deviation (SD) is the square root of the variance, which reflects the spread in data.

- Entropy (E) estimates the amount of information present in the image.
- Mutual Information (MI) quantifies the overall mutual information between source images and fused image.
- Information Symmetry or Fusion Symmetry (FS) indicates how much symmetric the fused image is with respect to source images.
- Correlation Coefficient (CC) measures a relevance of fused image to source images.
- Total fusion performance $Q^{AB/F}$ measures the quantity of edge information that is transferred to the fused image from source images
- Fusion loss $L^{AB/F}$ allows for assessment of the information lost during the fusion process.
- Fusion artifacts $N^{AB/F}$ allows assessing the artifacts introduced into the fused image.

Higher values of $Q^{AB/F}$, API, SD, H, MI, FS, and CC indicate a better fusion quality of the fused image, and when the values of $L^{AB/F}$ and $N^{AB/F}$ are small, the fusion performance is better.

K. Quantitative analysis

In this study, we will combine five pairs of medical images of a human brain, these images were obtained from different imaging methods, as shown in Figures 4 and 5. Image pairs are (CT/ MRI_1) and (CT/ MRI_2), (CT/ SPECT), (MRI/ SPECT), and (MRI/ PET), respectively. The results obtained are analyzed with the nine validation parameters, and quantitative analysis of various image pairs used are shown in Tables 1, 2, 3, 4 and 5. Where the best values are highlighted in bold.

Table 1 Quantitative analysis of various fusion algorithms for CT/MRI-1 image pair.

Method	MACBFF	TIF	ACBFF
API	60.246	56.342	51.054
SD	77.324	73.504	66.290
E	4.369	4.262	4.341
MI	3.199	2.941	2.996
FS	1.999	1.979	1.952
CC	0.971	0.965	0.971
$Q^{AB/F}$	0.784	0.764	0.814
$L^{AB/F}$	0.208	0.223	0.170
$N^{AB/F}$	0.006	0.011	0.015

Table 2 Quantitative analysis of various fusion algorithms for CT/ MRI-2 image pair.

Method	MACBFF	TIF	ACBFF
API	45.094	44.726	44.93
SD	56.130	55.732	54.929
E	5.091	5.191	5.352
MI	3.503	3.544	4.377
FS	1.962	1.961	1.89
CC	0.982	0.981	0.98

$Q^{AB/F}$	0.806	0.791	0.802
$L^{AB/F}$	0.171	0.176	0.183
$N^{AB/F}$	0.022	0.031	0.014

Table 4 Quantitative analysis of various fusion algorithms for CT/ SPECT image pair.

Method	MACBFF	TIF	ACBFF
API	53.386	51.525	52.335
SD	70.6	70	70.45
E	4.094	4.212	4.198
MI	3.907	3.141	3.259
FS	1.993	1.992	1.941
CC	0.996	0.978	0.993
$Q^{AB/F}$	0.874	0.879	0.901
$L^{AB/F}$	0.120	0.106	0.083
$N^{AB/F}$	0.005	0.014	0.015

Table 4 Quantitative analysis of various fusion algorithms for MRI/ SPECT image pair.

Method	MACBFF	TIF	ACBFF
API	46.322	40.774	41.192
SD	64.902	57.102	58.886
E	4.27	4.2	4.29
MI	3.718	2.674	3.265
FS	1.986	1.971	1.878
CC	0.986	0.974	0.983
$Q^{AB/F}$	0.793	0.793	0.862
$L^{AB/F}$	0.199	0.185	0.118
$N^{AB/F}$	0.007	0.021	0.018

Table 5 Quantitative analysis of various fusion algorithms for MRI/ PET image pair.

Method	MACBFF	TIF	ACBFF
API	55.666	45.23	38.39
SD	79.22	67.4	63.121
E	4.364	4.325	4.547
MI	3.466	2.887	3.839
FS	1.958	1.99	1.834
CC	0.842	0.836	0.837
$Q^{AB/F}$	0.703	0.711	0.841
$L^{AB/F}$	0.282	0.263	0.142
$N^{AB/F}$	0.013	0.025	0.016

Through the obtained results, the proposed algorithm showed a good ability to achieve fusion of medical images with high accuracy compared to other methods. Tables 3, 2, 1, and 4 of the 2 and 3 pairs respectively show that MACBFF gives good results in most validation parameters, while Table 1 shows an equivalent performance between the proposed method and the other methods.

L. Qualitative analysis

Consider the pairs of medical images taken from the different imaging methods (CT, MRI, PET, SPECT) as

shown in Fig 4 and 5. As explained in Section 1, each imaging method can show some information about the disease to be diagnosed, but it does not show some information that could be in the other imaging method, as is the case with CT and MRI. Therefore, it is necessary to combine two images from two different imaging methods into one image using the fusion process in order to properly diagnose and treat the disease.

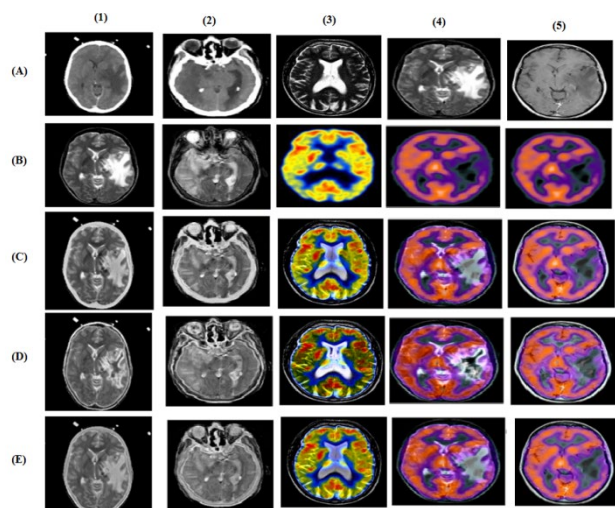


Fig. 6. Multimodal fusion results of medical images (a) Source image 1 (B) Source image 2, fused images obtained by the (C) TIF (D) ACBFF (E) Proposed method MACBFF.

Visual quality analysis of different fusion methods for images are presented in Figure 3. Figure 6a and b show the source images for the different imaging methods that have been combined, while Fig. 6C, D, and E show the visual results of the recording process using the TIF, ACBFF, and MACBFF methods, respectively. From the visual results, it appears that the proposed method gives a picture free of distortions and is clearer for the diagnosis of the disease compared to the TIF and ACBFF methods, which show some distortions in the fused image.

5. Conclusion

A new image fusion algorithm has been proposed by adopting multi-scale decomposition of source images using CBF. As this method was devised from a method "Alternative approach to CBFF" or ACBFF. To confirm the superiority of the proposed algorithm, it was applied to five pairs of different medical images, and based in nine evaluation metrics. Results reveal that proposed method is well suited for medical image processing. Our method showed promising results compared to the other two fusion methods.

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