A NOVEL APPROACH IN MEDICAL IMAGE FUSION USING SOCIAL SPIDER OPTIMIZATION

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***Abstract*— The process of integrating various modalities of medical images is known as image fusion. The medical image fusion is mainly used to detect and treat disease for the better diagnosis of brain tumor. Now a days, detection of tumor,analysis and treatment is the demanding task in health care applications .In this paper, we proposed a multimodality medical image fusion using social spider optimization (SSO). Here we consider two Medical images from different modalities Magnetic Resonance Imaging(MRI) and Computed Tomography (CT) as the input of the system and output is the fused image. Initially we enhance the input images by applying median filter for both the images which is used to remove the noise present in the input image. After the filtering process the images are decomposed using discrete wavelet transform (DWT) which produces four sub-band images namely HH, HL, LH and LL. After the decomposition process, the LL sub band coefficients of CT image (bone information) and HH, HL, LH sub band coefficients of MRI (soft tissue information) are added using adder1.The HH, HL, LH sub band coefficients of MRI and LL sub band coefficients of CT are added together. Finally, the source images are fused using the social spider optimization (SSO) algorithm.The proposed method contains more detailed information(both functional and anatomical).This fusion approach is validated using various fusion evaluation indexes**

***IndexTerms*— Magnetic Resonance Image (MRI), Computed Tomography (CT), Discrete wavelet Transform (DWT), Social Spider Optimization (SSO).**

I. Introduction

The process of collecting all the information from many images and combining them into a single image is known as image fusion. The image fusion techniques are generally resolute for joining the multi-source input image into a new image that is visible for human eye. Medical Diagnosis, Treatment planning, Medical research, Military application etc are the various areas in which image fusion is used. Fused Multimodality medical image fusion is nothing but combining the information acquired from two different sensors.Generally, we consider different types of medical images like Magnetic Resonance Imaging (MRI), Computed Tomography (CT), Positron Emission Tomography (PET), Single – Photon Emission Computed Tomography (SPECT) for medical image fusion. Each type of these medical images contain individual uniqueness and sensible restrictions. These images are used for clinical diagnosis. The MRI image will provide information on soft tissues and CT image will provide more information on bone irregularities Accurate and detailed information cannot be provided by the single modality medical image. Due to this drawback, the process of aligning anatomical and functional medical images is used. Multimodal fused images play a very vital role than individual image in medical diagnosis. For better clinical evaluation the biomedical information can be attained using medical image fusion techniques. Transformation functions are mainly used for multi scale decomposition.

In the recent times, various image fusion methods are discovered. Mostly the fusion processes are classified by the level of presentation. The three major levels are Pixel fusion level, decision fusion level and feature fusion level. The most critical in image fusion level is the choice of fusion rule. This also leads to the sub-optimal consequences. The fusion algorithms are carried over by two feasible methods namely subjective and objective. The assessment that takes place by means of medical specialists is known as subjective assessment .Another significance in image fusion technique is to reduce the storage size.

In this work we have proposed a novel multi-modality medical image fusion system based on Discrete Wavelet Transform and Social Spider Optimization. The multilevel decomposition is done using DWT. Using social spider optimization the optimal weight values are selected. The qualitative parameters are measured and analysed.

II. Proposed System

The proposed multimodality medical image fusion using social spider optimization. Here we have considered MRI and CT images for image fusion. Initially median filter is used to reduce image artifacts. The filtered image is decomposed using discrete wavelet transform (DWT). Social spider optimization based fusion is introduced to fuse the medical image. Parameters like mean, entropy, std are evaluated and composed with existing methods.

III. Median Filter

Generally, Image filtering is used to remove noise or to sharpen the contrast of an image and thereby enhancing the images. Here we have considered two different modalities (MRI and CT) images. Before decomposing the images here, we do median filtering to remove the noise or the artifacts present in the images which generally occurs because of the imperfection in the scanning process or image acquisition. Median filter is mainly used to reduce the salt and pepper noise.

