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An Efficient Directive Contrast Based Multi Modal Medical Image Fusion under Improved NSCT Domain.

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ABSTRACT

Multimodal medical image fusion, as a great tool for the clinical applications, has developed with the advent of numerous imaging modalities in medical imaging. Medical image segmentation has advanced crucial technique in clinical and research-oriented applications. As manual segmentation techniques are tedious and semi-automatic segmentation lacking of flexibility, fully-automatic techniques become the preferred kind of medical image segmentation. In this paper, a novel fusion framework is proposed for multimodal medical images based on fully automatic segmentation scheme based on the modified contouring technique and non-subsampled contourlet transform (NSCT). First the source medical images have transformed by NSCT followed by merging low and high frequency components. Fusion rules based on phase congruency and directive contrast have proposed and used to fuse low and high frequency coefficients. Aimed at that fused image local threshold is computed and the initial points are resolute by computation of global threshold and also searching process is started from each one initial point to get closed loop contours. The entire process is fully automatic. Lastly, the fused image has made by the inverse NSCT with all combined coefficients. Tentative results and comparative study are shown that the proposed fusion framework offers an effective method to aid more perfect analysis of multimodality images. Advance, the applicability of the proposed framework carried out by the three clinical models of people affected with Alzheimer, subacute stroke and recurrent tumor.

Keywords: Multimodal MIF (Medical Image Fusion), NSCT (Non-Subsampled Contour Transform) Automatic segmentation, threshold, MRI, CT and PET image

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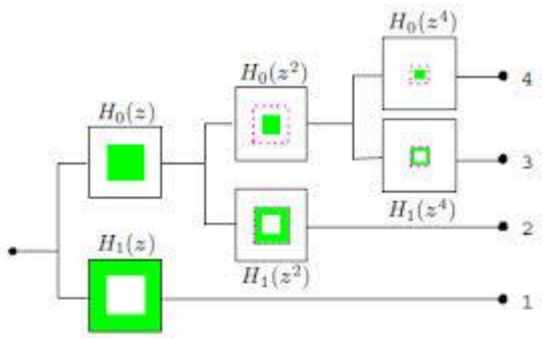
INTRODUCTION

Medical image fusion has been a current research topic. In general, medical image fusion means the matching and fusion between two or more images of the similar injury area from different medical imaging tools, and goals to obtain complementary information and increase the amount of information. Medical image fusion method is to combine the information of a multiplicity of images with computer-based image processing technique. It is using for medical image fusion so with regard to get a better image which clearer and has more information. In the medical diagnosis and treatment, the usage of fused images can provide more useful information. It is important for lesion location, analysis, making cure and pathological study F. Maes et al [2].

Medical imaging arena, can get different images of the identical part of the same patient with dissimilar imaging devices, and the information have provide by a variety of imaging approaches is often complementary. The medical images, CT could obviously reflect the anatomical structure of bone tissues. Oppositely, MRI could evidently reflect the anatomical structure of soft tissues, organs and blood vessels. CT, MRI and other kinds of medical images reproduce the human information from numerous outlooks. In the medical diagnosis and treatment, the problems about the comparison and synthesis between CT and MRI image had frequently encountered whereas PET has used to afford better information on blood flow and flood movement with low spatial resolution. Consequently, the anatomical and functional medical images have needed to be combined for a compendious view For this purpose, the multimodal medical image fusion has identified as a promising solution which purposes to integrating information from multiple modality images to acquire a more complete and accurate description of the same object.

Multimodal medical image fusion not only helps in analyzing diseases, but it also reduces the storage cost by decreasing storage to a single fused image in place of multiple-source images. As far as this, general work has been done on image fusion technique G. Bhatnagar et al [1]– Y. Chai et al [26] with various techniques keen to multimodal medical image fusion Q.Guihong et al [10] – T. Li et al [11]. These techniques have been categorized into three classes in keeping with integration stage. These contain pixel level, feature level and decision level fusion where medical image fusion typically employs the pixel level fusion because of the advantage of having the original measured quantities, easy implementation and computationally efficiency R. Redondo et al [15] and A. B.Watsonet al [14]. Therefore, in this propose paper, concentrate to pixel level fusion, and the relations image fusion or fusion is used for pixel level fusion. The distinguished pixel level fusions are based on principal component analysis (PCA), gradient pyramid (GP) filtering, contrast pyramid (CP), independent component analysis (ICA), etc. Meanwhile, the image sorts are profound to the human visual system exists in changed scales. So, these are not the greatly suitable for medical image fusionL. Yang et al [5]. Just, with the advance of multiscale decomposition, wavelet transform has well-known ideal method for image fusion. Nevertheless, it reasoned that wavelet decomposition is upright at sequestered discontinuities, however not good at edges and textured region. Advance, it captures restricted directional information beside vertical, horizontal and diagonal direction F. E. Ali (4). These subjects are resolved in a modern multiscale decomposition contourlet, and it is non-subsampled form. Contourlet is a "true"2-D sparse representation for 2-D signals comparable images where sparse expansion has expressed by contour segments. Such as a result,



It could capture 2-D geometrical structures in graphical information much more effectively than outdated multiscale methods A. L. da Cunha et al [27]. In a novel fusion framework has proposed for multimodal medical images based on Improved non-subsampled contourlet transform(NSCT). The fundamental idea is to perform Improved NSCT on the source images monitored by the fusion of low- and high-frequency coefficients. The phase congruency and directive contourlet contrast feature has integrated as the fusion rules for low- and high-frequency coefficients. The phase congruency affords a contrast and brightness-invariant representation of low-frequency coefficients while directive contrast capably decides the frequency coefficients from the perfect parts in the high-frequency. The combinations of these two has preserved further details in source images and more increase the quality of fused image.The efficiency of the recommended framework has carried out by the widespread fusion experimentations on different multimodal CT/MRI dataset. More, visual and quantitative analysis is shown that the proposed framework has provided a improved fusion outcome when related to conventional image fusion methods. The outstanding contributions of the recommended framework over existing methods has summarized as follows.

In this proposes a novel image fusion framework for multimodal medical images, which trusts on the Improved NSCT domain.

Two different image fusion rules has proposed for merging high and low frequency coefficients.

For fusing the low-frequency coefficients, the phase congruency based model has used. The main advantage of phase congruency is that it picks and combines contrast and brightness invariant representation confined in the low-frequency coefficients.

