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# Multi-level fuzzy contourlet-based image fusion for medical applications

*Saad M. Darwish*

*Department of Information Technology, Institute of Graduate Studies and Research, Alexandria University, 163 Horreya Avenue, El Shatby 21526, P.O. Box 832, Alexandria, Egypt*
*E-mail: saad.darwish@alex-igsr.edu.eg*

**Abstract:** Multi-modal images fusion is one of the most truthful and useful diagnostic techniques in medical imaging system. This study proposes an image fusion system for medical engineering based on contourlet transform and multi-level fuzzy reasoning technique in which useful information from two spatially registered medical images is integrated into a new image that can be used to make clinical diagnosis and treatment more accurate. The system applies pixel-based fuzzy fusion rule to contourlet's coefficients of high-frequency details and feature-based fuzzy fusion to its low-frequency approximations, which can help the development of sophisticated algorithms that consider not only the time cost but also the quality of the fused image. The developed fusion system eliminates undesirable effects such as fusion artefacts and loss of visually vital information that compromise their usefulness by means of taking into account the physical meaning of contourlet coefficients. The experimental results show that the proposed fusion system outperforms the existing fusion algorithms and is effective to fuse medical images from different sensors with applications in brain image processing.

## 1 Introduction

In recent years, the study of multi-modality medical image fusion attracts much consideration with the increasing demand in clinical application. The aim is to deliver a better medical decision, to suggest a prognosis or to help physicians in a surgical intervention. In general, image fusion is the process of integrating multiple registered images of the same scene into a single fused image to reduce uncertainty and minimising redundancy while extracting all the useful information from the source images [1, 2]. Image fusion process is required for different applications, like medical imaging, remote sensing, machine vision, biometrics and military applications.

For medical image fusion, the fusion of images can regularly lead to supplementary clinical information not apparent in the separate images. Another advantage is that it can decrease the storage cost by storing just the single fused image instead of multi-source images [3]. Fused images may be created from multiple images from the same imaging modality, or by combining information from multiple modalities (multi-sensor information fusion), such as magnetic resonance image (MRI) and computed tomography (CT). In radiology these images serve different purposes. For example, CT images are used more often to reveal any bone information whereas MRI images are classically used to distinguish subtle variations in soft tissues [4].

Considering the objectives of image fusion and its potential advantages, some generic requirements can be imposed on the fusion algorithm [1, 3]: (i) it should not remove any salient information contained in any of the input images; (ii) it should not present any artefacts that can confuse or mislead a human observer; and (iii) it must be reliable, robust and, as much as possible, tolerant of deficiencies such as noise or misregistrations. Although there are different fusion techniques for medical images in use, researches are being carried out to bring the best of all in order to obtain a fusion procedure, which would yield the maximum information content of all the given input images with enhanced quality and clarity. A more comprehensive description of the recent medical fusion methods is available in [3–6].

Fusion rule (fusion operator) is the key that influences the quality of image fusion and also represents an unsolved difficult problem until now. The fusion operator describes the merging of information from the different input images. Many fusion rules have been proposed in the literature. These rules can be categorised as pixel, decision and feature rules according to the amount of processing that is performed on the image prior to fusion and hence the format in which this information is fused. In pixel-based rules, the information fusion is performed in a pixel-by-pixel basis either in the transform or spatial domain. The complexity of pixel-based algorithms is lesser than other methods. Some scholars have studied pixel-level image fusion issues. Their algorithm improves the signal-to-noise ratio, but deteriorates the contrast [3, 7]. Decision fusion rules combine the results from multiple algorithms to yield a final fused decision. Various decision fusion rules, such as Boolean conjunctions, weighted methods, classical inference, Bayesian inference, have been proposed. For a more complete review on decision-based fusion rules, see [7].

Region (feature) fusion rules group image pixels to form contiguous regions, for example, objects and impose different fusion rules to each image region. This type of fusion rule requires the extraction of different features from the source data before features are merged together, which can be attributed to the inefficiencies faced by pixel-based algorithms in cases where the salient features in images are larger than one pixel [8, 9]. In general, pixel-based fusion algorithms concentrate on increasing image contrast whereas region-based algorithms provide edge enhancement. Recently, many attempts have been made; see for example [10–12] to mix both pixel and region fusion rules in a single fused image. The integration of image fusion algorithms offers immense potential for future research as each rule emphasises on different characteristics of the source image.

In addition to the above taxonomy, the strategies of image fusion can be classified into two types: simple fusion strategy and layered fusion strategy. While the former has several simple fusion rules that utilise localised spatial features such as logistic filtering, grey-weighting average, contrast modulation and so on [3–6], the latter includes the fusion strategy based on decomposition such as pyramid, wavelet and curvelet transform fusions [13–16]. The main motivation behind moving to a transform domain is to work in a framework, where the image's salient features are more clearly depicted than in the spatial domain. For traditional pyramid image fusion algorithm, the fusion operator optimises image fusion rules by affecting in each decomposed level, and for image fusion based on wavelet transform, the operator let algorithms achieve adaptability by adjusting wavelet coefficients of the low-frequency sub-images' fusion and high-frequency sub-images' fusion [5]. Hence, the choice of the transform is very important.