Median Filtering overcomes the disadvantage of the low pass filtering by preserving the discontinuities in an image by choosing an optimal window size. In Median filtering we generally choose a window of size MxN for the pixel (i,j) which is being considered. During the filtering the window slides over the images and the median intensity values of the window will be the output intensity value for the considered pixel of the image. For example suppose the pixel values in the window are 0,5,6,7,2,3,4,1,8. Initially we need to sort the values in ascending order as 0,1,2,3,4,5,6,7,8. Let us consider that the pixel being processed has a value of 8, then the output of the median filter on the current pixel value is 4. The modification of pixel (i,j) is given as below.

IV. Discrete Wavelet Transform

Discrete Wavelet Transform (DWT) is a transform for which the wavelets are discretely sampled. This is an implementation of wavelet transform using dyadic scales and positions. It is a mathematical tool for feature extraction, and has been used to extract the wavelet coefficients from MRI-CT images. Dwt uses sub band coding for image decomposition, HAAR transform & image pyramid for the edge detection & feature extraction. Discrete Wavelet Transform (DWT) is a transform for which the wavelets are discretely sampled. This is an implementation of wavelet transform using dyadic scales and positions. It is a mathematical tool for feature extraction, and has been used to extract the wavelet coefficients from MRI-CT images. DWT uses sub band coding for image decomposition, HAAR transform & image pyramid for the edge detection & feature extraction. Discrete Wavelet Transform (DWT) is a transform for which the wavelets are discretely sampled. This is an implementation of wavelet transform using dyadic scales and positions. It is a mathematical tool for feature extraction, and has been used to extract the wavelet coefficients from MRI-CT images. DWT uses sub band coding for image decomposition, HAAR transform & image pyramid for the edge detection & feature extraction.

The major advantage of the discrete wavelet transform is that it captures both frequency and location information. The wavelets have zero average value finite duration oscillatory functions. The asymmetry properties make them better for analyzing signals with discontinuities. Time series and image analysis are the two major users of wavelet decomposition. The wavelet transform has become the best substitute for Fourier transform mainly because of their suitability for analyzing non-stationary signals.

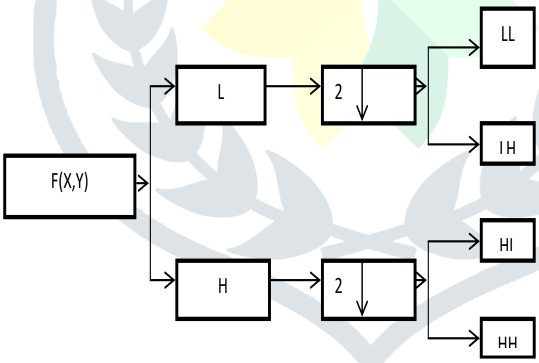


Fig 1 2-D DWT Image Decomposition

In a 2D DWT, a 1-D DWT is first performed on the rows and then columns of data separately filtering and down sampling. As a result of this process we get 1 set of approximation coefficients and 3 sets of detail coefficients. This represents the vertical, horizontal and diagonal directions of the image. According to the filter theory, the four sub images represents the output of L-L, L-H,H-L,H-H bands. The same is applied recursively to the L-L sub band, a multi-resolution decomposition with a desired level can be achieved.

V. Initial Fusion

In the Initial level of Fusion the frequency coefficient of MRI and CT decomposed images are fused. This initial level of fusion can be achieved by combining the approximation coefficient (LL) of input image MRI and detailed coefficients (LH HL & HH) of I2 (CT) and the resulting image can be represented as F_1 fusion. Similarly, we shall combine the approximation coefficient (LL) of input image CT and detailed coefficients (LH HL & HH) of MRI and the resulting image is represented as F_2 fusion. .

VI. Final Fusion

The Initially Fused frequency coefficients are fused using the rule which is given as

$$F^{final} = W_1{*}F_1{+}W_2{*}F_2$$

Where, F_1 and F_2 are the initially fused values. In order to achieve the high quality image which is more informative for the better diagnosis of brain tumor the optimal weight values are selected using Social Spider Optimization (SSO) algorithm.

