Contourlet Transform Approach for Medical Diagnosis

Mredhula.L.¹ and Dr.Dorairangaswamy.M.A²

¹Research Scholar, Sathyabama University, Chennai
mredhu@yahoo.com

²Senior Professor & HOD, CSE & IT, AVIT, Chennai
drdorairs@yahoo.co.in

Abstract: Fusion imaging is one of the most modern, accurate and useful diagnostic techniques in medical imaging today. The new technology has made a clear difference in patient care by compressing the time between diagnosis and treatment. Although image fusion can have different purposes, the main aim of fusion is spatial resolution enhancement or image sharpening also known as integrated imaging i.e. integrating information from multiple modality images to obtain a more complete and accurate description of the same object. There are three categories into which the common image fusion schemes are classified : pixel level, feature level, and decision level. Medical image fusion usually employs the pixel level fusion techniques. Since image features are sensitive to human visual system that exist in different scales, multiresolution analysis is more suitable for image fusion. Wavelet, curvelet, contourlet transforms comes under the multiresolution transforms. Contourlet transform is a sparse image expansion expressed by contour segments, so it can capture 2-D geometrical structures in visual information much more effectively than traditional multiresolution analysis methods.

Keywords: image fusion, contourlet, CT imaging, MR imaging

1. INTRODUCTION

Medical imaging is taking on an increasingly critical role in healthcare. Technological advances in medical imaging in the past two decades have enabled radiologists to quickly acquire images of the human body and its internal structures with unprecedented resolution and realism. X-ray computed tomography (CT) has become popular because of its ability to visualize dense structures like bones and implants with less distortion, but it cannot detect physiological changes. Despite being small, CT can pose the risk of irradiation because it uses X-ray for imaging. Normal and pathological soft tissue are better visualized by magnetic resonance (MR) imaging. MRI uses large external field RF pulse and 3 different gradient fields and also making use of the fact that body tissue contains lots of water and hence protons. There are no biological hazards in using MRI. CT is suited for bone injuries, Lug and Chest imaging, cancer detection while MRI is best suited for ligament and tendon injury, spinal cord injury and brain tumors.

2. IMAGE FUSION

The aim of image fusion is to integrate complementary information from multimodality images so that the new images are more suitable for the purpose of human visual perception and computer processing. Therefore, the aim of image fusion is to make many salient features in the new image such as regions and their boundaries. Image fusion consists of bringing together information coming from different modality of medical images, whereas registration consists of computing the geometrical transformation between two data sets. This geometrical transformation is used to resample one image data set to match other. An excellent registration is set for an excellent fusion. The process of information fusion can be seen as an information transfer problem in which two or more information sets are combined into a new one that should contain all the information from the original sets. During the process of fusion, input images 1 and 2 are combined into a new fused image F by transferring, ideally all of their information into F.

The combination of images from different modalities leads to additional clinical information which is not apparent in the separate imaging modality. For this reason radiologists prefer multiple imaging modalities to obtain more details. Image fusion is performed to extract all the useful information from the individual modality and integrate them into one image. In general, a successful fusion should extract complete information from source images into the result, without introducing any artifacts or inconsistencies. Medical image fusion usually employs the pixel level fusion techniques. The purpose of pixel-level image fusion is to represent the visual information present in input images, in a single fused image without the introduction of distortion or loss of information. Furthermore, the algorithms are rather easy to implement and time efficient.

The reason of image fusion is to integrate complementary and redundant information from multiple images to produce a combined that contains a superior description of the scene than any of the individual source images. Considering the objectives of image fusion and its potential advantages, some generic requirements can be
imposed on the fusion algorithm.

- Salient information contained in any of the input images should not be discarded.

- No artifacts should be introduced which can distract or mislead a human observer or any subsequent image processing steps.

- The final image must be reliable, robust and, as much as possible, tolerant of imperfections such as noise or misregistrations.