Although the wavelet transform is powerful in representing images containing smooth areas separated with edges, it cannot perform well when the edges are smooth curves because of their limited ability in capturing directional information. New developments in directional transforms, known as contourlets in two dimensions, which have the property of capturing contours and fine details in images can address this issue [17]. Despite the application of contourlet transform in image fusion study has been developed rapidly [12, 17], there are still some problems which need to be solved. Most fusion methods based on contourlet transform do not consider information from higher levels of abstraction. Often, these methods adopt the average values of the high-frequency part and low-frequency part, respectively, after the multi-scale decomposition of the individual images, which may result in a loss of some detailed texture information and important spectral information. Recently, the soft computing technology, especially the fuzzy logic algorithm, has its significant advantages in complicated image fusion.

In order to resolve the problem of uncertainty contribution of each source' image to the fused image and integrate as much information of each source as possible, a lot of state-of-the-art researches have adapted fuzzy reasoning to handle the drawbacks of traditional fusion algorithms [8–12, 18]. With the help of fuzzy if–then rules and membership functions designed for the image data set, the fuzzy logic approach can model and combine the images to enhance the contrast of the fused image. At present, neural networks have also been used to generate a fuzzy inference system structure automatically from the input image data obtained from different sensors [9].

In this vein, this paper contributes a novel multi-modality medical image fusion system based on a novel combination of multi-level fuzzy reasoning and contourlet transform. The system estimates the importance of every contourlet coefficient with fuzzy reasoning and uses fuzzy integral operators for fusion in two levels (pixel-level and region-level). The merit of the proposed system comparing with similar systems is that the resultant fused images are both qualitatively and visually superior as a result of using fuzzy perceptive to apply two different fusion rules according to the extracted features.

This paper is structured in the following way: Section 2 provides the details of the proposed fusion system. Section 3 presents a comparative performance evaluation of the fusion system and the experimental fusion results. Finally, Section 4 offers a summary of the paper and its main conclusions.

## 2 Problem statement and methodology

In order to support more accurate clinical information for physicians to deal with medical diagnosis and evaluation, multi-modality medical images fusion are needed. In recent years, numerous approaches of medical image fusion have been carried out and are reported in the literatures. However, these approaches suffer from the noise and artefacts as they tend to have higher contrast. For instance, the border of tumour with normal tissues cannot be very well defined on the images, therefore it is difficult for radiology experts to outline image. So, the aim of the study is to find a proper fusion operator for medical image fusion that considers the quality of the fused image. The result yielded by the fusion operator is a fuzzy set that identifies the certainty and uncertainty present in and among the inputs to the fusion process.

Formally, if $I$ is an ideal image and $C_1, \ldots,$ are acquired images capturing the same scene using different instrument modalities or capture techniques, allowing each image to have different characteristics, image fusion is a means to obtain an image $\widehat{I}$ that yields in some logic a better representation of the ideal image $I$ than is provided by each individual image $C_i$ [15]

$$\widehat{I}(x, y) = \oplus\big(C_i(x, y)\big) + e_i(x, y), \quad i = 1, 2, \ldots, k \tag{1}$$

where $e_i$ is an additive random noise describing the image degradation and $\oplus$ is the fusing operator. Fusion operator should conserve all important analysis information such as edges and structural details in the image and should not introduce any artefacts while suppressing the undesirable characteristics like noise and other irrelevant details.

Inside the proposed system, in order to eliminate artefacts the employed fusion operator fuses corresponding information in different resolutions and directions, which makes the fused image clearer. The advantages of the offered system are (i) both edge features and component information of the objects from different modalities are preserved in the fused image effectively; and (ii) features at different levels are extracted for fusion. Besides, it introduced a meaningful fusion performance evaluation metrics based on entropy, mutual in formation and image quality index.

Fig. 1 depicts a schematic view of different modules involved in the fusion system of this study. First, the input images are decomposed into multiple resolutions by using the contourlet transform that provides a better representation than the conventional transforms. In the second step, transformed coefficients are combined with a fuzzy fusion rules. Finally, the resultant image is found by performing inverse contourlet transformation of the composite image. Here, the images used in fusion should be registered. Misregistration is a major source of error in image fusion.

In the proposed multi-level fusion system, feature-level information used to guide the pixel-level fusion process is in the form of edges and image segment boundaries. The focus of this system is the object-based image fusion, in which the system considers not only the corresponding contourlet coefficients and their closing neighbourhood, but also the regions' coefficients. This paper carefully involves the important part of image fusion – fuzzy operator for the hierarchical fusion of processing – and conduct fusion experiments on these aspects. The following paragraphs describe system's steps in detail and discuss some of the prospects regarding the discrete contourlet frame and fuzzy c-mean clustering, which represents the key constituents of the examined fusion system.