On the conflicting, a new definition of directive contrast in Improved NSCT domain has proposed and uses to combine high-frequency coefficients. By means of directive contrast, the supreme prominent texture and edge information select from high frequency coefficients and combined in the fused images.

The explanation of directive contrast has consolidated by combining a visual constant to the SML based meaning of directive contrast which offers a better-off representation of the contrast.

The rest of the paper has organized as follows. NSCT and phase congruency have designated in II followed by the recommended multimodal medical image fusion framework in III. New results and discussions have given in IV and the concluding observations are designated in V.

METHODS

This section is provided the explanation of ideas on which the proposed framework is constructed. These models have included Improved NSCT and phase congruency and are described as follows.

Non-Subsampled Contourlet Transform (NSCT)

The above figure shows the recommended NSCT. The structure involves in a bank of filters that splits the 2-D frequency plane in the sub-bands which is show in the figure (1-b). Our proposed transformation can be divided into two shift-invariant parts:

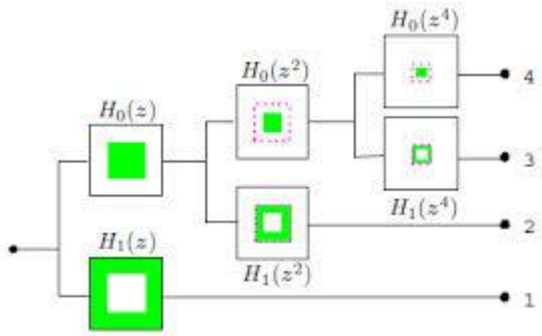


Figure 1: Three-stage non-subsampled pyramid decomposition.

1. Pyramid structure that ensures the Multiscale property
2. Directional Filter Bank (DFB) structure that gives directionality.

Non-sub sampled Pyramid (NSP)

The multi focus property of the NSCT is obtained from a shift-invariant filtering structure that achieves sub band decomposition likely to Laplacian pyramid. This can be achieved by using two-channel non sub sampled 2-D filter banks. Which has shown in Fig. 2 the figure exhibit that proposed non sub sampled pyramid (NSP) decomposition with J=3 stages. So such expansion is conceptually similar to the (1-D) NSWT computed with the taros algorithm X. Qu, et al [25] and has J+1 redundancy A. Toet et al [9]. Where J denotes the number of decomposition stages the ideal pass band filter support of the low-pass filter at the stage is the region as a result, the ideal support of the corresponding high-pass filter is the complement of the low-pass. The filters for following stages are acquired by up sampling the filters of the first stage. This provides the multi scale property without the need for additional filter proposal. The proposed structure is therefore dissimilar from the separable NSWT. In particular, one band pass image is produced at each stage resulting in redundancy. By contrast, the NSWT produces three directional images at each stage, resulting in 3J+1 redundancy.

Directional Filter Bank (DFB) structure that gives directionality

It is constructed by combining critically-sampled two channel fan filter banks and resampling operations. Finally, the result is a tree-structured filter bank that splits the image in 2-D frequency plane into directional sections. A shift-invariant directional extension is taken with a non sub sampled DFB (NSDFB). The NSDFB is constructed by eliminating the down samplers and up samplers in the DFB V. S. Petrovi et al [7]. This can be done by switching off the down samplers or up samplers in each two channel filter bank in the DFB tree structure and up sampling the filters respectively. These results in a tree composed of two channels NSFBs. which is shown in Fig. 2.this figure demonstrate that the four channel decomposition. Note that in the second level, the up sampled fan filters, checker board frequency support. When combined with the filters in the first level give the four directional frequency decomposition which shown in Fig. 2. The synthesis filter bank is taken likewise. Objective like the critically sampled directional filter bank, all filter banks are in the non-subsampled directional filter bank tree structure are obtained from a single NSFB with fan filters .However, each filter bank in the NSDFB tree has the same computational complexity as that of the building block NSFB.

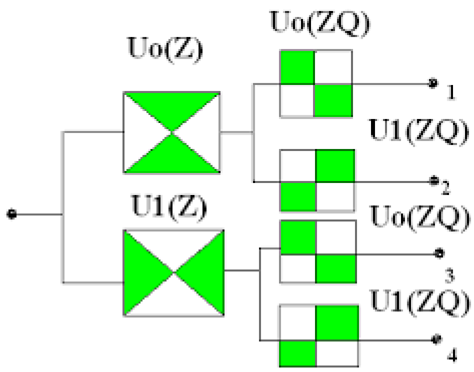


Figure 2: Four-channel non-subsampled directional filter bank.

Phase Congruency

It is a measure of feature observation in the images which offers a illumination and contrast invariant feature extraction technique P. Kovesi et al [8], P. Kovesi et al [18]. This method is based on the Local Energy Model, which proposes that significant features could be find at points in an image where the Fourier components are particularly in phase. As well, the angle at which phase congruency take place signifies the feature type Y. Chai et al [26] and A. L. da Cunha et al [27].

The phase congruency method to feature perception has used for feature detection. First, logarithmic Gabor filter banks at dissimilar Improved orientations applied to the image and the local amplitude and phase at a point obtained and then calculated for each orientation as shown in (1) at the bottom of the next page, where the weight factor depend on the frequency spread, and have the respective amplitude and phase for the scale is the weighted mean phase, a noise threshold constant and a small constant to avoid divisions by zero. The symbol signifies that the enclosed quantity is equal to itself when the value has positive, and zero otherwise. Only energy values that exceed the predictable noise influence and counted in the result. The proper noise threshold, is eagerly resolute from the statistics of the filter responses to the image. For information of this phase congruency measure and it implementation saw P. Kovesi et al [18]. The core properties, which performed as the motivation to use phase congruency for multimodal medical fusion are such as follows.

The phase congruency has invariant to different pixel intensity mappings. The images are captured with different modalities have considerably different pixel mappings, even though the object is similar. So, a feature that is free from pixel mapping has been chosen.