VII. Social Spider Optimization

In earlier social spider optimization algorithm can be used for swarm intelligence and global optimization problem. In this paper, SSOA can be used to diagnose tumor in CT&MRI images for better quality.

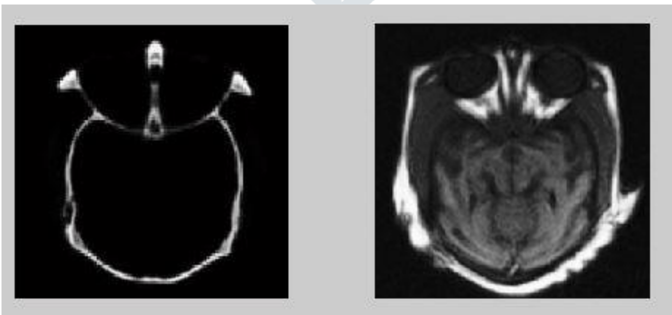
Social spider optimization Algorithm is a method with hyper-dimensions solution. In a spider web, most of the spiders cannot like to interact with other spiders but some spiders can interact with others and forms a group. Social-Spider Optimization Algorithm (SSOA) was developed based on these species of spiders for a better breakthrough of problems. Social members and communal web are the two vital components of SSOA. **.** The social members consist of both the genders In this problem, each spider is a solution. These spiders are randomly distributed with each attribute. 65-90% is the range within which the no females Nf are selected.

The interpretations of female and male spiders are characterized and weights are delegated to each spider. The communal web depicts the aspect of search space. A hyper-aspectual spider web could be considered as the search space of the breakthrough problem. Every spider position depicts each way-out within the search space. The fitness value of the key is depicted by the weight of each spider. The information among the group or colony members is relayed via the communal web ciphered as small vibrations. These vibrations are based on the distance and weight of the spider which has produced them. Female spiders exhibit either an attraction or gnloathe to other spiders based on their weight and distance from them. The stronger the vibrations the more attraction is the phenomenon, as per scientists' observations, as per the female spiders and hence the Euclidean distance is calculated. An index formed for the shortest distance between and around the spiders is calculated. Based on this index the female spider starts moving towards the strongest vibrations direction which is nearest to it.

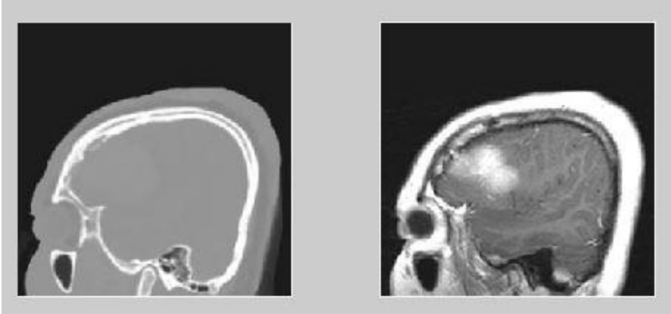
Dominate and non dominate are the two major categories of the male spiders. The weight of the male spider which is above the median value is the dominant male and the weight which is below the median value is the non dominant male. The males with best fitness value are the ones to perform mating. When a set of female spiders are identified by a dominant male within a specified range, it starts the process of mating thus forming a new offspring. The weight of the new spider is compared with the weight of the worst spider and the better will replace the worst one. This process is repeated until the best weighed spider gets to meet the best way-out.

VIII. Results and Discussion

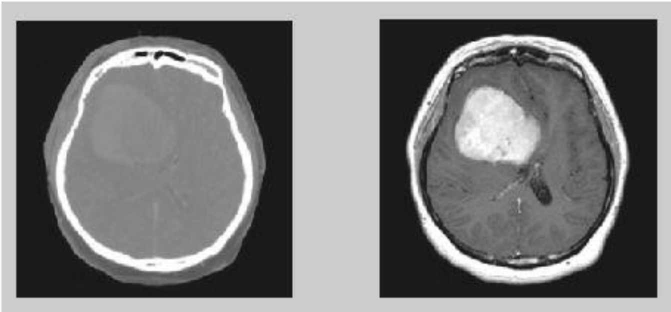
This section includes input images of CT & MRI, simulation results and the parameter analysis for the fusion algorithm. In our proposed method we have used Social Spider Optimization and Discrete Wavelet Transform for fusing MRI and CT images. For the evaluation process we have used three sets of MRI and CT images. Both functional and anatomical information's are fused into a single frame. The three set of source images (CT&MRI) are fused using the Social Spider Optimization Algorithm. The various multimodality human brain images of size 256 x 256 are taken and the experimental results were shown. The three set of images at various focal lengths (different modality). Here, the three set of brain data sets are used.



