Analysis and Identification of Tumor Cells In MRI And CT Images Based On Nanotechnology Using Neuro Fuzzy Image Fusion

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Abstract: Image fusion is a sub field of Medical imaging in which more than one images are fused to create an image where all the objects are in focus. The process of image fusion is performed for multi-sensor and multi-focus images of the same scene. Multi-sensor images of the same scene are captured by different sensors whereas multi-focus images are captured by the same sensor. In multi-focus images, the objects in the scene which are closer to the camera are in focus and the farther objects get blurred. Contrary to it, when the farther objects are focused then closer objects get blurred in the image. To achieve an image where all the objects are in focus, the process of images fusion is performed either in spatial domain or in transformed domain. In recent times, the applications of image processing have grown immensely. Usually due to limited depth of field of optical lenses especially with greater focal length, it becomes impossible to obtain an image where all the objects are in focus. Thus it plays an important role to perform tasks of analysis and identification of tumor cells in MRI and CT images based on neuro fuzzy image fusion. Hence, a novel feature-level multi-focus image fusion technique has been proposed which fuses multi-focus images. Thus the results of extensive experimentation performed to highlight the efficiency and utility of the proposed technique is presented. The proposed work further explores comparison between fuzzy based image fusion and neuro fuzzy fusion technique along with quality evaluation indices. In order to benefit from the highly conformal irradiation of, sophisticated treatment planning and simulation are required to analysis and identify the tumor in MRI and CT Scan images. The purpose of this study was to investigate the potential of MRI and CT for treatment plan simulation and adaptation using a neuro fuzzy image fusion.

Keywords— Fusion; Multi-focus images; Optimal block; Pixel based; Variance and Feed forward Neural Network.

1. Introduction

A wide variety of data acquisition devices are available at present, and hence image fusion has become an important subarea of image processing. There are sensors which cannot generate images of all objects at various distances with equal clarity. Thus several images of a scene are captured, with focus on different parts of it [9]. With the availability of multi-sensor data in many fields such as remote sensing, medical imaging, machine vision and military applications, sensor fusion has emerged as a new and promising research area. The current definition of sensor fusion is very broad and the fusion...
can take place at the signal, pixel, feature, and symbol level. The goal of image fusion is to create new images that are more suitable for the purposes of human visual perception, object detection and target recognition. In this paper we address the problem of pixel-level fusion [2] or the so-called image fusion problem. To achieve an image where all the objects are in focus, the process of images fusion is performed either in special domain or in transformed domain. Spatial domain includes the techniques which directly incorporate the pixel values. Multi-scale or multi-resolution approaches provide a means to exploit this fact. After applying certain operations on the transformed images, the fused image is created by taking the inverse transform. Image fusion is generally performed at three different levels of information representation including pixel level, feature level and decision level. In pixel-level image fusion, simple mathematical operations such as maximum or average are applied on the pixel values of the sources to generate fused image. However these techniques usually smooth the sharp edges or leave the blurring effects in the fused image. In the feature level multi-focus image fusion, the source images are first segmented into different regions and then the feature values of these regions are calculated. Using some fusion rule, the regions are selected to generate the fused image. In decision level image fusion, the objects in the source images are first detected and then by using some suitable fusion algorithm, the fused image is generated [1]. The block diagram of the proposed method is shown in figure 1.