The phase congruency feature has invariant to illumination and contrast modifications. The capturing environment of different modalities is different and caused in the modification of illumination and contrast. Consequently, multimodal fusion could be advanced by an illumination and contrast invariant feature.

$$P(x,y) \sum_n \left(\mathrm{W(x,y)[A(x,y)(cos\big(\varphi(x,y) - \varphi^{o}(x,y)\big) - |\, sin(\varphi(x,y) - \varphi^{o}(x,y)\, |) } - T \sum_n (\mathrm{A(x,y)} + \varepsilon) \right) \quad (1)$$

The edges and corners in the images have recognized by collecting frequency components of the image that are in phase. By way of phase congruency provides the Fourier components that have maximally in phase. As a result, phase congruency P. Kovesi et al [6], offers the better-quality localization of the image features, which lead to proficient fusion.

PROPOSED MULTIMODAL MEDICAL IMAGE FUSION METHOD

In this section has discussed some of the factors in the design of novel approach to multimodal medical image fusion. The proposed framework recognizes on the directive contrast and phase congruency in NSCT domain, which takings a couple of source image signified by A and B to make a composite image F. The basic condition in the proposed framework is that all the source images might be registered so as to align the corresponding pixels. The block diagram of the recommended framework has showed in Fig. 3 but previously describing it, the meaning of directive contrast is first described, which is as follows.

Directive Contrast in NSCT Domain

The contrast feature processes the dissimilarity of the intensity value at some pixel from the neighboring pixels. The human visual system has highly sensitive to the intensity contrast sooner than the intensity values that one. Generally, the same intensity value forms like a different intensity value dependent on intensity values of neighboring pixels. So, local contrast has developed and defined as A. Toet et al [9]

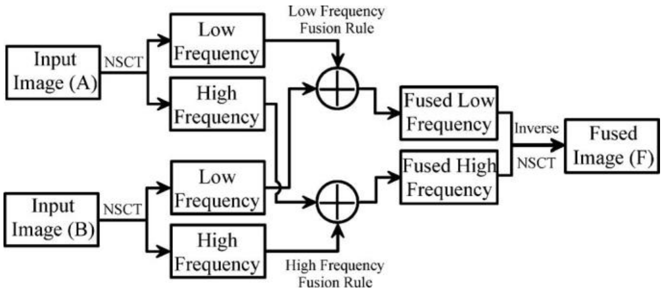


Figure 3: Block diagram of proposed multimodal medical image fusion framework.

$$C_L = \frac{l - lb}{lb} \; ; \; C_L = \frac{lh}{lb} \qquad (2)$$

Where is the local luminance C_L and lb is the luminance of the local background. Usually, is considered as local low frequency and hence, l-lb =lh is preserved as local high frequency. This depiction is more extended as directive contrast for multimodal image fusion G. Bhatnagar et al [12]. These contrast additions take high-frequency as the pixel value in multi-resolution domain. Nevertheless, in view of single pixel is inadequate to decide whether the pixels are from clear parts or not. So, the directive contrast is combined with the sum improved Laplacian W. Huang et al [13] to become further precise salient features.

In overall, the higher absolute values of high frequency coefficients relate to the sharper brightness in the image and lead to the salient features for instance edges, lines, region boundaries, and so on. Though, these are precise sensitive to the noise and hence, the noise is taken as the useful information and misapprehends the actual information in the fused images Gaurav Bhatnagar, et al [3] Therefore, a appropriate way to select high frequency coefficients has necessary to ensure enhanced information interpretation. From now, the sum improved Laplacian integrated with the directive contrast in Improved NSCT domain to produce precise salient features. Precisely, the directive contrast in Improved NSCT domain is given by

$$D_{con\, l,\theta}(i,j)=\begin{cases} SML\ l,\frac{\theta(i,j)}{I(i,j)}, & if\ I(i,j) \neq 0 \\ SMLl,\theta(i,j), if\ I(i,j) = 0 \end{cases} \qquad (3)$$

Where, $SML_{l,\theta}$ is the sum improved Laplacian of the NSCT frequency bands at scale l and orientation θ .Instead, $I(i,j)$ is the low-frequency sub band at the coarsest level (l) . The sum modified Laplacian defined by following equation

$$\mathrm{SML}_{l,\theta}(i,j) = \sum_{x=i-m}^{i+m} \sum_{y=j-n}^{j+n} \nabla^2_{l,\theta} I(x,y) \qquad (4)$$

So as to accommodate for probable differences in the size of texture elements, a variable spacing between the pixels is used to work out partial derivatives to acquire SML and is at all times equal to 1 W. Huang (13). More, the relationship between the contrast sensitivity threshold and background intensity is nonlinear, which makes the human visual system highly sensitive to difference variation A. B.Watson(14). Therefore, the above integration improved to offer improved specifics by exploiting visibility of low-frequency coefficients in the above stated definition. Later, the directive contrast in Improved NSCT domain is assumed as

$$D_{con\, l,\theta}(i,j)=\begin{cases} \left(\frac{1}{I(i,j)}\right)\Lambda\ \alpha\ SML\ l,\frac{\theta(i,j)}{I(i,j)}, & if\ I(i,j) \neq 0 \\ SMLl,\theta(i,j), if\ I(i,j) = 0 \end{cases} \qquad (5)$$

Where, α as a visual constant expressive the slope of the best-fitted lines over high-contrast data, which is resolute by biological vision experiments, and it ranges from 0.6 to 0.7 A. B.Watson(14). The suggested definition of directive contrast, distinct by (6), not only extract more valuable features from high frequency coefficients but also effectively deflect noise to be conveyed from high-frequency coefficients to fused coefficients.

Proposed Fusion Method

In this part, the proposed fusion framework will have discussed in detail. Considering, two effortlessly registered source images K and S the proposed image fusion method involves of the following steps:

1. Perform ℓ-level Improved NSCT on the source images to take one low-frequency and a series of high-frequency sub images at every level

$$K:\{I^{fu}_{L}(x.y)\} \text{ and } S: \{I^{fu}_{H}(x.y)\} \qquad (6)$$

Where $I^{fu}_{L}(x.y)\}$ are the low-frequency sub-images and represents $I^{fu}_{H}(x.y)$ the high-frequency sub-images at level l ε[1,l].

2. Fusion of Low frequency Sub images:

The coefficients in the low-frequency sub images represent the approximation component of the input images. The modest way is to custom the conventional averaging techniques to create the composite bands. Though, it cannot provide the fused low-frequency component of high quality for medical image since it leads to the compact contrast in the fused images.The complete process is described as follows.

