International Journal on Emerging Technologies 11(3): 122-126(2020)

ISSN No. (Print): 0975-8364
ISSN No. (Online): 2249-3255

Approximation Layer based Weighted Average Image Fusion using Guided Filter for Medical Images

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(Received 23 January 2020, Revised 24 March 2020, Accepted 27 March 2020)
(Published by Research Trend, Website: www.researchtrend.net)

ABSTRACT: In this paper, we developed Approximation layers based Weighted Average Image Fusion using Guided Filter for Medical images. The proposed algorithm is very efficient and requires less computational time. Medical image fusion is a technique for clinical imaging analysis that is rapidly emerging as a research area present day. It helps in identifying abnormalities. Medical Imaging technique provides visual images of the interior body's targeted organ (or) tissues in which we collect all the necessary information (or) complementary information based on the application. All the required information from the opted imaging modalities has to be combined to form a single output image. So here the challenge is to combine all the required information of opted image modalities to take accurate decisions clinically. Therefore, we proposed a Multi-modal fusion algorithm for medical images shown remarkable attainment in enhancing accurate decisions in medical images clinically. In comparison with recently existed methods, the proposed method yields greater values of fusion metrics for the presented medical data sets. Various performance evaluation metrics for a few data sets are taken experimentally and compared with other existed methods to analyze the evaluation of the proposed method visually and quantitatively.

Keywords: Fusion Metrics, Guided Filter, Image Fusion, Layer Fusion, Medical Imaging, Weighted Average, Weight Map.

I. INTRODUCTION

The Image Fusion, reduce some data, and retains necessary information, generates fused images most likely to be used for human/machine understanding for analysis. The spatial and Transform domain are the two most used domains where we can perform multi-view, multi-modal, multi-temporal and multi-focus [13] Fusion techniques. We can perform distinct levels of abstractions in image fusion such as the pixel level, Feature level, and Decision level [15]. The computer vision, medical and microscopic imaging and remote sensing are some of the applications of the image fusion. We have three simple Fusion rules namely Simple average, Select maximum, and select minimum.

A. Pre-processing of image Fusion

The Pre-Processing steps involved in generating the fusion image are shown in Fig. 1. The Image Registration transforms different datasets into one coordinate system. There are two Categories of image registrations namely Intensity-based and Feature-based where correlation metrics are used for image intensity patterns and the features that are to be registered such as points, lines, and contours present in the images are compared respectively.

Image Resampling is the process of changing the dimension of the pixel of an image. For conducting fusion, the images should have the same pixel dimensions. There are three Methods: nearest neighbor, bilinear, and bi-cubic (cubic convolution). Medical Image Fusion is the process where several images having the same modalities are merged or overlapped for further analysis in treating and diagnosis of patient medical conditions.

The motivation behind image fusion combination isn't just to diminish the measure of information yet in addition to build images that are increasingly suitable and justifiable for the human and machine discernment. The traditional methods discussed in previous work uses more than two scales to obtain the satisfactory results but we use a guided filter as local filtering of fusion, also spatial consistency is controlled through adjusting the parameters of the guided filter.

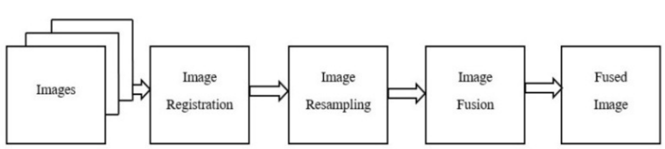

Fig. 1. Pre-processing of Image Fusion.

The widely used medical image modalities are such as MR-T1, MR-T2, CT, SPECT, and PET techniques. Each modality has an individual feature in medical diagnosis, whereas each modality has challenges in pathology. In this paper, we considered MR-T1 from BRATS 2015 dataset, CT from NIH dataset medical image modalities as first source image and second source images respectively. The generalized fusion consists of, enhancement algorithms, decomposition techniques, fusion rules, and performance measures. The pixel-based averaging rules were generally used for complementary information fusion. The features based fusion algorithms for images usually combines the region of interest of multiple- input multi-modalities that is it extracts various features like edges, corners, and lines from different source images and combines them into one (or) more featured maps that may be used for the future purpose of further processing. The pixel-level image fusion is a simple technique in image fusion that can be done at the lowest level.