Contourlet transform is now the most widely used method at the pixel-level fusion because it offers a flexible multi-resolution and directional decomposition for images, since it allows for different number of directions at each scale [17, 18]. The contourlet transform consists of two steps: first, the images are decomposed by Laplacian Pyramid (LP) into one low-frequency sub-band and various high-frequency sub-bands (LP is used to confine edge point discontinuities). Subsequently, high-frequency sub-bands are fed into directional filter bank (DFB) and segmented into multiple directional sub-bands (DFB is used to link edge points discontinuities into linear structures). Fig. 2 shows the contourlet transform for the MRI brain test image.

In our case, the fusion process applies a fusion operator repeatedly on the contourlet coefficients such that coefficients in low-frequency bands are selected with a visibility-based scheme, and coefficients in high-frequency bands are selected with a variance-based method. To improve the fusion accuracy, the region statistics idea based on contourlet transform is integrated in the fusion rule. For a complete mathematical foundation of contourlet transform, readers can refer to [18].

Medical diagnosis becomes effective if it identifies the defective areas. However, while focusing on those areas, designated as a region of interest, contextual information surrounding that region is important. In general, image region boundaries are a basic element in the perception of image structure. Recently, fuzzy clustering is used to separate out interesting areas and generates fuzzy partitions of the data instead of hard partitions [18, 19]. In this case, data patterns may belong to several clusters, having different membership values with different clusters. The fuzzy clustering of objects $o = \{o_1, o_2, \dots, o_r\}$ is described by a fuzzy matrix $\mu$ with $r$ rows and $c$ columns where $r$ is the number of data objects and $c$ is the number of clusters. $a_{ij}$ indicates the degree of association or membership function of the $i$th object with the $j$th cluster. Fuzzy C-means (FCM) algorithm is one of the most popular clustering techniques because it is efficient, straightforward and easy to implement [18]. The objective function of FCM is to minimise the following equation

$$\chi_y = \sum_{j=1}^{c} \sum_{i=1}^{r} a_{ij}^{y} d_{ij} \tag{2}$$

in which

$$d_{ij} = \left\| o_i - z_j \right\|, \quad z_j = \frac{\sum_{i=1}^{r} a_{ij}^{y} o_i}{\sum_{i=1}^{r} a_{ij}^{y}}, \quad y(y > 1)$$

is a scalar termed the weighting exponent and controls the fuzziness of the resulting clusters and $d_{ij}$ is the Euclidian distance from object $o_i$ to the cluster centre $z_j$ (centroid of the $j$th cluster). In our situation, FCM algorithm is utilised to extract region information that is considered by region fusion rule, so that its fusion effect is better. The complete FCM algorithm can be found in [20].

### 2.1 Proposed image fusion approach

The proposed image fusion system consists of the following steps with reference to Fig. 1. The inputs to the fusion

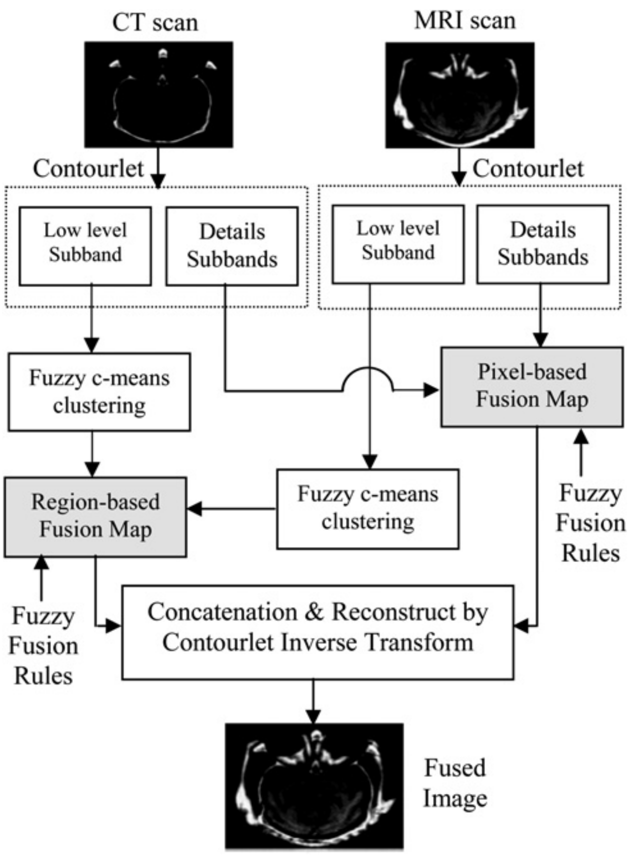


**Fig. 1** *Framework of the proposed image fusion system*

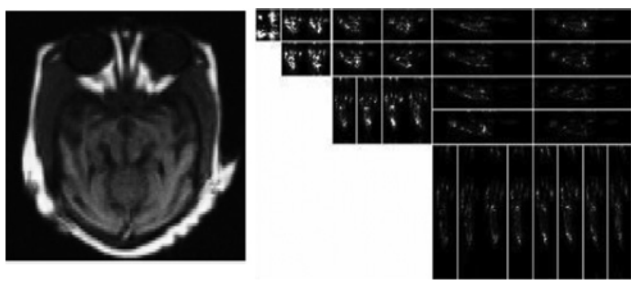

**Fig. 2** *Brain MRI image and its contourlet coefficients*




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algorithm are features extracted from both CT and MRI images while its output is a fused image formed from a set of fuzzy rules that employed as the basis to select fusion coefficients and to make an intelligent fusion decision. In our case, the objective of the fusion of an MRI and a CT image of the same organ is to obtain a single image containing as much information as possible about that organ for diagnosis.