Fuse the low-frequency sub images as

$$I_L^{FU}(i,j)=\begin{cases} IA(i,j) if\ IA(i,j) > IB(i,j) \\ IB(i,j) if\ IA(i,j) \leq IB(i,j) \end{cases} \quad (7)$$

3. Fusion of High frequency Sub images:

The coefficients in the high-frequency sub images generally contain details component of the source image. It is remarkable that the noise is also correlated to high frequencies and may reason mistaken of sharpness value and hence affect the fusion performance. Consequently, a new criterion is offered here based on directive contrast. The entire process is defined as follows.

First, the directive contrast for NSCT high frequency sub images at every scale and orientation using (3) (5), signified by $D_{con\ l,\theta}(i,j)$ and $D_{con\ l,\theta}(i,j)$ at each level.

$$I^{FU}_{HIGH}(x,y)=\begin{cases} IA\ high(x,y)\ if\ SFA(high) > SFB(high) \\ IB\ high(x,y)\ if\ SFA(high) < SFB(high) \\ IA\ high(x,y) + IB\frac{high\ (x,y)}{2} \quad Otherwise \end{cases} \quad (8)$$

spatial frequencies of two corresponding coefficient values in each blocks of $I^{F}_{HIGH}(x,y)$
Where spatial frequency

$$SF=\sqrt{RF \wedge 2 + CF \wedge 2} \qquad (9)$$

4. Complete ℓ-level inverse Improved NSCT on the fused low frequency $I_L^{FU}(i,j)$and high frequency $I^{FU}_{HIGH}(x,y)$ sub images, to become the fused image.

5. Determine the local threshold

The fused image is partitioned into A X B blocks. The maximum of the difference between the right and left neighboring points in direction of d are defined K.Karsch et al [20] as in equ. (10).

$$W_{a,b}(i,j)=Max(|I^F(U^l_{a,b}(i,j))- I^F(V^l_{a,b}(i,j)|) \qquad (10)$$

Where l=0 to 3

Where $U^l_{a,b}(i,j)$ and $V^l_{a,b}(i,j)$ are the right and the left neighboring points of (i, j) in direction of l respectively.

$$T_{g\ i,j}=max(W_{a,b}(i,j)) \qquad (11)$$

T_k=min($T_{g\,i,j}$)+max($T_{g\,i,j}$)/2 (12)

The coordinates of each block in an image frame are (a,b) both m and n range from 0 to B-1. The coordinates in each block are (i,j), where x ranges from 0 to (M/B)-1 and y ranges from 0 to (N/B)-1. a and b represent the width and the height of the image correspondingly.

6. Finding the global threshold for entire image using PSNR after T is computed, Here the m ranges from 0 to a-1 and n ranges from 0 to b-1.This indicates the whole image to compute the relation between all possible neighboring directions is considered.

$$PSNR=10\ Log_2(255^{\wedge}2/MN\sum\sum X(m,n)^2 - Y(m,n)^2) \quad (13)$$

7. Obtain the closed loop contours if is greater $W_{a,b}(i,j)$, than T, then the pixel value is set at 1 else 0. This gives segmented output.

RESULTS AND DISCUSSIONS

Some general necessities for fusion algorithm are: (1) it must be able to extract admiring features from input images, (2) it must not lead relics or variations along with Human Visual System and (3) it must be robust and reliable. Usually, these can be valued separately or objectively. The earlier relies on human visual features and the specified knowledge of the viewer, later vague, time consuming and poor repeatable but are usually precise if achieved correctly. The other one is comparatively formal and certainly realized by the computer algorithms, which mostly estimate the similarity between the fused and source images. Though, choosing a proper consistent condition with the subjective valuation of the image feature is rigorous. Therefore, there is a essential to create an assessment system. So, first an valuation index system is recognized to estimate the suggested fusion algorithm. These indices have determined consistent with the statistical parameters.

Estimate Index System

Normalized Mutual Information

Mutual information (MI) is a numerical quantity of the mutual dependence of two variables; it generally shows measurement of the information united by two images Y. B. Chenet al [19]. Precisely, MI between two Improved random variables X and Y is defined as

$$NMI(X,Y)=\sum\sum p(u,v)\log_2(p(u,v)|p(u)p(v)) \quad (14)$$

uƐU & vƐV

where p(u,v) is the joint probability distribution function of X and Y whereas are the marginal probability distribution unction of X and Y respectively

Structural Similarity based Metric

Structural similarity (SSIM) has designed by modeling any image distortion as the mixture of loss of correlation, radiometric and contrast distortion. Exactly, SSIM between two variables X and Y is defined as

$$SSIM(X,Y)=\frac{\sigma X,Y}{\sigma X\sigma Y}*\frac{2\mu X\mu Y}{\mu X2+\mu Y2}*\frac{2\sigma X\sigma Y}{\sigma X2+\sigma Y2} \quad (15)$$

Where, $\mu x \mu y$ are mean intensity and $\sigma x \sigma y \sigma xy$ are the variances and covariance respectively.

3.Edge Based Similarity Measure: The edge based similarity measure gives the relationship between the edges transferred in the fusion process. Mathematically, $Q_{AB/F}$ is defined as

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$$P^{ST/F}=\sum\sum P_{I,J}\ {}^{A}W^{X}_{I,J+}\ P_{I,J}\ {}^{B}W^{Y}_{I,J/}\sum\sum W^{X}_{I,J+}\ W^{Y}_{I,J} \qquad (16)$$

Where, ST and F represent the input and fused images respectively. The dynamic range for $P^{ST/F}$ is [0,1] and it must be as close to 1 as possible for improved fusion.

Experimentations on CT/MRI Image Fusion

To estimate the performance of the recommended image fusion approach, four different datasets of human brain have considered.These images are considered in two different groups 1) CT- MRI and 2) MR-T1-MR -T2. The images in Figures. 5.

It can be perceived that caused by various imaging principle and environment, the source images with dissimilar modality have complementary information. For all these image sets, results of proposed fusion framework are associated with the traditional PCA (MS rule), Contrast Pyramid A. Toet(9), Gradient Pyramid V. S. Petrovi et al [7], wavelet Q.Guihong et al [10] , contourlet L. Yang et al [5] and non-subsampled contourlet (NSCT-1 Q. Zhang et al [16] and NSCT-2 Y. Chai et al [17]) established procedures. {So as to do a just comparison, the same experimental images have used for all existing approaches. The level of decomposition is set to 3 for all the pyramid, wavelet and countourlet based procedures, with proposed. For wavelet based technique Q.Guihong et al [10] , images are decomposed using the 'db4' wavelet meanwhile it used frequently in the existing wavelet based methods. For implementing Improved NSCT, extremely flat filters and diamond max flat filters are used as pyramidal and directional filters respectively.

