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RESEARCH ARTICLE

FUSION OF MEDICAL IMAGES USING CURVELET TRANSFORM

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ABSTRACT

The term fusion means in general an approach to extraction of information acquired in several domains. The goal of image fusion (IF) is to integrate complementary multi sensor, multi temporal and/or multi view information into one new image containing information the quality of which cannot be achieved otherwise. This paper presents a Curvelet based approach for the fusion of magnetic resonance image (MRI) and computed tomography (CT) image. Since medical images have several objects and curved shapes, it is expected that the Curvelet transform would be better in their fusion. Fusion of images taken at different resolutions, intensity and by different techniques helps physicians to extract the features that may not be normally visible in a single image by different modalities. The objective of the fusion of an MRI image 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. This fused image can significantly benefit medical diagnosis and also the further image processing such as, Visualization (colorization), segmentation, classification and computer-aided diagnosis. The simulation results show the visual quality of the fused image using Curvelet transform and their Entropy, Root Mean Square Error (RMSE) and the Peak Signal to Noise Ratio (PSNR).

INTRODUCTION

Recently, some studies showed that a wavelet-based image fusion method provides high quality spectral content in fused images. However, most wavelet-based methods yield fused results with spatial resolution that is less than that obtained via the Brovey, IHS, and PCA fusion methods. Here a new method based on a Curvelet transform, which represents edges better than wavelets. Since edges play a fundamental role in image representation, one effective means to enhance spatial resolution is to enhance the edges. The Curvelet-based image fusion method provides richer information in the spatial and spectral domains simultaneously. Data fusion for images involves the combination of two or more images to form one image. The aim of such a fusion is to extract all the perceptually important features from all the original images and combine them to form a fused image in such a way that all the key features from each input image are still perceivable. The fusion of two or more images is often required for images captured using different instrument modalities, imaging modalities or camera settings of the same scene or objects. Important applications of the fusion of images include medical imaging, microscopic imaging, remote sensing, computer vision, and robotics Nunez and *et al*., 1999.

Medical Image fusion can be defined as the process by which several medical images or some of their features are combined together to form a single image for better diagnosis and thereby a better treatment planning. As the details from different modalities are brought into a single image, the new image includes more comprehensive, more accurate, more stable information. So with the availability of multi modal tissue information on a single image, clinicians are provided the salient features of each medical imaging modality and thus eliminating their individual limitations Cand`es and Donoho, 1999.

For medical diagnosis Computed Tomography (CT) uses X-Ray on its way through the body to reconstruct a two dimensional image of the absorption coefficient within an axial slice. CT shows highly detailed anatomical information on the distribution of the absorption coefficient with high contrast in bone but little in soft tissue. Magnetic Resonance Imaging (MRI) uses nuclear spin interaction with the magnetic field and resonance phenomena to generate an image of the tissue of the human body with finer soft tissue details. But MRI does not show the bony structures clearly. Positron Emission Tomography (PET) shows physiological processes but little anatomical information. Likewise each and every medical imaging modality provides images, which have complementary information. Hence if a local integration of the complementary information is done, it provides more information for accurate Starck *et al*, 2002.

Also backing up of individual modality medical images in the memory doubles the computational power. If fused images are stored, it provides an effective way of reducing memory and the total amount of information presented without loss in image quality and content.

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It is required that the fused image should preserve as closely as possible all relevant information obtained in the input images and the fusion process should not introduce any artifacts or inconsistencies, which can distract or mislead the medical professional, thereby a wrong diagnosis Starck *et al* ,2003.

Respective anatomical structures are matched against each other to make the fusion meaningful. So that Image registration is the fundamental task of image fusion. Hence before image fusion, the multimodality medical images must be registered perfectly. Registration is a one to one mapping function applied to modify corresponding physical image points whose information can then be combined. Improper registration adds artifacts in the fused image and affects the importance of fusion. Hence only registered images are considered for fusion. Some of the image fusion methods have been introduced in the literatures including simple pixel by pixel averaging using SNR (Chungli, 1999), Laplacian pyramid method (Burt and Adelson, 1983), conditional probability networks (Kiverri and Cacee, 1998), Neural network methods (Aguilar and Garret, 2001).