*Step 1:* Read the two multi-modality medical images $A$ and $B$ to be fused. The original CT scan and MRI scan images are geometrically registered to each other. The goal of image registration is to fix unaligned image into the coordinate system of the reference image and to make corresponding coordinate points in the two images fit the same coordinate location [21].
*Step 2:* Perform a contourlet decomposition on source images $A$ and $B$, respectively, and obtain the corresponding coefficients $\left\{\mathrm{Coff}^{(\mathrm{low},A)}, \mathrm{Coff}_{j,k}^{(\mathrm{high},A)}\right\}$ and $\{\mathrm{Coff}^{(\mathrm{low},B)}, \mathrm{Coff}_{j,k}^{(\mathrm{high},B)}\}$, where $\mathrm{Coff}^{(\mathrm{low},A)}$ and $\mathrm{Coff}^{(\mathrm{low},B)}$ represent low-frequency coefficients (approximation) of images $A$ and $B$ separately at the coarsest scale. $\mathrm{Coff}_{j,k}^{(\mathrm{high},A)}$ and $\mathrm{Coff}_{j,k}^{(\mathrm{high},B)}$ denote the high-frequency coefficients (details) of source images $A$ and $B$, respectively, at the $j$th scale and $k$th direction of transformation.
*Step 3:* The low-frequency sub-band for both images $\mathrm{Coff}^{(\mathrm{low},A)}$ and $\mathrm{Coff}^{(\mathrm{low},B)}$ are segmented into important and background regions using FCM clustering algorithm according to the pixel grey-level distribution.
*Step 4:* Employ a different fusion decision map based on a set of fuzzy fusion rules for the resultant sub-bands depending in accordance with contourlet decomposition characteristic (as illustrated in Sections 2.1.1 and 2.1.2) to reconstruct the contourlet coefficients of the fused image $F\left\{\mathrm{Coff}^{(\mathrm{low},F)}, \mathrm{Coff}_{j,k}^{(\mathrm{high},F)}\right\}$.
*Step 5:* The new coefficient's matrix is obtained by concatenating fused approximation $\mathrm{Coff}^{(\mathrm{low},F)}$ and detail coefficients $\mathrm{Coff}^{(\mathrm{high},F)}$.
*Step 6:* By sequentially performing inverse contourlet transform to the modified coefficients at all sub-bands, the final fused image can be reconstructed.

Decision map is the core of the fusion algorithm. Its output governs the actual combination of the coefficients of the various sources and controls the weights to be assigned to each source coefficients. The fusion decision map has the same size as the original image, where each value is the index of the source image which may be more informative on the corresponding contourlet coefficient. The conventional approach is to assign a weight which is directly proportional to the activity measure. But this has a contrast reduction effect in fused images. The suggested system utilises fuzzy space to assign a weight for each source's coefficients. This weight is based on: (i) local energy representation in place of details coefficients (pixel-based decision map) to tackle the contrast reduction effect; and (ii) fuzzy clustering for approximation coefficients (region-based decision map) to enhance the fusion quality.

*2.1.1 Fusion rule for high-frequency sub-bands:* Inside contourlet transform, high-frequency (details) sub-bands' coefficients generally correspond to salient features in the image such as the edges, lines and contours. In the literature, the local energy represents the major used selection principle to pick out these salient features [11]. However, the extent of each contourlet coefficients of the source image's contribution to the fused image is uncertain, thus how to combine the corresponding coefficients becomes the most important problem in image fusion systems based on contourlet transform. The offered system exploits the same concept in [12] to estimate the contributions of $\mathrm{Coff}^{(\mathrm{high},A)}$ and $\mathrm{Coff}^{(\mathrm{high},B)}$ to the fused image. Their concept is based on the assumption that if the energy of details coefficient is large and its information entropy is large, the coefficient may contribute more importance to the fused image. In this case, it is necessary to fuzzy the importance of the details' coefficients, so the fusion process is performed in fuzzy space.