The comparison of arithmetical parameters for fused images along with different fusion algorithms have shown in Table I and visually in Fig. 6. From figure and table, it is clear that the proposed algorithms not only preserve spectral information but also develop the spatial feature information than the existing algorithms (highlighted by red arrows), which can also be justified by the acquired maximum values of estimation indices (see Table I). The PCA algorithm provides baseline results. For all experimental images, PCA based approaches provide poor results relative to other algorithms. This had estimated because this mode has no scale selectivity hence it cannot captures prominent information contained in different scales. This limitation is resolved in pyramid and multi resolution based algorithms but on the cost of quality i.e., the contrast of the fuse image is reduced which is better in pyramid based algorithms and moderately less in multi resolution based algorithms.

Amongst multi resolution based algorithms, the algorithms based on Improved NSCT perform better. This is because of the fact that Improved NSCT is an multi-scale geometric analysis tool which develops the geometric regularity in the image and offer a asymptotic optimal representation in the terms of improved localization, multi -direction and shift invariance. This has too correct by the fact that shift-invariant decomposition overcomes pseudo-Gibbs phenomena effectively and advances the quality of the fused image around edges. If the Improved NSCT based approaches have compared then it can be perceived that the performance of the proposed technique is better than existing DNSCT based methods Q. Zhang et al [16] , Y. Chai et al [17]. The algorithm in Q. Zhang et al [16] provides poor results with respect to other NSCT methods. This algorithm uses a directional vector, attained from high frequency sub-bands, to fuse low frequency sub bands. This directional vector basically states the clarity factor and is used to collect pixels from blur and clear areas. This algorithm achieves fairly well in the case of multi focus images but the performance ruined when it applies to the medical images. This is since this algorithm is not capable to utilize noticeable information present in the low frequency proficiently and effects in the pitiable quality.

Currently, it is noteworthy to mention that the technique in Q. Zhang et al [16] still implement superior than other multi resolution based algorithms. The performance of the suggested and the technique in Y. Chai et al [17] is close to each other, providing the good quality fused images associated to others. Though, looking sensibly at the results, obviously the output from Y. Chai et al [17] suffer significantly from less contrast and less visibility in the quantity callosum,