![Block Diagram of the Proposed Method](image)

**Figure 1.** Block Diagram of the Proposed Method

2. Material And Methods - Fuzzy Based Image Fusion

Fuzzy image processing is not a unique theory. Fuzzy image processing is the collection of all approaches that understand, represent and process the images, their segments and features as fuzzy sets. The representation and processing depend on the selected fuzzy technique and on the problem to be solved. It has three main stages: Image fuzzification(Using membership functions to graphically describe a situation)Modification of membership values(Application of fuzzy rules) Image defuzzification(Obtaining the crisp or actual results). The coding of image data (fuzzification) and decoding of the results (defuzzification) are steps that make possible to process images with fuzzy techniques. The main power of fuzzy image processing is in the middle step (modification of membership values). After the image data are transformed from gray-level plane to the membership plane (fuzzification), appropriate fuzzy techniques modify the membership values. Multi-sensor data fusion can be performed at four different processing levels, according to the stage at which the fusion takes place: signal level, pixel level, feature level, and decision level. A novel CT/MR spine image fusion algorithm based on graph cuts has been proposed in [5]. In that algorithm, both soft tissue and bony detail can be assessed on a single fused image. Their fusion algorithm was evaluated for about 40 pairs of CT/MR images acquired from 20 patients, which demonstrate a very competitive performance in comparisons to the existing methods. Signal level fusion. In signal-based fusion, signals from different sensors are combined to create a new signal with a better signal-to-noise ratio than the
original signals. Pixel level fusion. Pixel-based fusion is performed on a pixel-by-pixel basis. It generates a fused image in which information associated with each pixel is determined from a set of pixels in source images to improve the performance of image processing tasks such as segmentation. Feature level fusion. Feature-based fusion at feature level requires an extraction of objects recognized in the various data sources. It requires the extraction of salient features which are depending on their environment such as pixel Intensities, edges or textures. These similar features from input images are fused.

3. Proposed Model - Algorithm For Neuro Fuzzy Based Image Fusion

In feature-level image fusion, the selection of different features is an important task. In multi-focus images, some of the objects are clear (in focus) and some objects are blurred (out of focus). The author has used five different features to characterize the information level contained in a specific portion of the image. This features set includes Variance, Energy of Gradient, Contrast Visibility, Spatial Frequency and Canny Edge information. Variance is used to measure the extent of focus in an image block[2]. It is a mathematical expectation of the average squared deviations from the mean. A pseudo center weighted local variance in the neighborhood of an image pixel determines the amplification factor multiplying the difference between the image pixel and its blurred counterpart before it is combined with the original image.

\[
VI = \frac{1}{m \times n} \sum_{(i,j) \in B_k} \frac{|I(i,j) - \mu_k|}{\mu_k^n}
\]

Where, V is Variance, \( \mu \) is the mean value of the block image, I(i, j) is rows and columns of the image and m \( \times \) n is the image size is calculated using equation 1. A high value of variance shows the greater extent of focus in the image block. Contrast Visibility calculates the deviation of a block of pixels from the block’s mean value. Spatial frequency measures the activity level in an image. It is used to calculate the frequency changes along rows and columns of the image. Spatial frequency refers to the number of pairs of Where, VI, \( \mu_k \), m \( \times \) n, I(i, j) refers Contrast Visibility, mean, size of the block and rows and columns of the image respectively. One-third of a millimetre is a convenient unit of retinal distance because an image this size is said to subtend one degree of visual angle on the retina. To give an example, index fingernail casts an image of this size when that nail is viewed at arm's length, a typical human thumb, not just the nail, but the entire width, casts an image about twice as big, two degrees of visual angle[8]. The size of the retinal image cast by some object depends on the distance of that object from the eye, as the distance between the eye and an object decreases, the object's image subtends a greater visual angle. The unit employed to express spatial frequency is the number of cycles clearness level of the block. SF is Spatial Frequency, RF is Row Frequency, CF is Column Frequency, m \( \times \) n is size of image, I(i, j) is the rows and columns of the image. Energy of Gradient (EOG) it is also used to measure the amount of focus in an. It is calculated using equation (2).

\[
EOG = \sum_{i=1}^{m-1} \sum_{j=1}^{n-1} \left( f_{i,j}^2 + f_{i,j}^2 \right)
\]

where,
\[
f_{i,j} = f(i,j + 1) - f(i,j)
\]
\[
f_{i,j} = f(i,j + 1) - f(i,j)
\]