Formally, for every coefficient $w$ in the high-frequency sub-bands at scale $j$ and direction $k$, let $\mu_0(w)$ is the membership function for the relation 'a coefficient is large' and $\mu_1(w)$ stands for the membership function for the relation 'the information entropy of the coefficient is large' then $\mu_{0\cap 1}(w)$ represents the importance of the coefficient to the fused image, where

$$\mu_{0\cap 1}(w) = \mathrm{Min}\big(\mu_0(w), \mu_1(w)\big) \tag{3}$$

$$\mu_0(w) = \frac{\mathrm{En}(w)}{\mathrm{Max}_{w\subseteq \mathrm{coff}_{j,k}^{(\mathrm{high})}}(\mathrm{En}(w))} \tag{4}$$

$$\mu_1(w) = \frac{I(P(w))}{\mathrm{Max}_{w\subseteq \mathrm{coff}_{j,k}^{(\mathrm{high})}}(I(P(w)))} \tag{5}$$

$\mathrm{En}(w) = w^2$, and $I(P(w)) = \exp(1 - P(w))$ are the energy and the information content of the coefficient $w$, respectively, and $P(w)$ is the probability of the coefficient. For the coefficient $w_{\mathrm{B}}$, which has the same spatial position with the coefficient $w_{\mathrm{A}}$, the system fuses the details of sub-bands using every coefficient's $\mu_{0\cap 1}(w_A)$ or $\mu_{0\cap 1}(w_B)$ where the fused coefficient $w_F$ is calculated as [12]

$$w_F = \frac{w_A \cdot \mu_{0\cap 1}(w_A) + w_B \cdot \mu_{0\cap 1}(w_B)}{\mu_{0\cap 1}(w_A) + \mu_{0\cap 1}(w_B)} \tag{6}$$

The above equation represents the fusion operator designed for high-frequency sub-bands. Based on this operator, the fused high-frequency components in contourlet domain can preserve all the salient features in source images and introduce as less artefacts or inconsistency as possible.

*2.1.2 Fusion rule for approximation sub-band:* To detect, compare and transfer the most important visual and structural information from source images into a fused image, the advised system also adopts region-based fusion for low-frequency sub-band. Approximation coefficients are interpreted as the mean intensity value of the source images with all salient features encapsulated by the detail coefficient sub-bands at their various scales. Therefore, fusing approximation coefficients by clustering maintains the appropriate mean intensity needed for the fusion result with minimal loss of salient features.

In this case, both the $\mathrm{Coff}^{(\mathrm{low},A)}$ and $\mathrm{Coff}^{(\mathrm{low},B)}$ are segmented into two regions (important and background) using FCM clustering procedure based on mean of coefficient's values in a region. The segmented approximations are then fed into a fusion based on fuzzy 'if–then' rules to obtain the fused approximation. These rules are as follows: If the region feature indicates the region is important, the region of image $A$ (CT scan) should be selected as fusion result. On the other hand, if the region feature indicates the region is background, the region is selected from image B (MRI scan).

Since the importance of image's regions is relative, it is necessary to fuzzy the importance attribute of regions. The fusion process is performed in fuzzy space where each feature of the regions is used to determine the region's degree of membership [11]

$$\mu_{i,j} = \exp\left[\frac{-\left(\mathrm{ME}_j - V_i\right)^2}{\left(V_{\max} - V_{\min}\right)/2}\right] \tag{7}$$

where $V_i$, $i \subseteq \mathrm{coff}^{(\mathrm{low})}$ symbols coefficients value, $V_{\min}$ is the lowest approximation's coefficient, $V_{\max}$ is the highest approximation's coefficient, $\mu_{i,1}$, $\mu_{i,2}$ are the values of membership function in important and background regions, respectively, and $\mathrm{ME}_j$ is the mean of coefficients in region $j \in \{1, 2\}$. At this instant, $\mathrm{ME}_j = E_1$ (indicates that the region $j$ is background) cause that fusion result $F_1$ is the corresponding region of image $B$; $\mathrm{ME}_j = E_2$ (indicates that the region $j$ is important) produce that fusion result $F_2$ in the corresponding region of image $A$. The final fusion result is achieved by defuzzification process using the function [11]

$$F = \frac{\sum_{j=1}^{2} \mu_{i,j} F_j}{\sum_{j=1}^{2} \mu_j}, \quad \forall i \in \mathrm{coff}^{(\mathrm{low})} \tag{8}$$

## 3 Experiments, results and discussion

To assess the performance of the suggested fusion system, extensive experiments were carried out on various modalities of medical images. This section reports the experiments on two datasets of human brain images, as shown in Fig. 3 that are selected from both BrainWeb database (http://www.bic.mni.mcgill.ca/brainweb/) and image fusion website (http://www.imagefusion.org). All images have the same size of $512 \times 512$ pixel, with 256-level greyscale. The corresponding pixels of two input images have been perfectly co-aligned. The algorithm in this paper is simulated using MATLAB with 3-level LP and 4-, 8-, 16-direction DFB for each high pass scales.

