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Guided Image Filter based Multimodal Medical Image Fusion

[1]Maruturi Haribabu, [2]Ch. Hima Bindu

[1]Assistant Professor, [2]Professor

[1,2]Department of ECE, QIS College of Engineering & Technology,

Ongole, Andhra Pradesh, India.

Abstract-Complementary data about a particular organ will be recorded during medical imaging using various modalities, such as MRI and CT. For improved diagnosis and treatment, all the pertinent data from these two modalities must be combined into a single image. Patient care is provided. It is the concept of merging information from various images that is helpful or complementary into a single image. In this work, we provide MRI and CT brain scans will be combined using a weighted average fusion method. Based on the image statistics and a guided image filter (GIF). The recommended method is as follows: the guided image filter is used to extract detail layers from each source image. Each source image's weights are determined using the statistics about images. Afterward, a weighted average fusion approach is put into practice .To combine data from multiple source images into one. Performance of fusion is statistically and qualitatively evaluated. Comparison between the proposed approach and strategies for fusing images that are both old and new. The outcomes indicated that our algorithm produces a higher performance**.**

Index Terms- datasets, GIF, Image fusion, Statistical Measurements.

1. INTRODUCTION

Different modalities are employed in medical imaging to collect supplementary data, including positron emission tomography (PET), single photon emission tomography (SPECT), computer tomography (CT), and magnetic resonance imaging (MRI). For instance, as seen in Fig 2, the CT image on the left gives information about hard tissues like bone, whereas the MRI image on the right gives information about soft tissues like flesh. For better diagnosis and therapy, a radiologist requires information from both the CT & MRI scans in a single picture. Therefore, it is necessary to incorporate relevant or complimentary information from many sensing technologies into an image. The technique of merging information from different source images into a single picture is known as image fusion. In computer assisted surgery, this merged image is useful. In this paper, we focused on the combination of "human brain" CT and MRI scans. Three layers can be used to perform the fusion process. They are the symbolic or choice level, the objective or feature level, and the pixel or signal level. In pixel-level image fusion, the information present in the co-registered input picture is processed pixel by pixel. In [1-3] offer contributions in this area. In objective level image fusion, object labels, features, and property descriptors that were derived from each source image were combined. A high-level fusion is symbolic level image fusion. Local decision-makers are derived from the findings of the objective level fusion in this case. The information about these decision makers' probabilistic judgments is then fused. The topic of this article is pixel-level fusion.

The remainder of the paper is structured as follows. The associated work is summarized in Section II. The suggested strategy is presented in Section III. The fusion metrics are described in Section IV. The experimental setup is covered in Section V. The article is concluded in Section VI.

2. RELATED WORK

In this regard, many pixel-level methods have been developed during the previous several decades for spatially registering pictures. Pixel-level image fusion may be widely characterized depending on the methods utilized, such as Edge-preserving approaches (EPF), Multi-resolution decomposition, artificial neural networks (ANN), and nonlinear operators. Min, and Max, are utilized in nonlinear techniques to achieve the aim of fusion. But generally speaking, this issue is challenging to resolve. By calculating edge aligned weights, Markov random field and generalized random walk approaches address this issue .Multiple rounds may have overly smoothed the merged image. Additionally, by drawing inspiration from biological signal fusion, ANNs have attracted a lot of attention in the field of image fusion. In addition to the fusion strategies mentioned above, multi resolution schemes have been extremely important. The HVS is able to detect even minute changes in edge information. Multi-resolution techniques include wavelet decomposition and image pyramid. Transform domain analysis is required for these strategies. Each image is broken down into a group of LPF images via an image pyramid. Each filtered image conveys the data of the original image in various scales [4-6].Successful multi-resolution fusion techniques in this category involve discrete wavelet transform (DWT) decompositions. Pyramid offers fewer advantages than DWT. It offers a concise representation and directional data for an image. These characteristics of DWT make it appropriate for fusion. Pyramid fused images have more blocking effects than wavelet fused images. Due to its multi rate operations, DWT is a shift version. The fused image may contain certain artifacts as a result of this shift variation characteristic. SWT, or stationary wavelet transform, was developed to address the DWT's drawbacks. Describe SWT image fusion techniques for images. Edge-preserving methods make up the final group of picture fusion strategies. The most modern EPF based image fusion techniques include edge preserving L0-gradient minimization, weighted least filter, guided image filters (GFF), anisotropic diffusion, and others. Compared to other of the multi scale decomposition algorithms, edge preserving filters are more trustworthy in extracting salient information (lines and details). For instance, linear filtering in pyramid decomposition may result in halo effects around the edges, whereas these filters use nonlinear filtering instead. For the extraction of salient information from detail layers, we favor guided image filters (GF). This edge-preserving filter, which was very recently proposed, offers the best edge information. The trade-off between edge preservation and blurring is favorable. It is a non-iterative technique that requires less processing time than anisotropic diffusion. In this paper, we provide a brand-new edge-preserving guided image filter-based weighted superposition image fusion technique [7-8].