However, a fusion approach is highly wanted as it produces a combined Image which is independent of the modalities of the inputs and appears accepted to a human interpreter.

3. Contourlet Transform

The contourlet transform is a discrete extension of the curvelet transform that aims to capture curves instead of points, and provides for directionality and anisotropy. The contourlet transform was proposed by Do and Vetterli to provide more efficient representation of an object because most natural images contain diverse orientations. The contourlet is mainly based on the Laplacian pyramid and the directional filter banks. In the Laplacian pyramid, the spectrum of the input image will be divided into the lowpass subband and the highpass subband. Then, the lowpass subband will be down sampled by two both in the horizontal and vertical direction and passed to the next stage. The highpass subband will be further separated into several directions by the directional filter banks.

3.1 Laplacian Pyramid

In the first stage of the contourlet transform, the Laplacian pyramid is used to achieve the multi scale decomposition. The Laplacian pyramid at each level generates a down-sampled lowpass version of the source image and the difference between the source image and the down sample lowpass image, resulting in a highpass image. The structure of the Laplacian pyramid is shown in Figure 1, where H and G are the analysis and synthesis filters, respectively, and M is the sampling matrix. It should be noted that in multidimensional filter banks, the sampling operation is represented by the sampling matrices. That is, the source signal x[n] down sampled by M will become xd[n] = xd[Mn]

![Figure 1](image.png)

The down sampled lowpass version of the source signal can be tied to the next level Laplacian pyramid, which will forms an iterated structure.

3.2 Directional Filter Banks

The directional filter banks (DFB) are used to derive of the high frequency subbands with diverse directionality. The DFB can be efficiently implemented via l-level binary tree decomposition that leads to 2l subbands with wedge-shaped frequency supports as shown in Figure 3. The directionality of the frequency supports can be controlled by the tree-structure directional filter banks, which is shown in Figure 4.

![Figure 3](image.png)

3.3 The Basic Architecture of the Contourlet Filter Banks

The obtained Laplacian pyramid and the directional filter banks can be combined to accomplish the contourlet transform, and the structure of the contourlet transform is
shown in Fig. 5. This is a multi-scale and directional decomposition using a combination of a Laplacian pyramid and directional filter banks. The highpass images are from the Laplacian pyramid and fed into the directional filter banks so the high frequency directional information can be captured. The coarse image from the Laplacian pyramid is down sampled and fed into another stage of the contourlet filter banks.

3.4 FUSION ALGORITHM
A good image fusion algorithm should preserve all the salient features in source images and introduce as less artifacts or inconsistency as possible. Contourlet can offer better anisotropy, multiresolution, directionality and localization properties for 2-D signals than existing image representation methods, so better image fusion performance can be expected. In this paper, we develop a novel medical image fusion algorithm by combing contourlet transform and some new fusion rules, which can create fused image that contains more information than single source image, and is more suitable for human visual perception and object detection in clinical applications. The general procedure of the proposed contourlet-based fusion algorithm is illustrated in figure. Here images A and B denote the input source images to be fused; F is the final fused outcome. All the input source images to be fused are already perfectly registered, so that corresponding features can coincide pixel to pixel. The source images A and B are decomposed using contourlet transform. For 1-level contourlet decomposition, the input images are decomposed into one lowpass subband and several highpass subbands in different directions and scales. The lowpass subband is an approximation of the original image; while the highpass subbands show high frequency details in different directions and scales. The same LP and DFB filtering process are then iterated on the lowpass subband till reaching the coarsest scale J.

4. IMAGE FUSION APPROACH
The proposed image fusion approach consists of the following steps:
Step1. Perform a Dual Tree Complex Contourlet Transform on source images A and B, respectively, and obtain the corresponding coefficients \{Coff(L,A), Coff(H,A)\} and \{Coff(L,B), Coff(H,B)\} where Coff(L,A) and Coff(L,B) represent low frequency coefficients of image A and B respectively at the coarsest scale. Coff(H,A) and Coff(H,B) denote the high frequency coefficients of image A and B respectively at the J-th scale and the I-th direction of DFP.
Step2. Some fusion rules are employed to reconstruct the DT-CCT coefficients of the fused image F as shown \{Coff(L,F), Coff(H,F)\}
Step3. Perform inverse dual tree complex contourlet transform to the modified coefficients at all decomposition, and the final fused image F can be reconstructed.