The results were evaluated through visual inspection (subjectively) and quantitative analysis (objectively). To evaluate the proposed fusion system objectively, we choose some performance metrics such as entropy ($E$), mutual information (MI) and image quality index (IQI) to measure the quality of fused images. These metrics, defined as the following equations, depend on estimating the amount of information transferred from each source image into the resulting fused image. Readers looking for a survey about fusion quality measures can refer to [5, 6, 15]

$$E = \sum_{i=0}^{g-1} P_i \log_2 P_i \tag{9}$$

where $g$ is the total of image's grey levels, and $P_i$ is the probability distribution of each level.

$$\mathrm{MI} = I_{FA}(f, a) + I_{FB}(f, b) \tag{10}$$

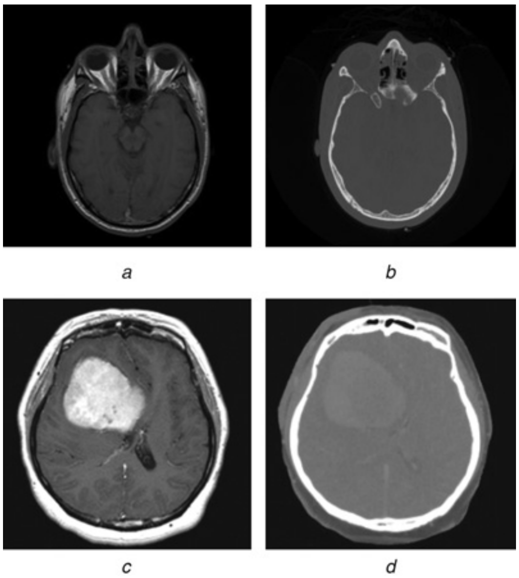

**Fig. 3** *Examples of source multimodality image dataset 1(a and b) and dataset 2 (c and d)*

*a* MRI
*b* CT
*c* MRI
*d* CT

$$I_{FA}(f, a) = \sum_{f,a} P_{FA}(f, a) \log_2 \frac{P_{FA}(f, a)}{P_F(f) P_A(a)} \tag{11}$$

$$I_{FB}(f, b) = \sum_{f,b} P_{FB}(f, b) \log_2 \frac{P_{FB}(f, b)}{P_F(f) P_B(b)} \tag{12}$$

where $P_A(a)$, $P_B(b)$ and $P_F(f)$ are histograms of images $A$, $B$ and $F$. $P_{FA}(f, a)$ and $P_{FB}(f, b)$ are the joint histograms of $F$ and $A$ and $F$ and $B$ separately

$$\mathrm{IQI}_F = \lambda Q_o(A, F) + (1 - \lambda) Q_o(B, F) \tag{13}$$

$$Q_o(A, F) = \left(\frac{\delta_{AF}}{\delta_A \delta_F}\right)\left(\frac{2\overline{AF}}{\left(\bar{A}^2 + \bar{F}^2\right)}\right)\left(\frac{2\delta_A \delta_F}{\delta_A^2 + \delta_F^2}\right) \tag{14}$$

$$Q_o(B, F) = \left(\frac{\delta_{BF}}{\delta_B \delta_F}\right)\left(\frac{2\overline{BF}}{\left(\bar{B}^2 + \bar{F}^2\right)}\right)\left(\frac{2\delta_B \delta_F}{\delta_B^2 + \delta_F^2}\right) \tag{15}$$

$$\lambda = \frac{H(A)}{[H(A) + H(B)]} \tag{16}$$

where $\delta_A$ is variance of $A$, $\delta_{AF}$ is covariance of $A$ and $F$, $\bar{B}$ is the mean of $B$, $\lambda$ is a weight giving more importance to one of the fused images, and $H$ is the spatial frequency of image and it measures the overall activity level of the image.

### 3.1 Visual analysis

We can see that the salient features and detailed information presented in Figs. 4*c* and *d* are much richer than Figs. 4*a* and *b*. That is because contourlet transform offers advantages of directionality, localisation, anisotropy and multi-scale, which cannot be perfectly achieved by wavelet transform [17]. With wavelet fusion, edges are blurred due



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to shrinking effect and shift variance whereas contourlet fused images provide clear representation at both edges and non-edge regions (i.e. preserves the multi-modal information). Furthermore, visual results were shown to medical professionals and they asserted that the proposed system (utilises multi-level fuzzy-based fusion rules in both low and high contourlet's sub-bands) provides better information for medical diagnosis compared to wavelet-based algorithm.

### 3.2 Quantitative analysis

In this study, we also compare the performance of the proposed fusion system with other three distinct schemes. One of these methods uses wavelet transform with pixel-based decision map, the second approach exploits also wavelet transform but with fuzzy region-based decision map, while the third technique employs the contourlet transform with mono-level fuzzy rules for pixel-based decision map. These methods are:

*3.2.1 Hybrid fusion based on wavelet transforms (HF-WT) [5]:* In this method, the discrete wavelet transform is applied to obtain the wavelet coefficients of the source images. The coefficients are processed with different fusion rules to obtain the primary fused image, which is again processed with the fusion rules to obtain the secondary fused image. The primary and secondary images are processed again with the most efficient fusion rule to obtain the final fused image.

*3.2.2 Image region fusion using wavelet and k-means clustering [11]:* With this method, the approximation sub-bands of the wavelet's coefficients for the source images are first segmented into three regions (important, sub-important and background) using k-means clustering algorithm. These regions are then fused using fuzzy 'if–then' rules.

*3.2.3 Fusion using fuzzy contourlet transforms [12]:* This algorithm can fuse corresponding information in different resolutions and directions by employing contourlet engine. The result sub-bands are then fused using fuzzy inference system to integrate as much information as possible into the fused image.