IMAGE FUSION

Image fusion is the process of merging two images of the same scene to form a single image with as much information as possible. The basic representation of image fusion is shown in Fig.1. Image fusion is important in many different image processing fields such as satellite imaging, remote sensing and medical imaging. The study in the field of image fusion has evolved to serve the advance in satellite imaging and then, it has been extended to the field of medical imaging. Several fusion algorithms have been proposed extending from the simple averaging to the Curvelet transform. Algorithms such as the intensity, hue and saturation (IHS) algorithm and the Wavelet fusion algorithm have proved to be successful in satellite image fusion. The IHS algorithm belongs to the family of color image fusion algorithms. The Wavelet fusion algorithm has also succeeded in both satellite and medical image fusion applications. The basic limitation of the Wavelet fusion algorithm is in the fusion of curved shapes. Thus, there is a need for another algorithm that can handle curved shapes efficiently. So, the application of the Curvelet transform for curved object image fusion would result in better fusion efficiency. A few attempts of Curvelet fusion have been made in the fusion of satellite images but no attempts have been made in the fusion of medical images.

The main objective of medical imaging is to obtain a high resolution image with as much details as possible for the sake of diagnosis. There are several medical imaging techniques such as the MRI and the CT techniques. Both techniques give special sophisticated characteristics of the organ to be imaged. So, it is expected that the fusion of the MRI and the CT images of the same organ would result in an integrated image of much more details. Researchers have made few attempts for the fusion of the MRI and the CT images. Most of these attempts are directed towards the application of the Wavelet transform for this purpose. Due to the limited ability of the wavelet transform to deal with images having curved shapes, the application of the Curvelet transform for MRI and CT image fusion is presented in this paper.

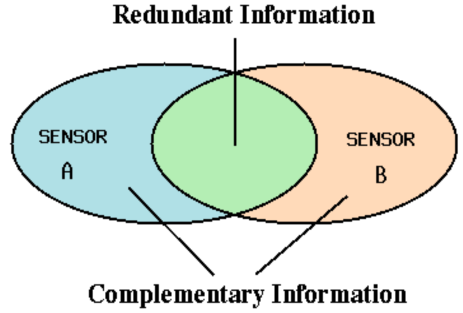

Fig.1 Basics representation of Image Fusion

The Curvelet transform is based on the segmentation of the whole image into small overlapping tiles and then, the Ridgelet transform is applied to each tile. The purpose of the segmentation process is to approximate curved lines by small straight lines. The overlapping of tiles aims at avoiding edge effects. The Ridgelet transform itself is a 1-D wavelet transform applied on the Radon transform of each tile, which is a tool of shape detection. The Curvelet transform was firstly proposed for image denoising. Some researchers tried to apply it in satellite image fusion. Because of its ability to deal with curved shapes, the application of the Curvelet transform in medical image fusion would result in better fusion results than that obtained using the Wavelet transform.

WAVELET TRANSFORM

The wavelet transform replaces the Fourier transform's sinusoidal waves by a family generated by translations and dilations of a window called a wavelet. Wavelet Transform is a type of signal representation that can give the frequency content of the signal at a particular instant of time. In this study we applied 2D discrete wavelet transform is applied to the registered input medical images. The transform produces the coefficients, which will have high pass and low pass details. By applying fusion rules we produce the fusion output. The fusion rule is the averaging the coefficients and the comparison of the coefficients of the wavelet transform.

In this study multi resolution transform (MRT) is used. In transform domain fusion, a transform is applied on the registered images to identify the vital details in the image. The technique is described in Fig.2. Fusion rule is applied over the transform coefficients and fusion decision map is obtained. Inverse transform over the decision map and the fused image is reconstructed. This fused image will have details of both the source images.

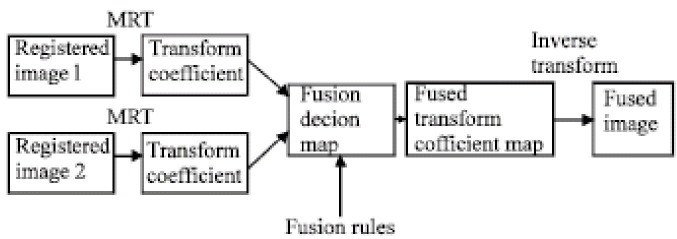

Fig.2 Block diagram of transform domain image fusion

The integral wavelet transform is the integral transform defined as

$$[W_\psi f](a,b) = \frac{1}{\sqrt{|a|}} \int_{-\infty}^{\infty} \overline{\psi\left(\frac{x-b}{a}\right)} f(x)dx$$

The wavelet coefficients c_{jk} are then given by

$$c_{jk} = [W_\psi f](2^{-j}, k2^{-j})$$

Here, $a = 2^{-j}$ is called the binary dilation or dyadic dilation, and $b = k2^{-j}$ is the binary or dyadic position.

Wavelet Fusion

The most common form of transform type image fusion algorithms is the wavelet fusion algorithm due to its simplicity and its ability to preserve the time and frequency details of the images to be fused.