(a)



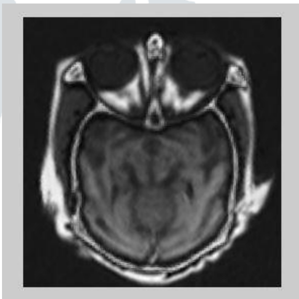
(b)



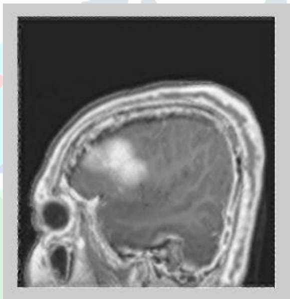
(c)

Fig 1.Source images

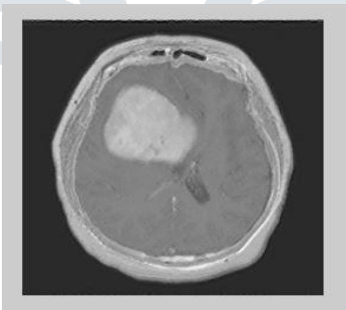
The proposed technique is performed multilevel decomposition. Fused images using the proposed algorithm using Discrete Wavelet Transform and Social Spider Optimization Algorithm are shown below:



(a)



(b)



(c)

Fig.2 Final Fused images

IX. Quantitative Measures

a) Entropy

It is a measure of randomness, that is used to characterize the texture of input image.Its values will be maximum when all the elements of the co-occurrence matrix are same

$$Ent \equiv -\sum_{i=1}^{l} P(i)log2_{p(i)}$$

b) Mean Square Error

$$MSE = \frac{1}{N}\sum_{i=1}^{N}(S_F - S_{in})^2$$

Where;

S_F → Fused image

S_{in} → Input image

N → Number of pixel

c) Root Mean Square Error

The RMSE is measured between the input and output image, is given by the following equation

$$RMSE = \sqrt{\frac{1}{MN}\sum_{x=1}^{M}\sum_{y=1}^{n}\left(R_F(x,y) - S_F(x,y)\right)}$$

R_F → Reference image

S_F → Fused image

d) Peak Signal to Noise Ratio

When the processed and the input images are alike the PSNR value will be high.PSNR is given by;

$$PSNR = 20\log_{10}\left(\frac{L^2}{\sqrt{\frac{1}{MN}\sum_{x=1}^{M}\sum_{y=1}^{n}\left(R_F(x,y) - S_F(x,y)\right)}}\right)$$

Table 1 Parameter Analysis

SI.NO	PARAMETERS			
	ENT	RMSE	PSNR	ELAPSED TIME(sec)
IMAGE SET1	6.6680	2.8977	43.5103	14.846303
IMAGE SET 2	6.6884	9.6160	38.3009	19.334917
IMAGE SET3	5.4904	8.4980	38.8376	18.099296
TOTAL	18.8468	21.0117	120.6488	52.280516

X. Conclusion

In the recent times, medical image fusion has become exigent in medical application. In this paper we have proposed a novel approach in medical image fusion for Brain Tumor detection using Discrete Wavelet Transform and population based optimization using Social Spider Optimization Algorithm. We have taken three sets of MRI and CT images and the proposed method has been analyzed. Quantitative result shows that the fused image contains more detailed information than other existing fusion techniques. In future the method can be extended by fusing the low frequency components and high frequency components using machine learning algorithm and optimization techniques.

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