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Ahmad AL Smadi
Xidian University

Ahed Abugabah
Zayed University, ahed.abugabah@zu.ac.ae

Atif Mehmood
Xidian University

Shuyuan Yang
Xidian University

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Brain Image Fusion Approach based on Side Window Filtering

Ahmad AL Smadi^a, Ahed Abugabah^{b,*}, Atif Mehmood^a, Shuyuan Yang^a

^a*School of Artificial Intelligence, Xidian University, No. 2 South Taibai Road, Xian 710071, China*

^b*College of Technological Innovation, Zayed University, Abu Dhabi Campus, FF2-0-056, UAE*

Abstract

Brain medical image fusion plays an important role in framing a contemporary image to enhance the reciprocal and repetitive information for diagnosis purposes. A novel approach using kernel-based image filtering on brain images is presented. Firstly, the Bilateral filter is used to generate a high-frequency component of a source image. Secondly, an intensity component is estimated for the first image. Thirdly, side window filtering is employed on several filters, including the guided filter, gradient guided filter, and weighted guided filter. Thereby minimizing the difference between the intensity component of the first image and the low pass filter of the second image. Finally, the fusion result is evaluated based on three evaluation indexes, including standard deviation (STD), features mutual information (FMI), average gradient (AG). The fused image based on this algorithm contains more information, more details, and clearer edges for better diagnosis. Thus, our fused image-based method is good at finding the position and state of the target volume, which leads to keeping away from the healthy parts and ensuring patients' soundness.

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Keywords: Medical image fusion; Image filtering; Side window filtering; MRI; PET

1. Introduction

Image fusion is a procedure of the combination of multimodal therapeutic images into a solitary image. This strategy procedure prompts growth greater progression in the region of therapeutic imaging. The resultant image will give more data to promote diagnosis [1]. The medical images which are obtained from various imaging systems, for instance, Computed Tomography CT, Magnetic Resonance Imaging MRI, and Positron Emission Tomography PET, represent a crucial part in the therapeutic diagnosis and other clinical applications by giving clear information [2, 3]. By using computers and rotating X-ray machines, the CT scan makes cross-sectional images of the body. Therefore, these images give more nitty-gritty data than typical X-ray images [4]. Unlike CT scans, MRI gives a better repre-

* Corresponding author

E-mail address: ahed.abugabah@zu.ac.ae

sentation of delicate tissues and is ordinarily utilized to discover tumor and other tissue variations from the norm. In other words, in the MRI picture, delicate's tissue is clear more than CT images [5]. Recently, numerous medical images fusion approaches have been implemented [6, 7, 8, 9]. Consequently, image fusion is acquired from various modalities to extricate adequate information for clinical diagnosis and treatment. Image fusion algorithms are classified into three main categories, which are [2, 8, 10, 11] 1) Pixel level analyzes the aggregate data from various images, it represents a fundamental level of fusion; 2) Feature level extracts noteworthy features from an image such as shape, length, and edges; 3) The high level of fusion is the decision level which represents the actual target. The most imaging techniques for clinical diagnosis are CT, MRI, PET. By joining the benefits of those imaging systems through fusion images. The fusion result obtained by intertwining those images contains more inexhaustible visual and exhaustive data; therefore, securing new conclusion data by image fusion will be useful for many aspects, for instance, accurately recognizing a spatial area, estimate, and raising the precision of disease diagnosis [12]. In [13], a review study for medical image fusion presented by Indira *et al.* to give an audit of a few image fusion strategies utilized for therapeutic application, for example, curvelet transform, wavelet transform, contourlet transform, stationary wavelet transform, framelet transform. Mehena [14] presented a mathematic morphological technique for removing salt and pepper noise from the medical images. Ramlal *et al.* [15] introduced a novel fusion technique to fuse CT and T2-weighted MRI images. They decomposed the source images into approximation and detail sub-bands using NSST. The work was taken by Nandeesh *et al.* [2] demonstrated different techniques accessible in literature to implement medical image fusion. Tamilselvan *et al.* [6] presented various CT and MRI medical fusion techniques for clinical diagnosis. Chen *et al.* [16] introduced a fusion technique based on a rolling guidance filter and spiking cortical model to fuse 2D images. Concerning the image processing field, we frequently need to utilize an assortment of filters; these filters are utilized for different aspects, such as image smoothing, sharpening, and edge enhancement [17]. Furthermore, these filters are partitioned into linear and nonlinear filters [18]. Baltrušaitis *et al.* [19] introduced a survey concentrated on a few themes that talk about the advantage of multimodal fusion and the difficulties. Additionally, James *et al.* [7] presented another review. This review contemplates engaged in the restorative image fusion process, beginning with imaging modalities, then combination calculations, and, at last, the intrigue organs utilized in the fusion of therapeutic image. These themes are united with a substantial number of practically equivalent contemplates in comparable subjects.