II. PREVIOUS WORK

Requirements that must be satisfied for a productive pixel-level fusion of image are that the fused image ought to preserve necessary information provided in input images and it must not produce any artifacts. The following four methods show previous work. These four methods we used as a literature review.

A. Method-1

Image Fusion using Cross Bilateral Filter (CBF) [1, 2] has applications in image denoising, image (or) video fusion, etc. The CBF uses a second source image to operate on the first source image by finding the kernel and vice versa. The Procedure involved for Image fusion using CBF is as follow:
– Consider two images having the same modalities as source images.
– Over both source images, apply the cross bilateral filter (CBF) [1, 2].
– Generate the detailed image by the subtraction of the output of CBF filter from the original image.
– Weights can be obtained with the strength of details from the detail image
– Perform weight normalization.

B. Method-2

Discrete Wavelet Transform (DWT) [3-5] generates wavelet coefficients by performing transforms on source images. The Fusion rules applied to these coefficients and inverse wavelet transform in the spatial domain brings the fused image. The Procedure involved for Image fusion using DWT is as follow:
– Consider two source images.
– Perform wavelet transform on the source image and generate wavelet coefficients.
– On the obtained wavelet coefficients apply Fusion rules.
Apply inverse wavelet transform in spatial domain to get fused image on fused coefficients.

C. Method-3

Image Fusion using Guided Filter (GF) [6-8] method utilizes spatial regularity for base and detail layers for fusion. Image fusion with a Guided filter is obtained by performing three steps namely two-scale decomposition and two-scale construction by performing weight map construction. The procedure involved in Image Fusion using GF is as follow:
– Consider two source images.
– The two-scale representations can be obtained by the use of an average filter.
– Using GF based weighted average [12, 14] technique, fuse the base and detail layers.

D. Method-4

Principal Component Analysis (PCA) [9-11] produces the principal components by converting the correlated variable into the uncorrelated values from the set of observations [6]. The PCA algorithm fundamentally creates the results of the fusion image by the weighted pixels average values at each pixel location for all pixels of the source images. The procedure involved here is as follow:
– Consider two source images I_1, I_2 and perform PCA as shown in the below steps.
– Determine first source image I_1 pixel values and generate Eigen values.
– Determine the Eigenvectors for the Eigen values generated and arrange them in the descending order of their Eigenvectors. The maximum value (P1) is considered and a multiplier is used to multiply both I_1 and P_1. Then the product is (I_1P_1).
– Perform the same operation on the source image, I_2.
Outputs from both the multipliers are added to get the fused image.

III. PROPOSED WORK

The proposed work creates a fused image, more focused and sharpened by preserving its edges with less computational time which is shown in Fig. 2. In contrast to the previous work fusion methods, the method in proposed work uses an average filter and hence is computationally simple and efficient. To find the weight of a pixel at the location (x, y) of an image, it depends on horizontal and vertical edge strengths. The Weight map is constructed using image statistics for guided filtered approximations and later approximation layer fusion is accomplished by guided filtered approximations and weight map computation. Detail layer fusion is acquired by fusing details of the guided filtering of two images. The fused image finally is acquired by integrating the fused approximation layer and fused detail layer.

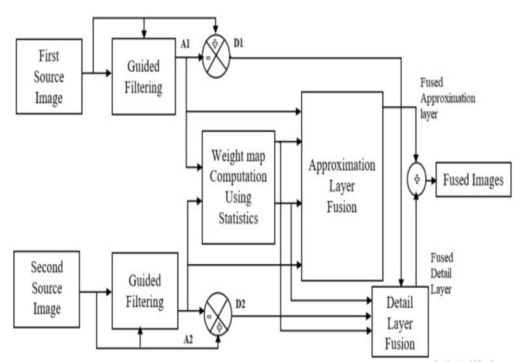

Fig. 2. Block Diagram of Proposed Work: Approximation Layer based Weighted Average Image Fusion using Guided Filter.

