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Medical Image Fusion To Urge On Perspicacity Using Discrete Fractional Wavelets

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Abstract: Technological improvements have subjugated the medical arena in the recent past. Discrimination and precision of the medic is analogous to the precise judgments acquired by the image acquisition and analytical devices. Single source radiological scan only partially confines diagnostic data and it is proposed to combine multimodal images from different modalities. The fused image is obtained using the Grey Wolf Optimizer meta heuristic with Discrete Fractional wavelets. This improves the diagnostic confidence factor to provide a clinically more rationale output. Medical neuro images of Alzheimer's degeneration acquired using MRI and SPECT modalities illustrates the proposal. Prior to the processing, random noise removal image enhancement elucidate the underlying details and exemplifies the processing. The proposal is well evaluated for comparisons with benchmark techniques. The subjective and objective parameters are assessed and metrics in results indicate higher values and more information in the fused image with better contrast.

Keywords. Image fusion; Spectral Information; Transform Domain; Functional Modality; Anatomical Modality.

1. Introduction

Image fusion finds widespread use in image interpretation, analysis, diagnosis and further processing. Medical image fusion unites patient imagery from same or complementary modalities to merge all the visual clinical information into a single fused image [1]. Most software based image fusion techniques in literature are limited in their ability to retain key diagnostic content and direct robust diagnosis.

Medical images are segregated into anatomical and functional image modalities [2,3]. Magnetic Resonance Imaging (MRI) is an anatomical modality Single photon emission computed tomography (SPECT) is a functional modality. Each modality provides limited diagnostic value Multimodal fusion of medical scans combines attributes of both for precise diagnosis [4].

Image fusion methods in literature are reported in Spatial and Transform Domain [5]. The medical images when processed in transform domain better localize the clinical feature content at proper scale and orientations [6]. Discrete fractional wavelet transform is a recent effort in the direction of improved fusion results. We propose a novel technique for fusion of multimodal brain ailment images using discrete fractional wavelets transform with Grey

Wolf Optimizer(GWO) and median filtering as preprocessing. The sections are organized as follows. Section 2 provides medical perspective, section 3 pre-processing techniques. Result and Discussion is in section 4, followed by conclusion in section 5.

2. Medical perspective and Clinical Data

There are several primary imaging modalities in neuro imaging as MRI, CT, X-Ray, DSA, PET, SPECT, fMRI. The imaging modalities work together on principles to depict normal brain functioning and ailments. The medical images are acquired from Med Harvard. http://med.harvard.edu/AANLIB/home.html[7], brain atlas benchmark database website. Images from a case of clinical neuro brain ailment of size 256 by 256, is obtained. Dataset comprises of MRI T2 and SPECT image set pertaining to the case of degenerative Alzheimer. The image set is shown in Figure 1. The histogram of the benchmark images are given in figure 2.