3. **PROPOSED WORK**The fundamental principle of our suggested solution is to sharpen the source photos by subtracting the blurred images from the matching source images after blurring the source images using GF. For the purpose of calculating weights for fusion, use the details of sharpened photos. We have illustrated this method's steps with visuals for easier comprehension by outlining the changes made at each one. There are two main steps in this algorithm. The first step is to use GF to obtain the detail layer images. Using a fusion strategy based on entropy, combine the detail images. Here is an explanation of the suggested methodology.

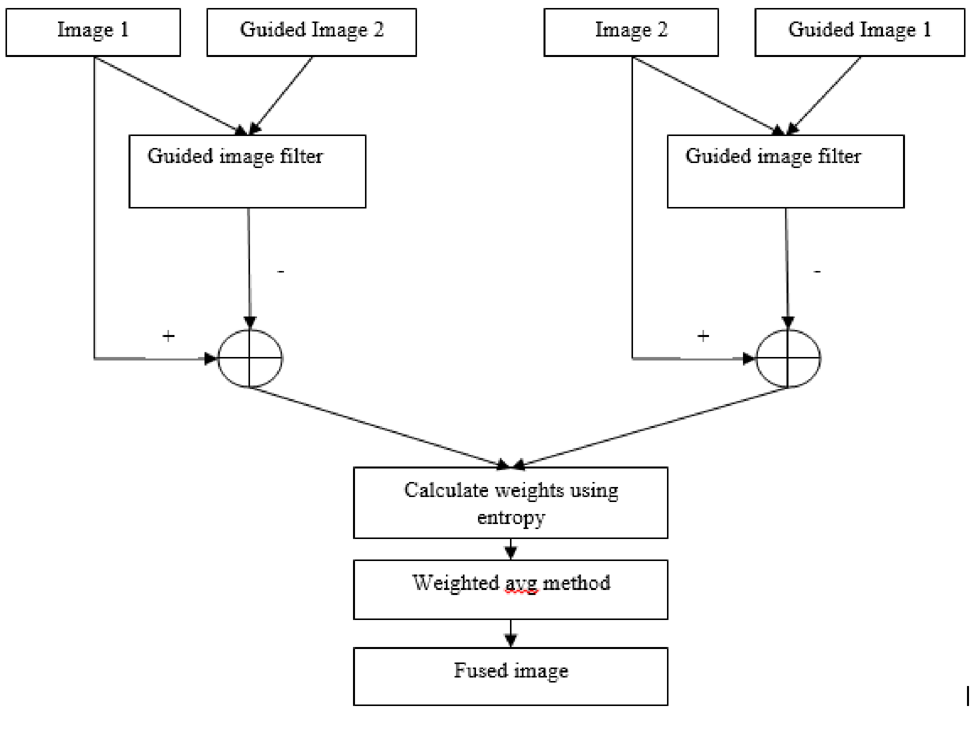

Fig. 1: Flow Chart of Proposed work

Algorithm:

1. Take an input image 1 i.e c1 (i,j).
2. Take a Guidance image for reference c2(i,j).
3. Apply Guided image filter on both the images, then obtain blurred Image B1(i,j), Subtract This from the input image to get an Image D1(i,j).
4. Repeat these steps for image 2 you get D2(i,j)
5. Calculate the weights of the detail layers using entropy, and then used weighted average fusion algorithm, to get the fused image.
6. Calculate the evaluation metrics for the images such as Mean, Standard deviation, Average Gradient, Spatial Frequency, Mutual information, and Fusion information Score.

4. EXPERIMENTAL RESULTS

Any fusion algorithm's goal is to combine the necessary data from the two source images into the final image. It is not possible to evaluate a fused image solely by looking at the fused image or by examining fusion metrics. You should evaluate it. Objectively and qualitatively utilizing visual displays hybrid metrics. We give visual quality and quantitative analysis of several methods in this part.