Fusion algorithm of two registered images $I_1(x_1, x_2)$ and $I_2(x_1, x_2)$ can be represented by the following equation:

$$I(x1, x2) = W^{-1}(\varphi(W(I_1(x_1, x_2)), W(I_2(x_1, x_2))))$$

where W, W^{-1} and φ are the wavelet transform operator, the inverse wavelet transform operator and the fusion rule, respectively. There are several wavelet fusion rules which can be used for the selection of the wavelet coefficients from the wavelet transforms of the images to be fused. The most frequently used rule is the maximum frequency rule which selects the coefficients that have the maximum absolute values. The wavelet transform concentrates on representing the image in multiscales and it's appropriate to represent linear edges. For curved edges, the accuracy of edge localization in the wavelet transform is low. So, there is a need for an alternative approach which has a high accuracy of curve localization such as the Curvelet transform.

THE CURVELET TRANSFORM

The Curvelet transform proposed by Donoho and Candes (1999) is a multi scale transform like the wavelet transform, with frame elements indexed by scale and location parameters. Unlike the wavelet transform, it has directional parameters, and the Curvelet pyramid contains elements with a very high degree of directional specificity. In addition, the Curvelet transform is based on a certain anisotropy scaling principle, which is quite different from the isotropic (Non parabolic) scaling of wavelets.

The Curvelets are new multi-scale systems, has basis elements, which exhibit high directional sensitivity and are highly anisotropic. The Curvelets are localized along curves in 2 dimensions. In finer scales the curves can be approximated to straight edges, which are efficiently represented using Ridgelets. The Curvelet transform opens the possibility to analyze an image with different block sizes, but with a single transform. The idea is to first decompose the image into set of wavelet bands and to analyze each band with an inbuilt Ridgelet transform. The block size can be changed at each scale.

The Curvelet transform has evolved as a tool for the representation of curved shapes in graphical applications. Then, it was extended to the fields of edge detection and image denoising. Recently, some authors have proposed the application of the Curvelet transform in image fusion.

The algorithm of the Curvelet transform of an image *P* can be summarized in the following steps:

- The image *P* is split up into three subbands Δ1, Δ2 and *P*3 using the additive Wavelet transforms.
- The discrete Ridgelet transform is performed on each tile of the subbands Δ1 and Δ2.

A detailed description of these steps is presented below.

A. Subband Filtering

The purpose of this step is to decompose the image into additive components; each of which is a subband of that image. This step isolates the different frequency components of the image into different planes without down sampling as in the traditional wavelet transform. The "*a trous*" algorithm given below is used for this purpose. Given an image *P*, it is possible to construct the sequence of approximations:

$$\mathbf{f} \rightarrow (\mathbf{P_0 f}, \Delta_1 \mathbf{f}, \Delta_2 \mathbf{f}, \ldots)$$

$$f_1(P) = P_1, f_2(P_1) = P_2, f_3(P_2) = P_3, \ldots f_n(P_{n-1}) = P_n$$

where n is an integer which is preferred to be equal to three. To construct this sequence, successive convolutions with a certain low pass kernel are performed. The wavelet planes are computed as the differences between two consecutive approximations P_{l-1} and P_l, i.e.,

$$\Delta l = Pl_{-1} - P_l$$

Thus, the Curvelet reconstruction formula is given by:

$$P = \sum_{l=1}^{n-1} (\Delta l + Pn)$$

B. Smooth Portioning

$W_Q(x_1, x_2)$ is a smooth window function around dyadic squares.
Windowing is applied to each sub band

$$\Delta_s f \rightarrow (W_Q \Delta_s f)_{Q \in Q_s, Q=Q}(s, k1, k2)$$

where k1, k2 translation is varying and scaling s is fixed.

C. Renormalization

Each resulting square is renormalized to unit scale

$$g_Q = (T_Q) = (W_Q \Delta_s f); \; Q \, \varepsilon \, Q_s$$

D. Ridgelet Transform

The Ridgelet transform belongs to the family of discrete transforms employing basis functions. To facilitate its mathematical representation, it can be viewed as a wavelet analysis in the Radon domain. The Radon transform itself is a tool of shape detection. So, the Ridgelet transform is primarily a tool of ridge detection or shape detection of the objects in an image. Hence, the Ridgelet transform is the application of the 1-D wavelet transform to the slices of the Radon transform where the angular variable θ is constant and t is varying. To make the Ridgelet transform discrete, both the Radon transform and the wavelet transform have to be discrete. This is shown in Fig.3.4.