In [20], the authors introduced the basic definition of image integration, its applications, advantages, and disadvantages of the fusion process, a summary of imaging patterns for a comprehensive overview of medical imaging patterns. They suggested ways of hybridization to obtain a better view of brain images. Their research ends with some recent trends in the fusion of medical images. Another survey investigation was presented in [21]. The authors pointed to a portrayal of image fusion ventures with an uncommon consideration for the enrollment and combination steps. After that, the restorative imaging modalities were discussed. At last, proposed of some of the normal difficulties that stand up to the enlistment and fusion technique are acquainted with the further examinations that enhance restorative image enrollment and fusion techniques. Recently, image filtering has been widely used for medical image fusion, such as bilateral filter, guided filter, gradient guided filter, and weighted guided filter [22]. These filters endeavor to evaluate a yield of a pixel depends on its neighbors within the window in which, window's center is aligned with the pixels being processed. Therefore, Yin *et al.* [23] introduced the side window filtering approach, which aligns the window's side or corner with the processed pixel. Extending to our previous work [24], this paper utilizes the side window filtering among guided filter types to enhance magnetic resonance imaging MRI from positron emission tomography PET images to acquire high-resolution fusion images, which leads to better diagnoses.

The contributions of this method are partitioned as follows. Firstly, the bilateral filter is employed for generating frequency components from both source images. Secondly, side window image filtering is used among various types of guided filters for image enhancement.

The rest of this paper is organized as follows. Section 2 introduces the methodology of this paper. Section 3 presents the experiments and results based on four groups of data. Section 4 concludes the paper.

2. Methodology

Image fusion has been a hot topic in medical image applications. In the current era of technological development, medical imaging plays an important role in many applications in medical diagnosis and treatment. This requires more accurate images with much more detail and information to obtain a healthy medical diagnosis, thus, a correct