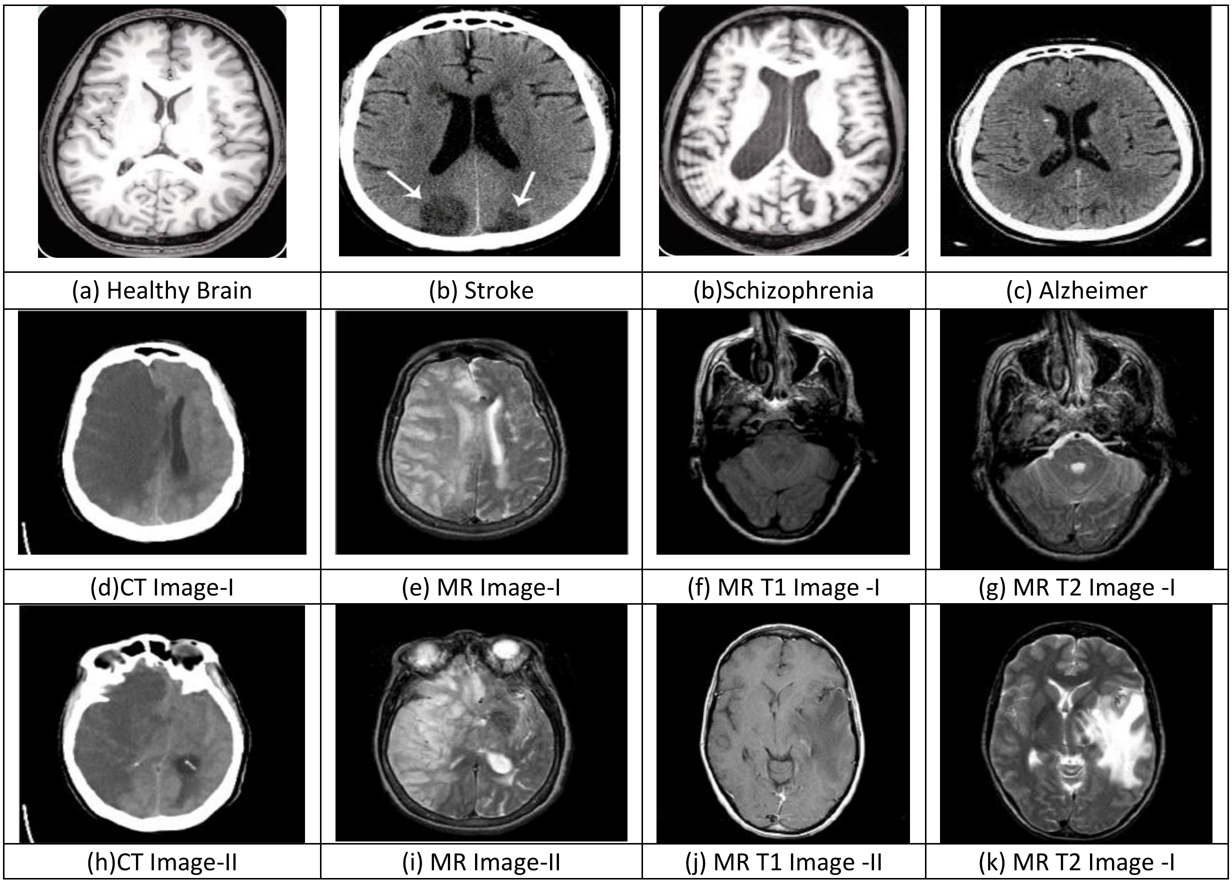


Figure 4: Multimodal Medical image data sets

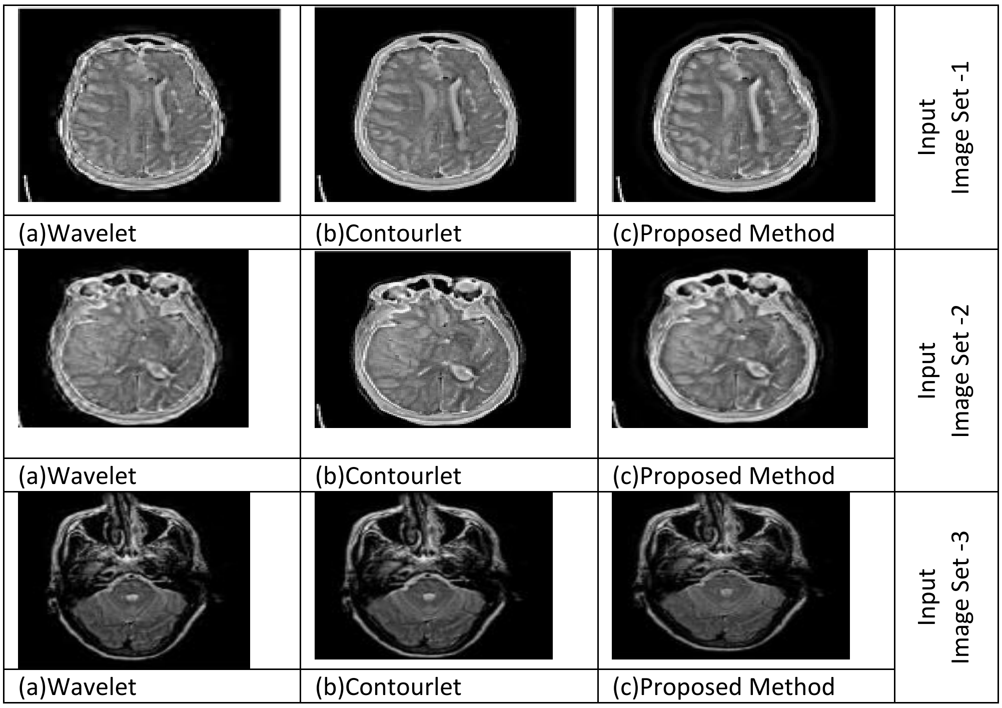


Figure 5: The multimodal medical image fusion results of different fusion algorithms

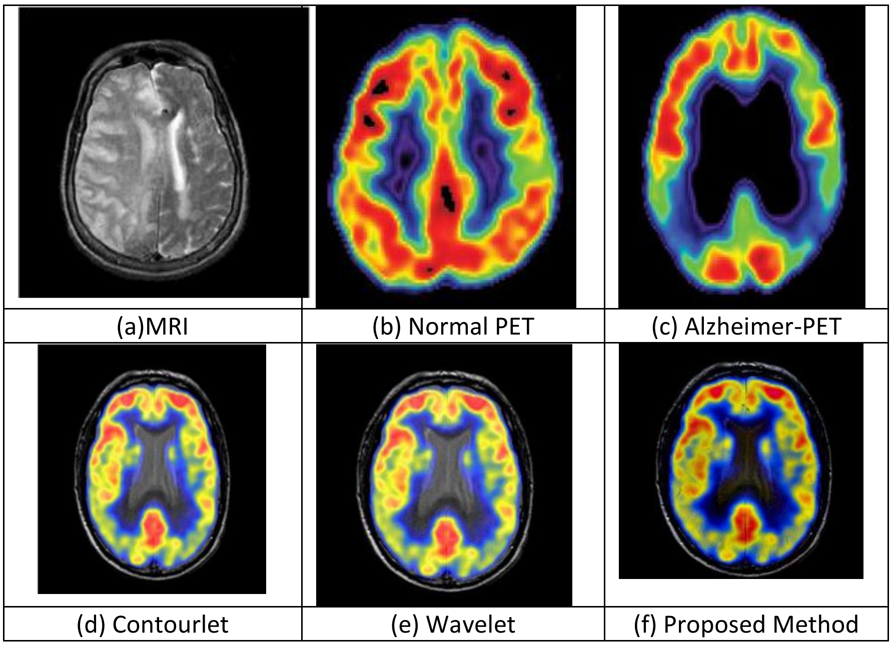


Figure 6: Brain images of the man affected with Alzheimer

Septum pellucidum, sulcus, flax cerebri and other structures which is quiet well in the output of the offered technique Fig. 6. The main purpose behind the well performance has the proposed fusion rules for low and high frequency coefficients which remove all prominent data from the images and offer more usual output with increased chromatic quality. So, it can be decided from Fig. 5 and Table I that both the visual and statistical estimation shows the superiority of the projected technique over existing techniques.

Medical Samples on PET/MRI and SPECT/MRI Image Fusion

In spite of the great achievement of the MRI-CT fusion, it is part in neuroscience and considered to be limited associated with the possible of PET-MRI and SPECT/MRI fusion. PET can afford well-designed eloquent brain areas such as motor or speech areas by using precise activation tasks. Instead, single photon emission computed tomography (SPECT) images expose the metabolic variation that is significant medical values. So, F. E. Ali et al [4] in modern era PET/MRI and SPECT/MRI fusion have analyzed over MRI-CT fusion for the better diagnosis in different syndromes. So that demonstrate the practical value of the proposed system in medical imaging, three medical cases have considered where PET/MRI and SPECT/MRI medicinal modalities have used. These include the case of Alzheimer, subacute stroke and brain tumor respectively.

The first case is of the old age people who was begin experiencing difficulty with memory about 10 months prior to imaging those had a history of atrial fibrillation and was being taken warfarin. He had come to be lost on some occasions, and had difficulty orienting himself in unused environments. This person had affected by the diseases namely Alzheimer Fig. 6.shows the MRI and PET images the person K.Karsch et al [22]. MRI image presented comprehensively widened hemispheric sulci, which is more conspicuous in parietal lobes. Regional cerebral metabolism is obviously abnormal, with hypo metabolism in anterior temporal and posterior parietal regions. These variations are bilateral, but the right hemisphere is somewhat more affected than the left, and the posterior cingulate is comparatively spared.