4.1 LOWPASS SUBBAND FUSION
As the coefficient in the coarsest scale sub band aJ represents the approximation component of the source image, the simplest way is to use the conventional averaging method to produce the composite coefficients. However, it cannot obtain fused approximation of high quality for medical image. Here the local energy in contourlet domain is developed as the measurement, two distinct combination modes: selection and averaging are used to compute the final coefficients.
4.2 HIGHPASS SUBBAND FUSION

In traditional multiresolution fusion algorithm, the multiresolution coefficients with large absolute values are considered as sharp brightness changes or salient features in the corresponding source image, such as the edges, lines, contours and object boundaries. Therefore, the selection of highpass coefficients only depends on their absolute value without taking any consideration of lowpass coefficients, that is, all the information in the lowpass subband is neglected. According to physiological and psychological research, the human vision system (HVS) is highly sensitive to the local image contrast level, but insensitive to real luminance at independent positions. To meet this requirement, Toet and Ruyven developed the local luminance contrast in their research in CP. It can be represented as

\[ C = (L - LB) / LB = LH / LB \]

where, \( L \) is the luminance level of the object or foreground, \( LB \) is the local luminance of the background; therefore \( LH \) can be taken as the high frequency component.

4.3 RECONSTRUCTION OF FUSED IMAGE

By successively performing inverse contourlet transform to the modified coefficients at all decomposition subbands, the final fused image can be reconstructed. This reconstruction step can be seen as a inverse procedure of the contourlet decomposition:

\[ \{ b_j^F , b_{j-1}^F , \ldots , b_{j-1}^F , b_{j-1}^F , a_j^F \} \rightarrow f'(x, y) \]

where, \( b_j^F \) denotes the fused lowpass subband at the coarsest scale \( j \), \( b_j^F \), \( j = 1, \ldots, J \) is the fused directive highpass subband set.

5. EXPERIMENTAL RESULTS AND ANALYSIS

To evaluate the performance of the proposed image fusion approach, human brain images and chest images were used. The two brain images in Fig.7 are produced by CT and MR. The corresponding pixels of two input images have been perfectly co-aligned. All images have the same size of 256×256 pixel, with 256-level grayscale. It can be seen that due to various imaging principle and environment, the source images with different modality contain complement information. The proposed contourlet-based medical fusion algorithm is applied to these image sets. In our experiment, 4-level LP and 4-, 8-, 16-direction DFB are used for each highpass scales, respectively. To compare the fusion performance, several classical fusion methods are also applied. They are fusion based on wavelet, curvelet and contourlet transforms. The DWT method uses the bi-orthogonal Daubechies 9-7 wavelets available in Matlab Wavelet Toolbox.

**Image set 1:**
CT and MR image of brain. The two CT and MR images are of type jpeg and it comes in the class of uint8 with size 256×256×3. It is the normal scan of brain. The fused image becomes more clear and contains more details especially the edges become more visible.
CONCLUSION:

The fused image using contourlet transform will be more informative than any of the input images and will be very useful in diagnosis of diseases.

References


AUTHOR
Mredhula.L obtained her BE degree in Electronics and Communication Engineering from Bharathiar University, Coimbatore, India in 1990 and MTech degree in Electronics with specialization in Digital Electronics from Cochin University of Science & Technology, Kerala, India, in 2004. She is currently a Research Scholar in the Department of CSE, Sathyabama University, Chennai, India. Her research interests include areas of Medical Imaging. She has also presented papers at the National and International level conferences. She is also Member of IEEE and Life Member, ISTE.