EOG is Energy of Gradient. Energy of the row, is the Energy of the column, m \( \times \) n is the size of the image is calculated using equation 2.
The edge pixels can be found in the image block by using Canny edge detector. It returns 1 if the current pixel belongs to some edge in the image otherwise it returns 0. The edge feature is just the number of edge pixels contained within the image block. Edge detection is a fundamental tool in image processing and computer vision, particularly in the areas of feature detection and feature extraction, which aim at identifying points in a digital image at which the image brightness changes sharply or more formally has discontinuities[7]. The purpose of detecting sharp changes in image brightness is to capture important events and changes in properties of the world. Edges extracted from non-trivial images are often hampered by fragmentation, meaning that the edge curves are not connected, missing edge segments as well as false edges not corresponding to interesting phenomena in the image, thus complicating the subsequent task of interpreting the image data. Edge detection is one of the fundamental steps in image processing, image analysis, image pattern recognition, and computer vision techniques.

3.1 Quantitative Measures

There are different quantitative measures which are used to evaluate the performance of the fusion techniques. In this paper three measures Root Mean Square Error (RMSE), Peak Signal to Noise Ratio (PSNR) and entropy (He) are calculated. Root Mean Square Error The analytical performance studies were aimed to quantitatively assess image fusion performance in a straightforward manner[2]. The root mean square error (RMSE) , defined by the deviations between the reference image pixel value R(i, j) and the fused image pixel value F(i, j). Where m × n is the input image size. If the value of 0 correspond to the complete image reconstruction for block m × n, it is a perfect image, which has been achieved through accurate reconstruction of multi focus to the reference image. Root mean square error (RMSE) is a frequently used measure of the differences between values predicted by a model or an estimator and the values actually observed from the thing being modeled or estimated. RMSE is a good measure of accuracy and is calculated using 3 equation. These individual differences are also called residuals, and the RMSE serves to aggregate them into a single measure of predictive power.

\[
RMSE = \sqrt{\frac{\sum_{i=-1}^{m} \sum_{j=-1}^{n} (R(i, j) - F(i, j))^2}{m \times n}}
\]  

(3)

Entropy is known to be a measure of the amount of uncertainly about the image. A digital image consists of pixels arranged in rows and columns. Each pixel is defined by its position and by its grey scale level. The entropy of a given source is affected by the number of elements. Thus a normalized measure, redundancy, is better for comparing multiple sources. The entropy or average information of an image can be determined approximately from the histogram of the image. It is given by equation 4.

\[
H = -\sum_{i=0}^{L-1} P_i \log_2 P_i
\]  

(4)

Where L is the number of gray levels.

Peak Signal to Noise Ratio determines the degree of resemblance between reference and fused image. A bigger value show good fusion result. Peak Signal to noise Ratio (PSNR) is a metric that compares a set of reference values to a set of estimated values, usually incorporating the mean squared error as the error function. Here the reference image is not known therefore the PSNR cannot be calculated using equation 5 directly. It determines the degree of resemblance between reference and fused image.
4. Experiments and Results