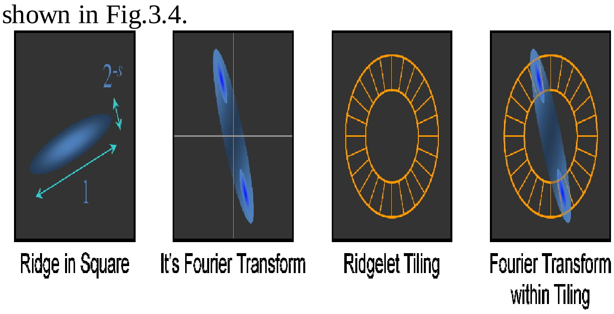

Fig.3.4 Ridgelet representation

THE PROPOSED FUSION ALGORITHM

It is known that different imaging modalities are employed to depict different anatomical morphologies. CT images are mainly employed to visualize dense structures such as bones. So, they give the general shapes of objects and few details. On the other hand, MRI images are used to depict the morphology of soft tissues. So, they are rich in details. Since these two modalities are of a complementary nature, our objective is to merge both images to obtain as much information as possible.

A Curvelet based algorithm is introduced for this purpose. This algorithm is summarized as follows with the fusion of CT image and MRI image as an example to illustrate the method.

- The CT image and MRI image are registered geometrically using control points, and resized into 256 X 256 matrix dimension.
- The CT image and MRI image are decomposed separately into S1, S2, S3 sub bands by applying "a trous" filtering algorithm through wavelet band pass filtering using equation

$$I = CJ + \sum_{I=1}^{j} WJ$$

- Each decomposed image includes C_J (S1 subband) which is the coarse or low pass version of the image and W_J which represents the detail or high pass contents of the image.
- The detail contents of the image in the image subband S2 and S3 are partitioned and C_J is kept as it is.
- Ridgelet transform is applied over each block of the partitioned images to get Ridgelet coefficients for bands S2 and S3.
- Steps 2, 3 and 4 are done for MRI image separately to get the MRI Ridgelet coefficients at subbands S2 and S3.
- Fusion rule is applied over the Ridgelet transform coefficients. Two fusion rules are implemented in this work namely addition of coefficients and maximum absolute value of coefficients.

QUANTITATIVE ANALYSIS

In addition to the visual analysis, we conducted a quantitative analysis. The experimental results were analyzed based on the combination entropy and PSNR.

A. ENTROPY

The combination entropy of an image is defined as

$$\mathbf{H\ (f_1, f_2, f_3) = -\sum_{i=0}^{255} P_{i1,\,i2,\,i3}\ (\log_2 P_{i1,\,i2,\,i3})}$$

where $P_{i1,\,i2,\,i3}$ is the combination probability of the image $f1$, $f2$ and $f3$, in which pixel values are $i1$, $i2$ and $i3$, respectively, for the same position. The combination entropy (C.E.) represents the property of combination between images. The larger the combination entropy of an image, the richer the information contained in the image.

B. RMSE

Root Mean Square Error (RMSE) is a frequently-used measure of the differences between values predicted by a model or an estimator and the values actually observed from the thing being modeled or estimated. RMSD is a good measure of precision. These individual differences are also called residuals, and the RMSD serves to aggregate them into a single measure of predictive power.

$$\mathbf{RMSE = sqrt\ (sum(sum((Input*Output)^2)) / (m*n))}$$

C. PSNR

The PSNR of the fusion result is defined as follows:

$$\boldsymbol{PSNR = 10 \times \log((fmax)^2 / RMSE^2)}$$

where f_{max} is the maximum gray scale value of the pixels in the fused image. The higher is the value of the PSNR, the better the performance of the fusion algorithm.

EXPERIMENTAL RESULTS

Image Fusion was performed for different Medical images and its entropy and PSNR values were tabulated. The following figures (Fig.4.1, 4.2, 4.3) show the Image Fusion process for two different medical images.

Table 1 Fusion Results

Fused Image	Input Image 1	Input Image 2	Entropy	PSNR(dB)	RMSE
A	BRAIN CT	BRAIN MRI	16	37.04	19.17
B	BONE CT	BONE MRI	16	35.39	22.29
C	BONE	BONE CT	16	30.97	64.90
D	SKULL	SKULL CT	16	31.80	71.30
E	BLOOD CELL	SEM BLOOD CELL	16	21.23	94.31
F	VEIN CT	VEIN MRI	16	28.57	125.17