The goal of picture fusion is to retain all pertinent data from the original images. It shouldn't produce any artifacts while going through this process. We require some quantitative measures to confirm a certain fusion algorithm's efficacy. In the literature, numerous fusion metrics have been suggested. The most recent is petrovic Metric. Below is a succinct explanation of performance review. Consider a p*q-sized input image f(m, n).

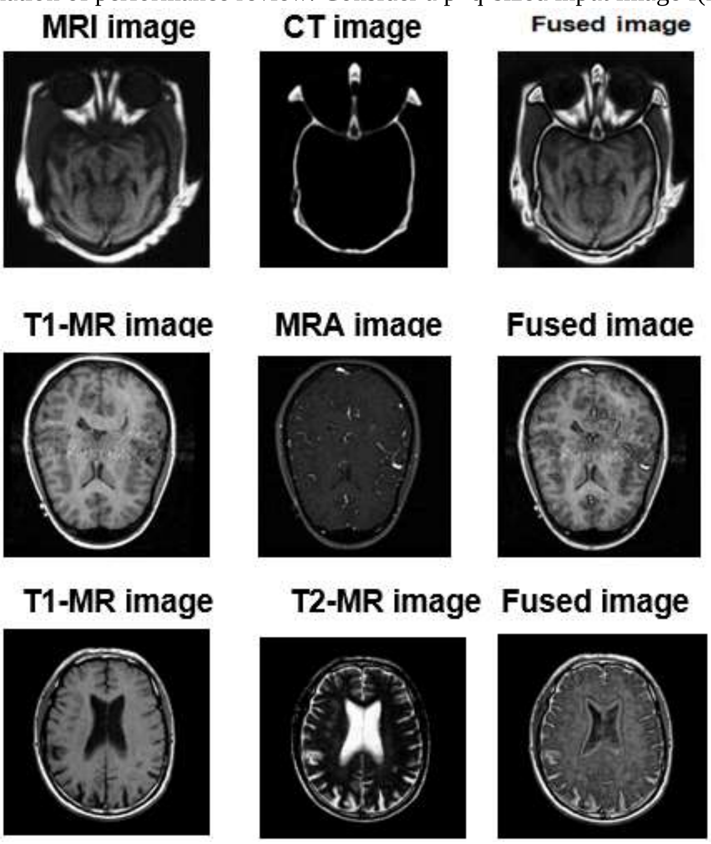

Fig 2: Fusion results

Table 1: Evaluation metrics

Metrics	Expressions
Mean or Average (f) Pixel intensity(μ)	$\overline{F}=\mu=\frac{\sum_{m=1}^{p}\sum_{n=1}^{q}f(m,n)}{pq},$
Standard deviation(SD or σ)	$SD=\sigma=\sqrt{\frac{\sum_{m=1}^{p}\sum_{n=1}^{q}\left(f(m,n)-\overline{F}\right)^2}{pq}},$
Average Gradient (AG)	$AG=\sum_{m=1}^{p}\sum_{n=1}^{q}\frac{\sqrt{((f(m,n)-f(m+1,n))^2+((f(m,n)-f(m,n+1))^2)}}{pq}$
Mutual information (MI) or Fusion factor	$MI=MI_{XF}+MI_{YF},$
Spatial frequency (SF)	$SF=\left(RF^2+CF^2\right)^{\frac{1}{2}},$ where $RF=\sqrt{\frac{\sum_m\sum_n(f(m,n)-f(m,n-1))^2}{pq}},$ $CF=\sqrt{\frac{\sum_m\sum_n(f(m,n)-f(m-1,n))^2}{pq}}.$

Table 2: Evaluation metrics values

Datasets	Fusion metrics					
	Mean	STD	AG	SF	MI	$Q_{AB/F}$
MRI-CT	53.3930	58.0984	8.3566	21.2830	3.8038	0.7739
T1 weighted MR-MRA	58.7358	61.4592	9.7124	23.9320	3.9370	0.6002
T1-T2 weighted MR	40.1273	53.4478	10.3740	30.8816	2.6937	0.5765

5. CONCLUSION

The merging of CT and MRI images is proposed using a new pixel-level fusion technique. First, an edge-aware smoothing guided filter is used to filter each source image. Weights are determined depending on the detail layers' entropy's. A fused image is then derived by using the source's weighted average images. Our approach exhibited encouraging outcomes in comparison to the conventional and modern fusion methods. Although trials with CT and MRI modalities are shown, the suggested approach can also be used with other medical imaging modalities. Two image dataset's results and analyses are shown in this article for clear presentation. For a random picture fusion dataset of our choosing, however, our fusion method can also deliver greater performance.

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