Modern spectral scanners gather up to several hundred of spectral bands which can be both visualized and processed individually, or which can be fused into a single image, depending on the image analysis task. In this section, input images are fused using fuzzy logic approach. So it is concluded that results obtained from the implementation of neuro fuzzy logic based image fusion approach performs better for first two test cases and fuzzy based image fusion shows better performance for third test case. So further investigation is needed to resolve this issue. Our experimental results show that neuro fuzzy logic based image fusion approach provides better performance when compared to fuzzy based image fusion for first two examples. Image quality index (IQI), the similarity between reference and fused image (0.9999, 0.9829, and 0.3182) are higher for first two cases when compared to values obtained from fuzzy based fusion technique (0.9758, 0.9824, and 0.8871). The higher values for fusion factor (FF) from first two examples(2.8115, 3.3438, 1.0109) obtained from the neuro fuzzy based fusion approach indicates that fused image contains moderately good amount of information present in both the images compared to FF values (1.0965,2.1329,1.9864) obtained from fuzzy based fusion approach. The amount of information of one image in another, mutual information measure (MIM) values (1.4656,1.5079,0.7634) are also significantly better which shows that neuro fuzzy based fusion method preserves more information compared to fuzzy based image fusion. The other evaluation measures like root mean square error (RMSE) with lower and peak signal to noise ratio (PSNR), Correlation Coefficient (CC) with higher values (0.9459, 0.8979, 0.1265) obtained form neuro fuzzy based fusion approach are also comparatively better for first two cases. The entropy, the amount of information that can be used to characterize the input image (7.2757, 7.3202, 4.4894) are better for two examples obtained from neuro fuzzy based image fusion technique. The figure 3 shows the Medical images (CT and MRI Brain) fused by different fusion techniques and the proposed method. Figure a and b are the input CT and MRI images respectively. The algorithm has been successfully developed and implemented in MATLAB to fuse images with comparatively less information when considered separately and MRI Simulator and Bloch simulator were used for identifying the tumour cells in CT and MRI scan. The fused images have better and complete information with better geometric resolution. Nine features are extracted from the tumor region and stored in a database along with clinical details in different categories such as patient wise and is used to determine the feature subset and its range that discriminates the grade of the tumor. Based on this outcome, a triangular based fuzzy qualitative reasoning model is built with optimal set of rules (disjunction free, unambiguous and minimum number of rules) and validated using real datasets and it is simulated using ANFIS Editor GUI.

![Fused images](image_url)
Figure 2. Medical images (CT and MRI Cartilage) fused by different image fusion techniques using MATLAB.

The MRI Simulator allows for the instruction of clinical MRI procedures and the results are shown in figures 4 and 6. Manix, Cerebrix and Brainix MRI brain images – Training dataset were taken into considerations for identification of tumor cells. Enchondroma Chondrosarcoma and Benign MRI Cartilage images – Training dataset were taken into considerations for identification of tumor cells.
Figure 3. Simulation Result of MRI (BRAIN) Images using Bloch simulator
Figure 4. Simulation Result of MRI (BRAIN) Images using MRI simulator

Figure 5. Simulation Result of MRI (cartilage) Images using Bloch simulator
In the present study, experiments were performed with 10%, 30% and 50% training samples drawn randomly from the whole dataset and the remaining 90%, 70% and 50% are used for testing. This also helped us to show that size of the training data does not affect the performance.

5. Conclusion and Future Work
In this paper, block-based feature-level multi-focus image fusion technique is proposed for fusing images that are not in focus. A feed forward neural network is first trained with the block features of a pair of multi-focus images. A feature set including spatial frequency, contrast visibility, edges, variance and energy of gradient is used to define the clarity of the image block. Block size is determined adaptively for each image. The trained neural network is then used to fuse any pair of multi-focus images. The experimental results clearly show that the proposed image fusion using fuzzy logic gives a considerable improvement on the quality of the fusion system and neuro fuzzy based image fusion preserves more texture information. Experimental results show that the proposed method can preserve more useful information in the fused image with higher spatial resolution and less difference to the source images. The effects of different fusion rules, as well as new techniques to compute the parameters of the neurons of the PCNN, are some of the future scopes of the proposed technique. The developed system is open for analyzing the images with tumor at multiple locations and small lesions. The sample space considered constitutes only MRI and CT images of Brain and
cartilage tumor but it is significant to note that the same approach can be extended to several other types of tumors also. The parameters used for the analysis are image based features and limited clinical features, thus allowing for the extension of the system to categorize tumor based on various modalities of images like PET and SPECT images. In the future the proposed technique may be complemented for the treatment planning process for ion radiotherapy and improve the accuracy so as to reap the rewards of highly conformal irradiation of tumors with charged particles.

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