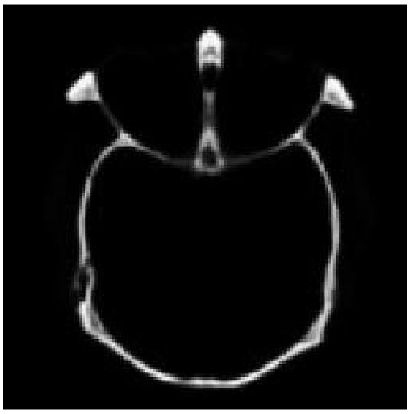

Fig.4.1: Input image 1-CT image

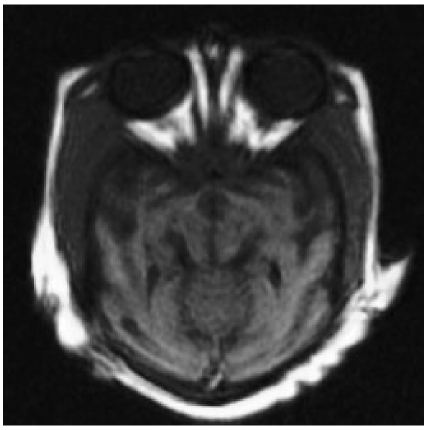

Fig.4.2: Input image 2-MRI image

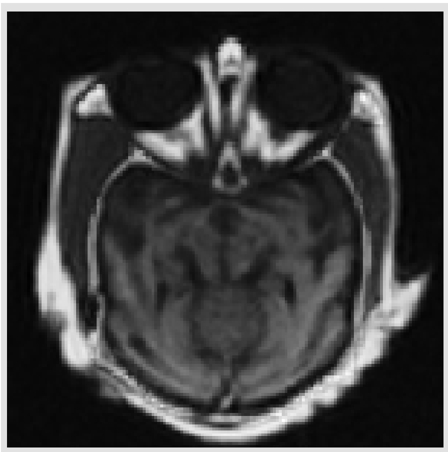

Fig.4.3: Output Fused image

Thus Image Fusion was performed for different medical images and their entropy and PSNR values were determined and tabulated.

From the above table, it is clear that Entropy value remains constant for the fusion of medical images using Curvelet transform.

In the Chart 1 and Chart 2, X axis represents the fused images as mentioned in Table 1 and the Y axis represents the values of PSNR and RMSE respectively.

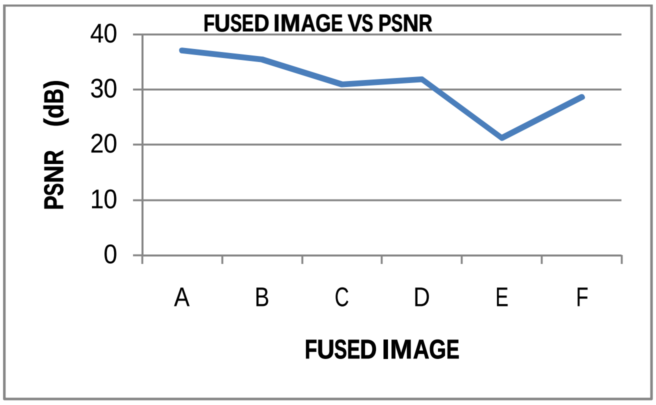

Fig.5 Fused image Vs PSNR

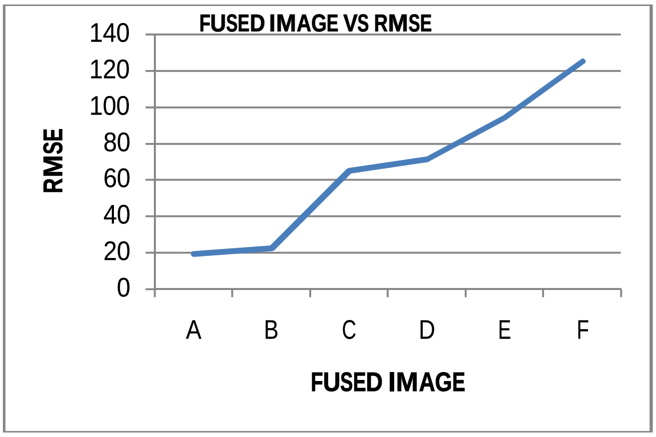

Fig.6 Fused image Vs RMSE

We have presented a newly developed method based on a Curvelet transform for fusing complicated medical images. In this paper, an experimental study was conducted by applying the proposed method to the fusion of medical images. Based on experimental results pertaining to two indicators - the combination entropy and the PSNR- the proposed method provides better results, both visually and quantitatively, for medical fusion. Since the Curvelet transform is well adapted to represent medical images containing edges and the Wavelet transform preserves the spectral information of the original medical images, the fused image has both high spatial and spectral resolution.

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