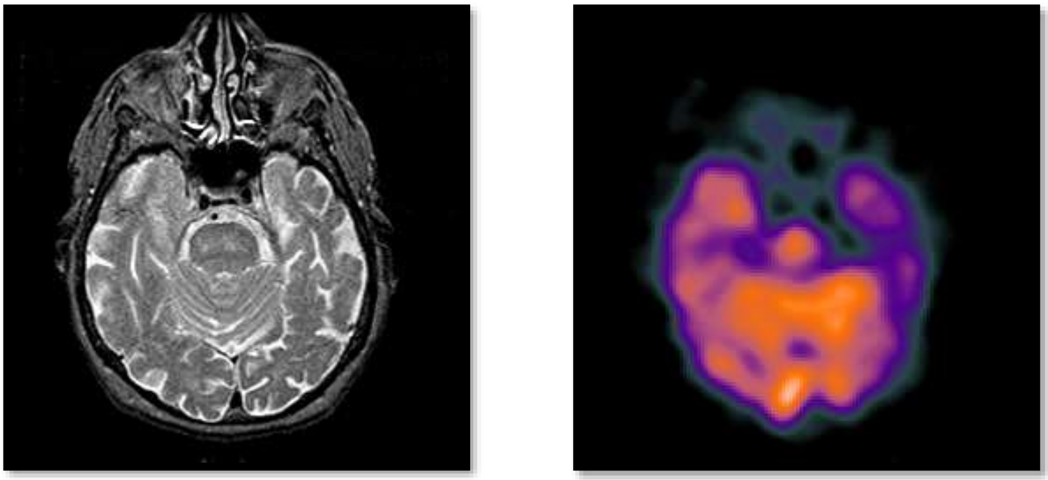


Figure 1. Dataset (a) MRI T2 (b) SPECT

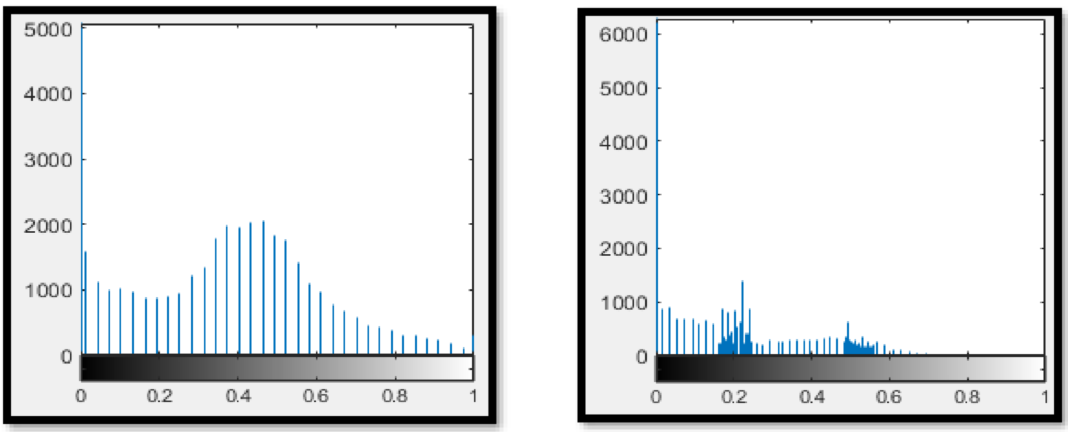


Figure 2. Histogram Dataset (a) MRI T2 (b) SPECT

3. Proposed Medical Image Fusion

Fusion studies in literature are analyzed jointly from the perspective of the organ under observation, the capturing modality and the fusion technique [8]. The assessing parameters once selected, need to be critically dealt with. The fusion process must selectively combine the patient anatomy with correlating physiological functions. This in turn must mark and abet Medical Discernment. In the proposed method is implemented at pixel-level. Smoothening Median filter is applied at each decomposition to eliminate random noise, speckle and impulsive noise [9-10]. The decomposition is performed by discrete fractional wavelet transform. As the transform uses fractional convolution derivative from different scales,it iteratively captures singularities at various scales[11]. An optimization technique of grey wolf optimizers is used to obtain the promising parity orderp to better captivate the clinical details and diagnostic content. Discrete fractional wavelet is a special case of multi-resolution analysis [12]. The decomposed images are fused using weighted energy based for both low and high frequency coefficients. The inverse discrete fractional wavelet transform produces the final fused outcome. The proposed medical fusion method is as depicted in Figure 3.

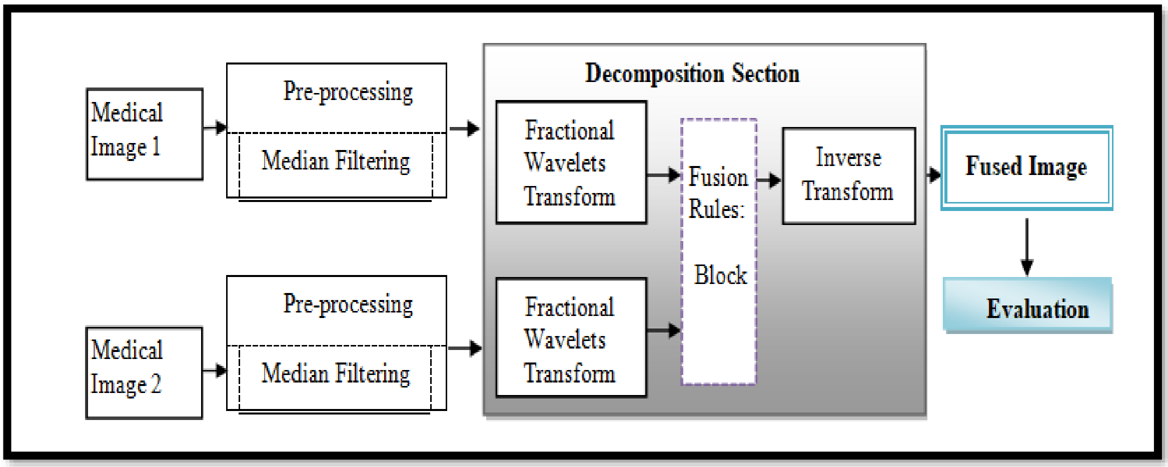


Figure 3. Proposed Fusion Method

The consolidated steps in the proposed fusion mechanism are as depicted below:

The medical fusion algorithm steps:

1. Two dimensional MRI and SPECT images from functional and anatomical modality of brain are accessed.
2. Grey Wolf Optimizer algorithm selects the fitting parity order value for discrete fractional wavelets.
3. The images are decomposed using discrete fractional wavelet transform.
4. Smoothening Median filter is applied.
5. Weighted energy based fusion rule is used for both low and high frequency coefficients.
6. Inverse discrete fractional wavelet transform is applied to obtain the fused image.

7. Visual subjective and objective evaluation is performed based on metrics.

With cascading low and high frequency sub sampling operation by specifically designed filters keep the basic information intact [13]. The Discrete fractional wavelet transform engages down-sampling and can analyze the signal from time to frequency domain in fractional increments [14]. The scaling and wavelet function of wavelets is given by φ(c, d) and ψ(c, d). The basic functions are defined as

$$\varphi j\ (c, d) = 2j/2\ \varphi\ (2j\ c-m, 2j\ d-n) \quad (1)$$

$$\psi ij,(c, d) = 2j/2\ \psi i\ (2jc-m, 2j\ d-n) \quad (2)$$

where m, n are the pixel values and i lies in directions {H, V, D}.

The wavelets decomposes the image into various coefficients in different directions and bands in transform domain. The kernel function of fractional wavelet is represented by Ψα,r,s(t) and is given by the expression

$$\Psi_{\alpha,} r, s(t) = e^{-\left(\frac{1}{2}\right)(n^2-s^2)\cot\alpha}\Psi\ r, s(t)$$

The inverse transform is given by

$$b = (r * k\operatorname{cosec}\alpha)K^{-\alpha} \quad (4)$$

$$W^{\alpha}(r, s)=\int^{\infty} \sqrt{2\pi r}\ X^{\alpha}\ (k)\Psi^{*}bd\alpha \quad (5)$$

Where α is the rotation angle, r and s are scaling and translation parameters respectively. The parity order p in fractional Fourier transform is optimised for selection of most suitable value using GWO.

In order to better correlate the diagnostic content in single and multimodal imaging and support content retention at inter and intra scales. The low and the high frequency coefficients are fused using weighted energy based rule given as exemplify the fine clinical content.

$$A_b w_e^{F} = E^1.(Im^1L_1) \pm E^2.(Im^2L_2) \quad (6)$$

4. Results and Discussion

The performance evaluation is performed using both subjective and objective measures. The performance of the proposed method is compared with existing techniques as Averaging and Undecimated discrete wavelet transforms (UDWT). The evaluation parameters are as given below.

The objective criteria for evaluation metric used in the plan are selected to extensively exhibit

the merits of the technique proposed.
The formulae and elaborations of adopted definitions are as below:

Peak signal to noise ratio (PSNR) [15] compares the quality of the fused image, based on Computational indexes given by higher values well retain the information content.

$$\text{PSNR} = 10\log10 \frac{L^2}{MSE} \quad (7)$$

2. Mean square error [16] computes difference inerror values in original and final image given as

$$\text{MSE}(X_f) = \frac{1}{I \times J} \sum_{i=1}^{I} \sum_{j=1}^{J} |X_f(i,j) - X_o(i,j)|^2 \quad (8)$$