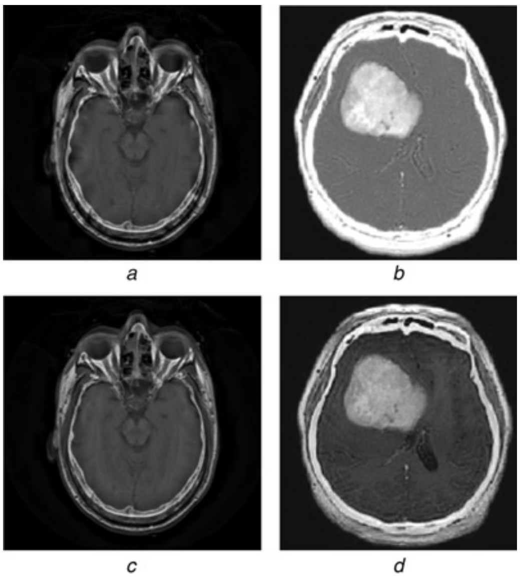

**Fig. 4** *Visual analysis*

*a* and *b* Wavelet-based fusion results
*c* and *d* Proposed method-based fusion results

Tables 1 and 2 show the objective performance measures of planned system and existing fusion methods taken on image sets shown in Fig. 3. It is clear that the proposed method outperforms the other classical techniques and yielded optimum fusion results. Using all the brain samples of image set 1, the average value of IQI pertaining to the proposed system is 0.93 whereas existing algorithms yield IQI values in the range of 0.65 to 0.80 (higher value of IQI means that more information is preserved while higher value of MI means that the fused image is clearer and contains more details and texture features). These results are expected by reason of the proposed system's abilities to accumulate boundary information and structural details without introducing any other inconsistencies to the image. Furthermore, fuzzy logic is used in the last two methods for comparison, but the suggested method applies multi-level fuzzy fusion rule to participate as much information as possible into the fused image. For the other sets of source images used in the experiments Figs. 3*c* and *d*, similar results have been found.

In summary, subjective and objective evaluations show that the multi-level fuzzy contourlet approach is effective as a whole, and medical images fused by this approach appear natural and sharp to the human observer (contains almost all of the salient features of the input images). However, the contourlet transform methods give the maximum computation time as shown in Table 3 (experiments ran on a PC equipped with P4 2.26 GHz Intel processor, 512 MB main memory and 40 GB disk drive running Microsoft Windows XP Professional SP2) because the construction of the contourlet transform consists of double filter banks which take higher time to generate the coefficients. Despite this time, the proposed algorithm can be efficiently used for real-time applications. Finally, the overall computation complexity of the proposed system is estimated by $O(NM)$ and by this, it is linear with respect to the length of the input images where $N$ and $M$ encode the number of image's rows and columns, respectively. This gives us a chance to integrate the system with other tools for medical images' diagnosis mechanism entrenched inside an automated real-time medical treatment system.

**Table 1** Results of quality measures for various fusion methods using image set 1

| Methods | EN | MI | IQI |
|---|---|---|---|
| HF-WT [5] | 5.962 | 5.195 | 0.7690 |
| fuzzy *K*-means [11] | 6.482 | 5.423 | 0.6562 |
| fuzzy contourlet [12] | 6.710 | 7.526 | 0.8013 |
| proposed system | **6.952** | **8.137** | **0.9299** |

**Table 2** Results of quality measures for various fusion methods using image set 2

| Methods | EN | MI | IQI |
|---|---|---|---|
| HF-WT [5] | 6.326 | 5.502 | 0.7753 |
| fuzzy *K*-means [11] | 6.571 | 5.931 | 0.6932 |
| fuzzy contourlet [12] | 6.954 | 6.958 | 0.8235 |
| proposed system | **7.124** | **8.286** | **0.9451** |

**Table 3** Performance evaluation results of the test image

| Methods | Average computational time (in seconds) |
|---|---|
| HF-WT [5] | 3.05 |
| fuzzy *K*-means [11] | 4.17 |
| fuzzy contourlet [12] | 4.86 |
| proposed method | 4.93 |

## 4 Summary

Medical image fusion has revolutionised medical analysis by improving the precision and performance of computer-assisted diagnosis. This paper proposes a local energy fusion strategy based on both pixel and region-level image fusion. The suggested system uses fuzzy operators for the hierarchal fusion of processing. The proposed system adopts fuzzy activity level comparison based on spatial frequency to fuse the contourlet's detail coefficients and fuzzy clustering to fuse approximate image. The introduced fusion system has the following advantages: (i) it improves the reliability by taking care of the redundant information (2); (ii) it improves the capability as it keeps complementary information.

This work is based on the suggestion that subjectively applicable fusion could be achieved if information at higher levels of abstraction such as image edges is used to lead the basic pixel-level fusion process. Images produced by inclusion of multi-level information in the fusion process are clearer and of generally better quality than those obtained through conventional low-level fusion. This is verified through objective evaluation for medical images. Meanwhile, because of the fuzzy logic's capacity of resolving uncertain problems, the offered system overcomes the drawbacks of traditional fusion algorithm based on contourlet transform, and integrates as much information as possible into the fused image.