Fig 5 shows the sub acute stroke case of a old man who rapidly experienced tickling in the left hand and arm, and on investigation had a syndrome of left neglect: he botched to explore the left half of space, and quenched together left tactile and left visual stimuli when obtainable on both sides simultaneously. The MRI study shown that the frontal pole in the old infract is changed with the high signal of cerebrospinal fluid left subsequently liquifaction necrosis. The beginning of new warning sign corresponds to the right parietal infarction with hyper per fusion. There is a refined abnormality in the MRI image and a luxury hyper per fusion in the SPECT image

Fig. 6 shows the regular tumor case of an old woman required medical attention owing to progressively increasing right hemiparesis (weakness) and hemianopia. By craniotomy, left parietal anaplastic astrocytoma has found. A right frontal lesion had biopsied. The progress of high tumor Thallium acceptance, indicating astrocytoma reappearance is shown by the SPECT study, which pointed in the SPECT image while a large region of mixed signal on MRI image provides the signs of the probability of active tumor.

Now, the results are associated with the best four algorithms found with the prior study,. From Figures. 7, it can be saw that all the fusion algorithms must have fairly good spatial data but the spectral distortions are slightly high in the existing algorithms, i.e., spectral data is absent in the case of existing algorithms which is better in the case of Q.Guihong et al [10] and somewhat lesser in Q. Zhang et al [16] , Y. Chai et al [17], L. Yang et al [5] and Y. B. Chen et al [21] [23] and [24]. The color information has also distorted in the existing algorithms.

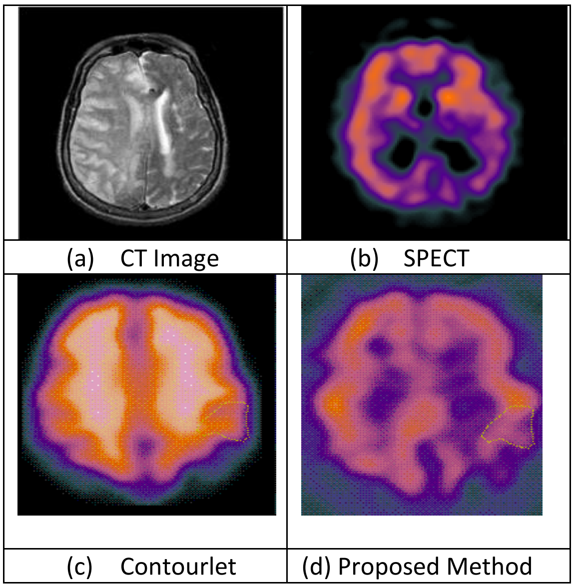
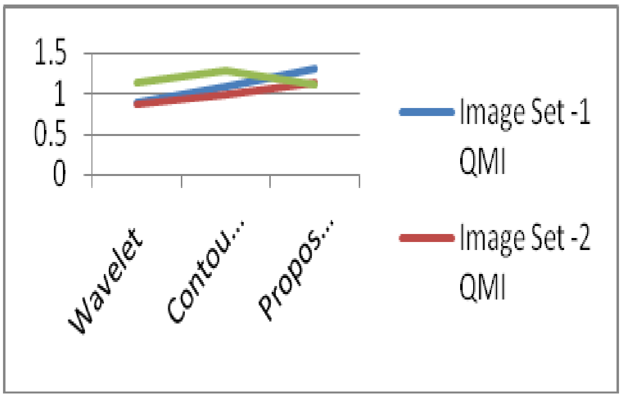
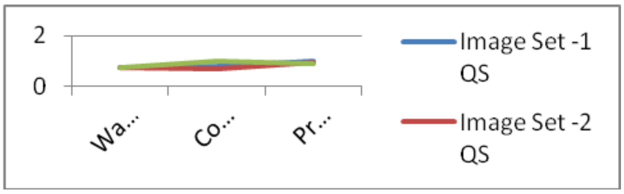


Figure 7: Brain affected with Subacute Stroke

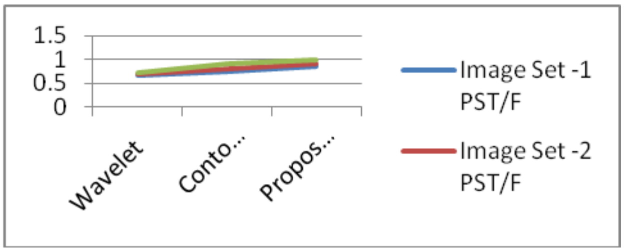
Not at all, the color information is smallest amount distorted and the spatial information are as richer as the original MRI image, and the spectral features are also normal. This detail is also justified from the Table II, where the proposed technique is with greater estimation indices among all approaches. These estimation indices have defined for gray scale images and the PET image has a color image. Hence, these metrics are estimated with each color channel consecutively and then proceeds the average of all values as the absolute result. So, the proposed system not only reserve the vital features exist in both original images but also advances the color information when associated to existing techniques.



(a) QMI vs Different Method



b)QS vs Different Method



C) $P^{ST/F}$ vs Different Method

Figure 8: (a) (b) and (c) Input Image vs different method

Table I: Image Model Indices For Different Fused Method

Image Model	Indices	Wavelet	Contourlet	Proposed Method
Input Image Set -1	Q_{MI}	0.8986	1.0965	**1.2987**
	Q_S	0.7598	0.7895	**0.9874**
	$P^{ST/F}$	0.6623	0.7398	**0.8651**
Input Image Set -2	Q_{MI}	0.8567	0.9785	**1.1356**
	Q_S	0.7287	0.6875	**0.9676**
	$P^{ST/F}$	0.6912	0.7891	**0.8999**
Input Image Set -3	Q_{MI}	1.1296	1.2908	**1.0987**
	Q_S	0.7654	0.9897	**0.9001**
	$P^{ST/F}$	0.7109	0.8976	**0.9823**

Table II: Disease Indices For Different Fused Medical Images

Disease	Indices	Wavelet	Contourlet	Proposed Method
Alzheimer	Q_{MI}	1.2416	1.3091	**1.7297**
	Q_S	0.7088	0.7560	**0.7984**
	$P^{ST/F}$	0.6045	0.7108	**0.7861**
Schizophrenia	Q_{MI}	1.1678	1.2785	**1.6396**
	Q_S	0.6257	0.7075	**0.9116**
	$P^{ST/F}$	0.6112	0.7008	**0.8009**
Stroke	Q_{MI}	1.3926	1.2908	**2.0987**
	Q_S	0.7144	0.9809	**0.9900**
	$P^{ST/F}$	0.6909	0.8070	**0.9923**

CONCLUSION

Here in this paper, a new image fusion framework proposes for multi modal medical images, which is based on Improved non-sub-sampled contourlet transform and directive contrast. For fusion, two different rules have used by which additional information can be conserved in the fused image with better quality. The low frequency bands have fused by in view of phase congruency however directive contrast is implemented as the fusion measurement for high frequency bands. In our tryout, two sets of CT/MRI and two sets of MR-T1/MR -T2 images are fused using predictable fusion algorithms and the proposed framework. The visual and statistical evaluations show that the proposed algorithm can improve the facts of the fused image, and can increase the visual effect with greatly less distortion information than its rivals. These statistical valuation conclusions agree with the visual assessment. More, so as to demonstration the practical applicability of the proposed technique, three clinical samples are also considered which contains examination of diseased person's brain with alzheimer, sub-acute and stroke.