A. Algorithm for Proposed Work

Steps	**Algorithm for proposed work**
Step 1	Firstly read the two source images where input image, F_{in} and guidance image, G_d.
Step 2	Consider local window radius(r) and regularization parameter ε.
Step 3	Estimate mean and variance values of F_{in}, G_d along with their average cross product.
Step 4	Compute the following values. a = cov G_d F_{in}./ (var G_d + ε) b = mean F_{in} -a.* mean G_d
Step 5	Determine the mean values for above computed values a and b.
Step 6	Perform the following by the mean values of a and b to obtain the filtered image q. q= mean a.*G_d + mean b

IV. RESULTS DISCUSSION

The Fused Image is an integration of two or more source images containing all the necessary information. It should be evaluated qualitatively by visual representation and quantitatively by measuring fusion metrics. The Fusion of MR/CT images combines anatomical and physiological characteristics of the human body, more precisely, CT imaging provides better information on denser tissue with less distortion. MR images have more distortion but can provide information on soft tissue. Here we extracted features from source images such as edges or regions and combine them into a single fused image

A. Qualitative Analysis

Consider different medical image datasets. Here we considered four datasets. Visual (Perceptible) analysis of dataset 1 for various fusion methods CBF, GFF, PCA, and DWT are shown in Fig. 3 for source images 1 and 2 are 3(A) and 3(B), the fused output for the proposed method is displayed in 3(G) and fused image for method CBF as 3(C), GFF as 3(D), PCA as 3(E) and DWT as 3(F). Sharpened image is more observed for the proposed fused image. Likewise, the visual analysis of datasets 2, 3 and dataset 4 are shown in Fig. 4, 5 and 6 respectively for various fusion methods CBF, GFF, PCA, and DWT simultaneously.

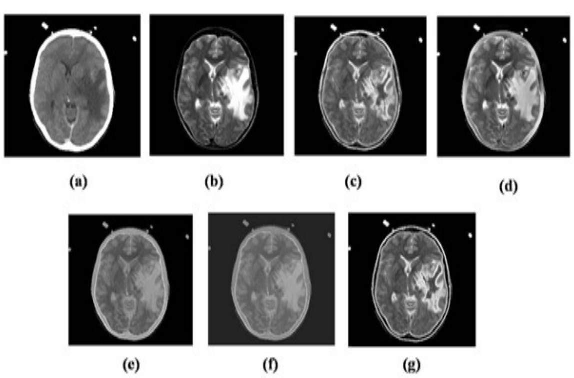

Fig. 3. Different Fusion Methods Qualitative Analysis on Dataset-1: (a) First Source image (b) Second Source image (c) CBF (d) GFF (e) PCA (f) DWT and (g) Proposed Method.

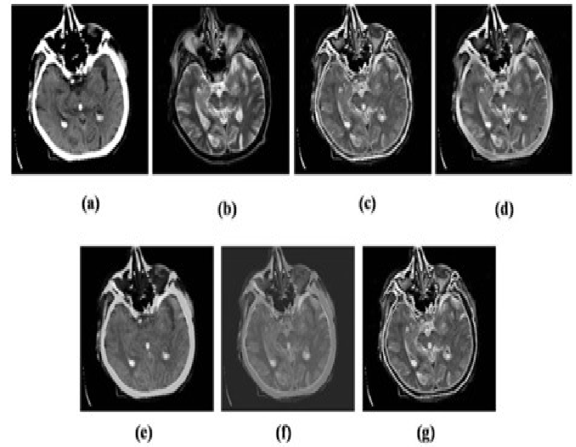

Fig. 4. Different Fusion Methods Qualitative Analysis on Dataset-2: (a) First Source Image (b) Second Source Image (c) CBF (d) GFF (e) PCA (f) DWT and (g) Proposed Method.