Experiments on the brain images show that the proposed fusion system preserves both edge and component information and provides improved performance compared to existing fusion algorithms. Furthermore, the system is rather easy to implement and time efficient. In future, the plan is to extend the proposed system by incorporating learning techniques and evaluate the performance with other medical images.

## 5 References


1 Kaur, J., Ubhi, J.S.: 'Enhancement of context by image fusion'. Proc. World Congress on Engineering (WCE'11), UK, 6–8 July 2011, vol. II, pp. 1–5

2 Praveena, S.M.: 'Multiresolution optimization of image fusion'. Int. Conf. Recent Trends in Communication & Signal Processing (RTCSP'09), India, 4 April 2009, pp. 111–118

3 Chiorean, L., Vaida, M.F., Suta, L.: 'A medical image fusion method for web distributed applications', *J. Electron. Telecommun.*, 2009, **50**, (3), pp. 31–38

4 Das, S., Chowdhury, M., Kundu, M.: 'Medical image fusion based on ripplet transform type-I', *Progr. Electromagn. Res. B*, 2011, **30**, pp. 355–370

5 Chandana, M., Amuth, S., Kumar, N.: 'A hybrid multi-focus medical image fusion based on wavelet transform', *Int. J. Res. Rev. Comput. Sci. (IJRRCS)*, 2011, **2**, (4), pp. 948–953

6 Al-Azzawi, N., Ahmed, A.W.: 'Medical image fusion scheme using contourlet transform and PCA bases' (inTech Publisher, 2011), Chapter 6, pp. 93–110

7 Petrovic, V.: 'Multi-level image fusion'. Int. Society for Optical Engineering, USA, 2003, pp. 87–96

8 Singh, H., Raj, J., Kaur, G., Meitzler, T.: 'Image fusion using fuzzy logic and application'. IEEE Int. Conf. Fuzzy Systems, Hungary, 25–29 July 2004, pp. 337–370

9 Zheng, Y., Zheng, P.: 'Multi-sensor image fusion using fuzzy logic for surveillance systems'. Proc. Seventh Int. Conf. Fuzzy Systems and Knowledge Discovery, China, 10–12 August 2010, pp. 588–592

10 Zaveri, T., Zaveri, M.: 'A novel region based multimodality image fusion method', *J. Patt. Recogn. Res.*, 2011, **2**, pp. 140–153

11 Liu, G., Jing, Z.-L., Sun, S.-Y.: 'Multiresolution image fusion scheme based on fuzzy region feature', *J. Zhejiang Univ. Sci. A*, 2006, **7**, (2), pp. 117–122

12 Zhao, Z., Li, Y.X.: 'A novel image fusion method based on fuzzy contourlet transform'. Int. Conf. Computer and Communication Technology in Agriculture Engineering, China, 12–13 June 2010, pp. 404–407

13 Mengyu, Z., Yuliang, Y.: 'A new image fusion algorithm based on fuzzy logic'. Int. Conf. Intelligent Computation Technology and Automation, China, 20–22 October 2008, pp. 83–86

14 Kong, J., Zheng, K., Zhang, J., Feng, X.: 'Multi-focus image fusion using spatial frequency and genetic algorithm', *Int. J. Comput. Sci. Netw. Secur.*, 2008, **8**, (2), pp. 220–224

15 Perfilieva, I., Dankova, M., Vajgl, M.: 'The use of F-transform for image fusion algorithms'. Int. Conf. Soft Computing and Pattern Recognition, France, 7–10 December 2010, pp. 472–477

16 Choi, M., Kim, Y., Nam, M.-R., Kim, H.O.: 'The curvelet transform for image fusion'. Int. Society for Photogrammetry and Remote Sensing (ISPRS Congress), Turkey, 12–23 July 2004, pp. 1–6

17 Melkamu, H.A., Vijanth, S.A., Lila, I., Hani, A.F.: 'Image enhancement by fusion in contourlet transform', *Int. J. Electr. Eng. Inf.*, 2010, **2**, (1), pp. 29–42

18 Tamilarasi, M., Palanisamy, V.: 'Medical image compression using fuzzy C-means based contourlet transform', *J. Comput. Sci.*, 2011, **7**, (9), pp. 1386–1392

19 Beevi, S., Sathik, M., Senthamaraikannan, K.: 'A robust fuzzy clustering technique with spatial neighborhood information for effective medical image segmentation', *Int. J. Comput. Sci. Inf. Secur.*, 2010, **7**, (3), pp. 132–137

20 Izakian, H., Abraham, A.: 'Fuzzy *C*-mean and fuzzy swarm for fuzzy clustering problem', *Expert Syst. Appl.*, 2011, **38**, pp. 1835–1838

21 Al-Azzawi, N.A., Sakim, H.A., Abdullah, W.A.: 'MRI image mono-modal registration based on the non-subsampled contourlet transform and mutual information'. Int. Conf. Computer Applications and Industrial Electronics (ICCAIE 2010), Malaysia, 5–7 December 2010, pp. 481–786





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