REFERENCES

[1] G. Bhatnagar, Q. M. J. Wu, and B. Raman, "Real time human visual system based framework for image fusion," in Proc. Int. Conf.Signal and Image Processing, Trois-Rivieres, Quebec, Canada, 2010,pp. 71–78.

[2] F. Maes, D. Vandermeulen, and P. Suetens, "Medical image registration using mutual information," Proc. IEEE, vol. 91, no. 10, pp.1699–1721, Oct. 2003.

[3] Gaurav Bhatnagar,Q.M. JonathanWu and Zheng Liu,"Directive Contrast Based Multimodal Medical Image Fusion in NSCT Domain" IEEE transactions on multimedia, vol. 15, no. 5,pp. 1014-24, August 2013

[4] F. E. Ali, I. M. El-Dokany, A. A. Saad, and F. E. Abd El-Samie,"Curvelet fusion of MR and CT images," Progr. Electromagn. Res. C,vol. 3, pp. 215–224, 2008.

[5] L. Yang, B. L. Guo, and W. Ni, "Multimodality medical image fusion based on multiscale geometric analysis of contourlet transform," Neurocomputing, vol. 72, pp. 203–211, 2008.

[6] P. Kovesi, "Image features from phase congruency," Videre: J.Comput. Vision Res., vol. 1, no. 3, pp. 2–26, 1999.

[7] V. S. Petrovic and C. S. Xydeas, "Gradient-based multire solution image fusion," IEEE Trans. Image Process., vol. 13, no. 2, pp. 228–237, Feb. 2004.

[8] P. Kovesi, "Phase congruency: A low-level image invariant," Psychol.Res. Psychologische Forschung, vol. 64, no. 2, pp. 136–148, 2000.

[9] A. Toet, "Hierarchical image fusion," Mach. Vision Appl., vol. 3, no.1, pp. 1–11, 1990.

[10] Q.Guihong, Z. Dali, andY. Pingfan, "Medical image fusion bywavelet transform modulus maxima," Opt. Express, vol. 9, pp. 184–190,2001.

[11] T. Li and Y.Wang, "Biological image fusion using a NSCT based variable-weight method," Inf. Fusion, vol. 12, no. 2, pp. 85–92, 2011.

[12] G.Bhatnagar and B. Raman, "A new image fusion technique based on directive contrast," Electron. Lett. Comput. Vision Image Anal., vol. 8,no. 2, pp. 18–38, 2009.

[13] W.Huang and Z. Jing, "Evaluation of focus measures in multi-focus image fusion," Pattern Recognit. Lett., vol. 28, no. 4, pp. 493–500, 2007.

[14] A.B.Watson, "Efficiency of a model human image code," J. Opt. Soc.Amer. A, vol. 4, no. 12, pp. 2401–2417, 1987

[15] R.Redondo, F.Sroubek, S. Fischer, and G. Cristobal, "Multi focus image fusion using the log-Gabor transform and a multisize windows technique," Inf. Fusion, vol. 10, no. 2, pp. 163–171, 2009.

[16] Q. Zhang and B. L. Guo, "Multifocus image fusion using the nonsubsampled contourlet transform," Signal Process., vol. 89, no. 7, pp. 1334–1346, 2009.

[17] Y.Chai, H. Li, and X. Zhang, "Multifocus image fusion based on features contrast of multiscale products in nonsub sampled contourlet transform domain," Optik, vol. 123, pp. 569–581, 2012.

[18] P. Kovesi, "Phase congruency: A low-level image invariant," Psychol.Res. Psychologische Forschung, vol. 64, no. 2, pp. 136–148, 2000

[19] Y.B.Chen, T.-C. Chen, Semi-Automatic image segmentation using dynamic direction prediction, Proc Of IEEE ICASSP 2002, Vol. 4, May 2002, pp.3369-3372.

[20] K.Karsch, Q.He, Y.Duan, A fast, semi-automatic brain structure algorithm for magnetic resonance imaging, Proc. Of IEEE BIBM 2009, November 2009, pp.297-302

[21] Y.B.Chen, T.-C. Chen, Semi-Automatic image segmentation using dynamic direction prediction, Proc Of IEEE ICASSP 2002, Vol. 4, May 2002, pp.3369-3372.

[22] K.Karsch, Q.He, Y.Duan, A fast, semi-automatic brain structure algorithm for magnetic resonance imaging, Proc. Of IEEE BIBM 2009, November 2009, pp.297-302

[23] Y.B. Chen, O.T.C. Chen, Image segmentation method using thresholds automatically determined from picture contents, EURASIP j.Image Video Process, 2009 (15).

[24] Y.B.Chen, O.T.C.Chen, High accuracy moving object extraction using background subtraction, ICIC Express Lett., December 2009 , pp.649- 652.

[25] X. Qu, J. Yan, H. Xiao, and Z. Zhu, "Image fusion algorithm based on spatial frequency-motivated pulse coupled neural networks in non sub sampled contourlet transform domain," Acta Automatica Sinica, vol. 34, no. 12, pp. 1508–1514, 2008.

[26] Y. Chai, H. Li, and X. Zhang, "Multi focus image fusion based on features contrast of multiscale products in non sub sampled contourlet transform domain," Optik—Int. J. Light Electron Opt., vol. 123, no. 7, pp. 569–581, 2012.

[27] A. L. da Cunha, J. Zhou, and M. N. Do, "The nonsubsampled contourlet transform: Theory, design, and applications," IEEE Trans. Image Process., vol. 15, no. 10, pp. 3089–3101, Oct. 2006.