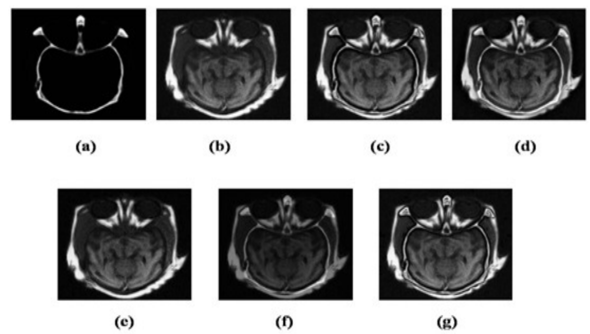

Fig. 5. Different Fusion Methods Qualitative Analysis on Dataset 3: (a) First Source Image (b) Second Source Image (c) CBF (d) GFF (e) PCA (f) DWT and (g) Proposed Method.

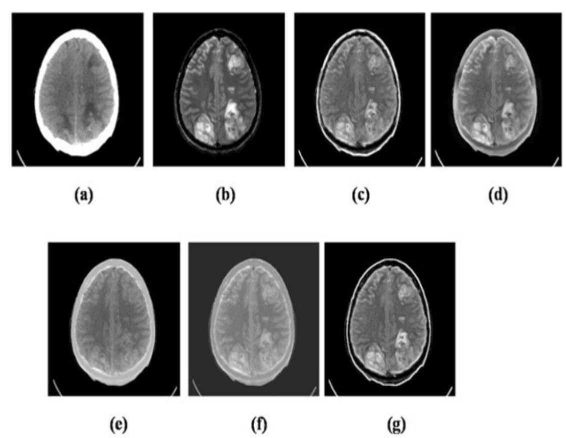

Fig. 6. Different Fusion Methods Qualitative Analysis on Dataset 4: (a) First Source Image (b) Second Source Image (c) CBF (d) GFF (e) PCA (f) DWT and (g) Proposed Method.

B. Performance Measures

Average Pixel Intensity (API): It is the measure of the average index of a contrast of an image.

$$\mathrm{API}= \overline{\mathrm{F}} = \frac{\sum_{p=1}^{M} \sum_{q=1}^{N} F_{in}(p,q)^{\,1}}{MN} \quad (1)$$

Where the intensity of the pixel at a location (p,q) is $F_{in}(p,q)$ and the size of an image is MxN.

Standard Deviation (σ): It estimates the fused image contrast. If more the contrast then more will be the Standard deviation.

$$SD=\sqrt{\frac{\sum_{p=1}^{M}\sum_{q=1}^{N}(F_{in}(p,q)-\bar{F})^{2}}{MN}} \quad (2)$$

Average Gradient (AG): It determines the sharpness and amount of clarity in an image by the directional change in the intensity or color, and is given by

$$AG=\frac{\sum_p\sum_q((F_{in}(p,q)-F_{in}(p+1,q))^2+(F_{in}(p,q)-F_{in}(p,q+1))^2)^{1/2}}{MN} \quad (3)$$

Mutual information (MI): The better quality of images will have larger MI value which is the estimation of similar image intensity between reference and fused image.

$$MI=\sum_{p=1}^{M}\sum_{q=1}^{N} hI_RI_F(p,q)\log_2\frac{hI_RI_F(p,q)}{hI_R(p,q)hI_F(p,q)} \quad (4)$$

Spatial Frequency (SF): It evaluates the frequency in the fused image represents the whole activity level.

$$SF=(RF^2+CF^2)^{1/2} \quad (5)$$

Where

$$RF=\sqrt{\frac{\sum_p\sum_q(F_{in}(p,q)-F_{in}(p,q-1))^2}{MN}} \quad (6)$$

$$CF=\sqrt{\frac{\sum_p\sum_q(F_{in}(p,q)-F_{in}(p-1,q))^2}{MN}} \quad (7)$$

Fusion Information score $Q^{XY/F}$: This is indicated by $Q^{XY/F}$, where source images are indicated by X, Y and fused image is F. The $Q^{XY/F}$ measures the overall information which is transferred between input image and the final output image that is fused.