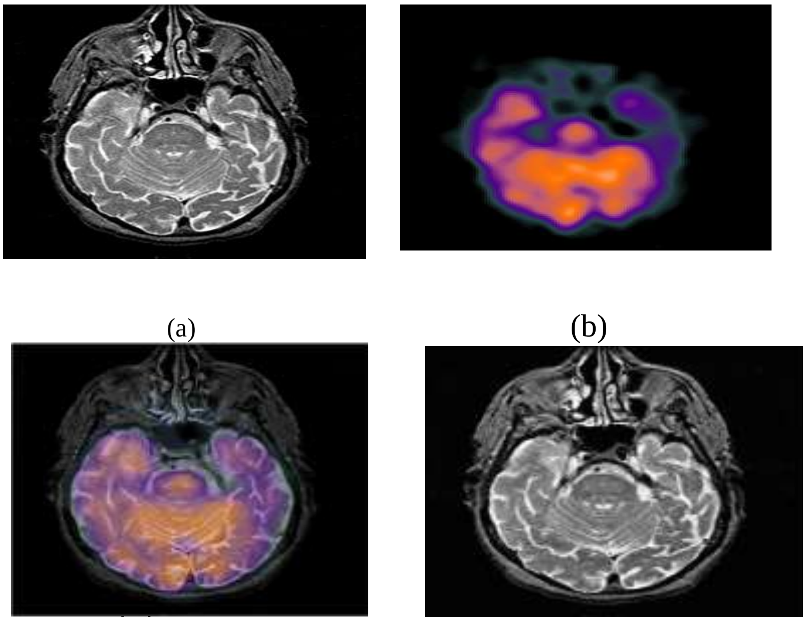
3. Mutual information measures of the imagematching metrics given by

mi = Im(i)* E1 + Im (j)* E2 –Jt.E (Im1, Im2)   (9)

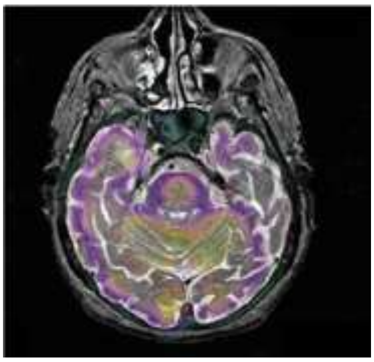
Subjective evaluations validate in terms of structural or functional information. Each modality functions in its own preview to provide precise insight into the structural details, functionality and ailment under observation. The resultant fused image along with the results from state of art methods are represented in Figure 4 for the selected dataset.

4.2 a) Dataset MRI T2-SPECT:

The resultant subjective fused image is given in Figure 4. The algorithm is compared with averaging and Undecimated discrete wavelet transform, state of art methods.



(a) (b) (c) (d)



(e)

Figure 4. Fused Image (a) MRI T2 (b) SPECT (c) Alpha Blending (d) UDWT (e) Proposed

Averaging does not reveal clinical content in an appealing manner. UDWT depicts loss in representation of diagnostic content. The fused image directs concentration towards segments more relevant in clinical perspective. The final fused image depicts clarity in terms of diagnostic output with better contrast. The objective metric results are given in table 1. The results reveal PSNR in the fused image. Low error is depicted by MSE. With more diagnostic content visible the structural components are better depicted. The results outperforms the existing methods.

Table1. Objective Evaluation Results DS1

Evaluation	Average	UDWT	FRWT
PSNR	18.930	10.355	**19.441**
MSE	0.1280	0.0797	**0.0113**
MI	1.32	1.861	**1.862**

The combination of physiological, structural and functional data from multimodal anatomical and functional input helps improve diagnosis of malignancies [17]. The proposed technique gathers spatial and spectral information well exemplifying its superior diagnostic performance with clarity in clinical localization over existing benchmarks. . The objective analysis along with subjective evaluations corroborates the visual content.

5. Conclusion

A novel medical image fusion algorithm is proposed using Grey Wolf Optimizer meta heuristic along with Discrete Fractional wavelets. Medical neuro images of Alzheimer's degeneration acquired using MRI and SPECT modalities illustrates the proposal. Prior to the processing, random noise removal image enhancement elucidate the underlying details and exemplifies the processing. The Grey Wolf Optimizer selects the parity order for Discrete Fractional wavelet transform. The processed images produce ortho- normal functions post decomposition based on selected fusion rules of weighted energy. Both objective and subjective assessment epitomizes theperformance. The comparision with state of art methods reinforces statistically to further manifest the proposed methodology and maintains superior clinical performance with better preserved spatial coefficients.

6. Competing interests

The author has no Competing interests at stake andthere is No Conflict of Interest.

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The benchmark images used in the study are downloaded from the neuro imaging website ofMed Harvard Brain atlas http://med.harvard.edu/AANLIB/home.html.

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