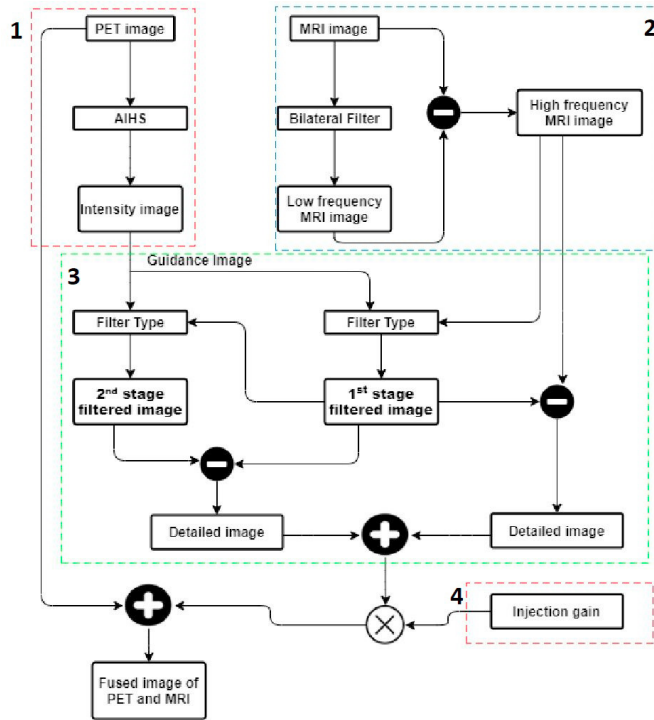


Fig. 1. Flowchart of PET and MRI images fusion based on side window filtering

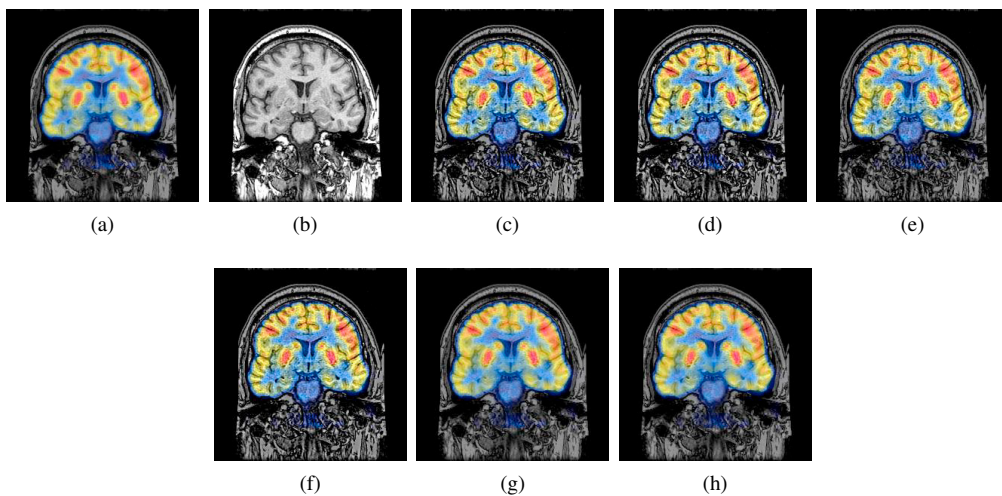


Fig. 2. Fusion result of the first group of medical images (a) Coronal PET-T1 image. (b) Coronal MRI-T1 image. (c) GF method. (d) SWGF method. (e) GGF method. (f) SWGGF method. (g) WGF method. (h) SWWGF method

treatment. Medical image fusion is a solution to get both high spatial and spectral information in a single image. The flowchart of our method is shown in Figure 1. Our method comprises a progression of steps: 1) The bilateral filter BF is used to generate the high-frequency component of the MRI image. 2) The Adaptive Intensity Hue Saturation [25] is employed to acquire the intensity component of the PET image. 3) The side window image filtering is used to obtain the approximation image using PET’s intensity component as a guided image. 4) Compute the injection gain, which has an impact on the combination results.

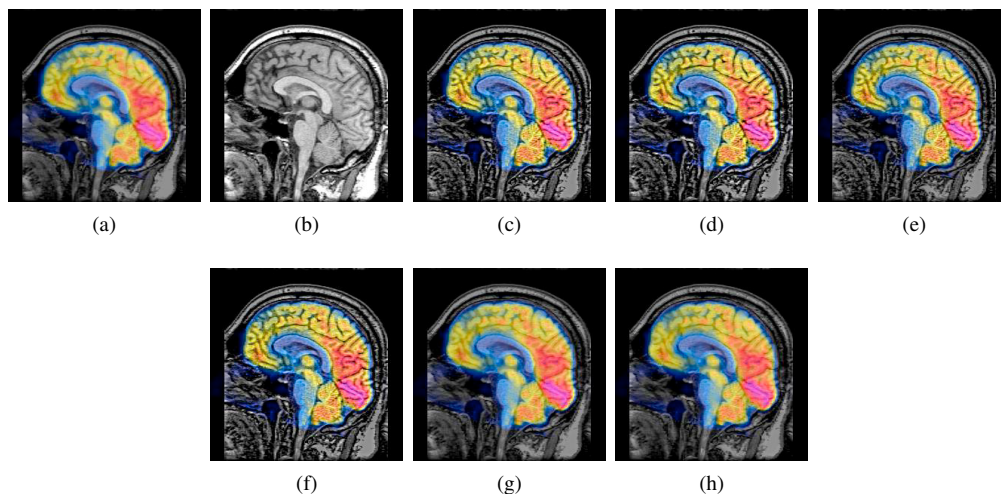


Fig. 3. Fusion result of the second group of medical images (a) Sagittal PET-T1 image. (b) Sagittal MRI-T1 image. (c) GF method. (d) SWGF method. (e) GGF method. (f) SWGGF method. (g) WGF method. (h) SWWGF method

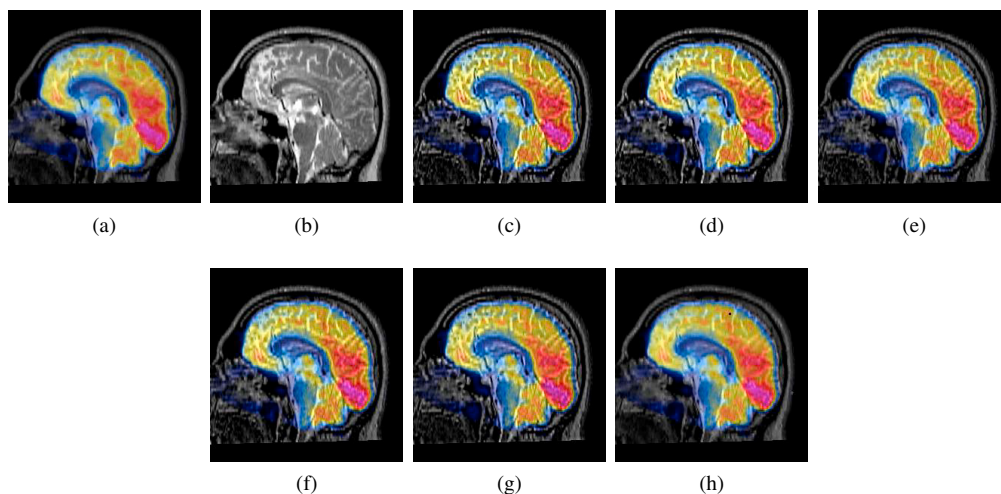


Fig. 4. Fusion result of the third group of medical images (a) Sagittal PET-T2 image. (b) Sagittal MRI-T2 image. (c) GF method. (d) SWGF method. (e) GGF method. (f) SWGGF method. (g) WGF method. (h) SWWGF method