C. Quantitative Analysis

The Quantitative analysis is performed by evaluating fusion metrics API, SD, AG, MI, SF and $Q^{XY/F}$ for various fusion methods CBF, GFF, PCA, DWT, and Proposed method are shown in Table 1, 2, 3 and 4 respectively for four datasets.

The Fused image with high metric values possesses to be the best-qualified image. From Table 1, it is noticed that GFF yields high API and SD values and the proposed method having the highest AG, SF, and $Q^{XY/F}$ values. Similarly in Table 2, 3 and 4, the proposed method yields higher AG, SF, and $Q^{XY/F}$ values.

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Table 1: Fusion Performance Measure for Dataset 1.

Method	Fusion Performance Measure for Dataset 1					
	API	SD	AG	MI	SF	$Q^{XY/F}$
Proposed	49.765	67.215	13.521	3.601	35.423	0.827
CBF	51.049	66.125	11.881	3.470	29.449	0.788
GFF	53.743	66.125	9.015	3.149	24.193	0.788
PCA	51.590	61.591	6.343	3.838	17.812	0.609
DWT	50.684	60.649	8.331	3.300	20.485	0.588

Table 2: Fusion Performance Measure for Dataset 2.

Method	Fusion Performance Measure for Dataset 2					
	API	SD	AG	MI	SF	$Q^{XY/F}$
Proposed	52.310	66.176	20.067	3.481	44.395	0.804
CBF	54.226	66.336	18.192	3.305	39.224	0.785
GFF	54.734	66.956	14.099	2.895	33.712	0.772
PCA	53.589	66.014	11.141	4.044	28.439	0.677
DWT	50.515	57.18	14.005	2.985	28.103	0.570

Table 3: Fusion Performance Measure for Dataset 3.

Method	Fusion Performance Measure for Dataset 3					
	API	SD	AG	MI	SF	$Q^{XY/F}$
Proposed	55.419	57.879	11.54	5.611	21.100	0.911
CBF	54.735	57.690	11.033	5.329	19.816	0.893
GFF	50.734	55.477	9.553	3.387	17.464	0.908
PCA	51.725	54.240	7.646	6.267	13.750	0.634
DWT	32.076	35.025	6.288	3.724	11.625	0.640

Table 4: Fusion Performance Measure for Dataset 4.

Method	Fusion Performance Measure for Dataset 4					
	API	SD	AG	MI	SF	$Q^{XY/F}$
Proposed	47.110	65.501	11.542	3.471	33.974	0.830
CBF	49.831	66.492	10.650	3.283	29.736	0.824
GFF	55.518	68.421	7.516	2.830	22.950	0.802
PCA	58.075	71.405	5.767	3.835	19.085	0.672
DWT	52.630	63.21	7.168	3.001	18.034	0.610

V. CONCLUSION

Image Fusion reads various images of a similar scene and retrieves important information from them and forms one output image. The final fused image is additional instructive and worthy of visual perception compared to other images provided which thereby enhances the quality of the image and data applicability depending on the application. It is used in disparate fields like medical imaging, computer vision, remote sensing, manufacturing process, medical image fusion, etc. Every fusion method has some advantages and drawbacks. Therefore to conclude, no algorithm used for fusion surpasses the others. A meld of qualitative and quantitative evaluation procedures may be the finest way to discover which fusion algorithm fits the most for a particular application.

VI. FUTURE SCOPE

The present study is on the MR-T1 and MR-T2 image data sets. We can observe the performance metrics of this algorithm on ultrasound images. Also, there is scope for performing image fusion by taking the color image and is the big challenge now.

ACKNOWLEDGMENT

We confirm that the manuscript has been read and approved by all named authors and that there are no other persons who satisfied the criteria for authorship but are not listed. We further confirm that the order of authors listed in the manuscript has been approved by all of us. We wish to confirm that there are no known conflicts of interest associated with this publication and there has been no significant financial support for this work that could have influenced its outcome.

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How to cite this article: Gopatoti, A., Billa, P. and Gopathoti, K. K. (2020). Approximation Layer based Weighted Average Image Fusion using Guided Filter for Medical Images. *International Journal on Emerging Technologies*, *11*(3): 122–126.