3. Experiments and results

We conducted experiments on 4 groups of medical datasets. The datasets were obtained from the [Harvard Medical School](#). The positron emission computed tomography PET image is fused with corresponding magnetic resonance imaging MRI image, the size of these images in these experiments 256×265 . The fusion results are evaluated based on some quality metrics. The metrics include Feature Mutual information FMI, Standard Deviation STD, and Average Gradient AG. Note that the highest value of these indexes means better performance. The fusion results of medical groups of data sets are shown in Figures. 2-5. It can be seen that while employing the side window among filters, including Guided filter GF, Side window guided filter SWGF, Gradient guided filter GGF, Side window gradient guided filter SWGGF, Weighted guided filter WGF method and Side window weighted guided filter SWWGF; the fused image improves in terms of subjective and objective evaluations. The objective evaluation of the fusion images

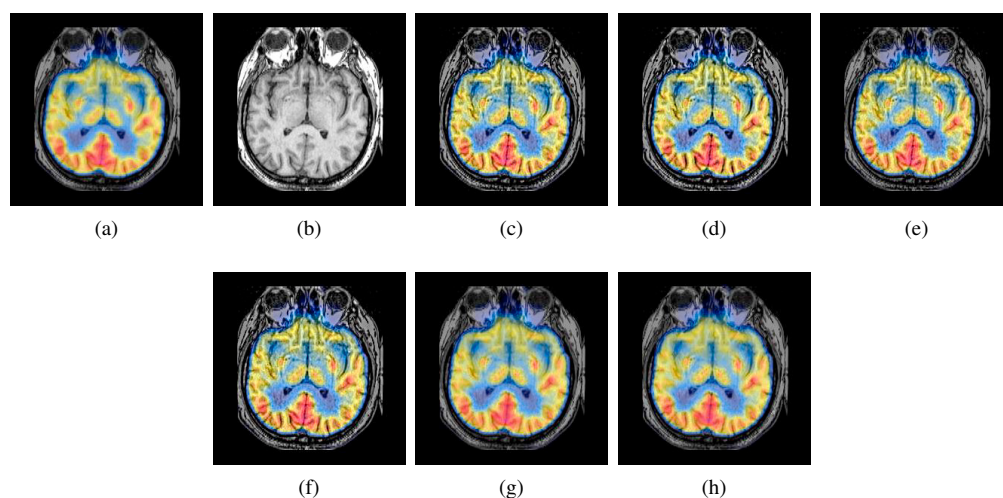


Fig. 5. Fusion result of the fourth group of medical images (a) Transaxial PET-T1 image (b) Transaxial MRI-T1 image (c) GF method. (d) SWGF method. (e) GGF method. (f) SWGGF method. (g) WGF method. (h) SWWGF method

Table 1. Objective evaluation for medical data groups.

Filter	GF	SWGF	GGF	SWGGF	WGF	SWWGF
First group Fig.2						
STD	0.2844	0.2841	0.2469	0.2505	0.2542	0.2530
FMI	0.5912	0.6046	0.5774	0.5695	0.5766	0.5781
AG	0.3001	0.3023	0.2241	0.2451	0.1666	0.1697
Second group Fig.3						
STD	0.2763	0.2758	0.2453	0.2488	0.2470	0.2458
FMI	0.5599	0.5768	0.5475	0.5422	0.5491	0.5506
AG	0.2949	0.2963	0.2376	0.2527	0.1505	0.1506
Third group Fig.4						
STD	0.2574	0.2597	0.2360	0.2362	0.2442	0.2439
FMI	0.7655	0.7677	0.5851	0.5701	0.5810	0.5826
AG	0.2000	0.2005	0.1643	0.1744	0.1601	0.1094
Fourth group Fig.5						
STD	0.2521	0.2547	0.2297	0.2290	0.2377	0.2520
FMI	0.7966	0.7971	0.7946	0.7728	0.7854	0.7872
AG	0.1907	0.1911	0.1567	0.1640	0.1570	0.1843

is reported in Table 1. Overall, the SWGF method performed the highest value in terms of FMI and AG for all medical data; in terms of STD index, the GF method performed the best value, followed by SWGF.

4. Conclusion

The characteristic of this paper is that side window filtering was employed among existing filters for the medical image fusion task. In this paper, the PET image was fused with MRI based on side window kernel filtering. Four groups of datasets were used for experiments. We have demonstrated that side window filtering might be utilized perfectly for medical image fusion. To summarize, the SWGF outperformed the other filters.

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