FUSION OF MEDICAL IMAGES USING WAVELET TRANSFORM AND SECOND GENERATION CURVELET TRANSFORM

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***Abstract*—This paper analyzes the characteristics of combination of wavelet transform and second generation Curvelet transform. In the existing system, Wavelet transform of two images (i.e.) the image may be CT image or MRI image is obtained and the curvelt transform is taken for the wavelet transformed image. Finally the two curvelet transformed images are fused. The limitation of this method is loss of curved ends in WT image and loss of sharp ends in the Curvelet transformed image. Wavelet transform takes block base to approach the singularity of C^2. So curved ends are missed in this transformation but we can obtain the sharp ends. By using Curvelt transform we can able to recover the curved ends of the image because it takes wedge base to approach the singularity of C^2. But we missed the sharp ends in the Curvelet transformed image. But in the proposed system, Wavelet transform as well as Curvelet transform is taken for two CT images. These two transformed images are then fused. The similar technique is applied for MRI image also. So that we can able to recover both the sharp ends and the curved ends when we use these two transformed images. The fused image is more informative than the original image.**

***Keywords-component; I*mage Processing, Image fusion, Regional Activity, Wavelet Transform, Second generation curvelet transform**

1.Introduction

Image fusion is the one of the data fusoin technique which is the process of combining relevant information from two or more images into a single image.Also it refres to the technique that integrate multi-images of the same scene from multiple image sensor data or multi-images of the same scene at different times from one image sensor.[1]

Fused images may be created from multiple images from the same imaging modality, or by combining information from multiple modalities, such as magnetic resonance image (MRI), computed tomography (CT), positron emission tomography (PET), and single photon emission computed tomography (SPECT). In radiology and radiation oncology, these images serve different purposes. For example, CT images are used more often to as certain differences in tissue density while MRI images are typically used to diagnose brain tumors [2]

The image fusion algorithm based on wavelet transform which is used for multi resolution analysis image fusion method in recent decade [3].Also Wavelet transform has better time-frequency characteristics. It was applied successfully in image processing field. But simply its characteristics in one dimension can't be extended to two dimensional or multi dimension [4]

In order to overcome the limitations of Wavelet transform, E.H.Candes and D.L.Donoho introduces new transformation in 2000 called Curvelet transform [5]. It consists of special filtering process and multi-scale ridgelet transform.However,Curvelet transform had complicated digital realization including Sub-band division,Smooth block, normalization and so on[6] .So E.H.Candes put forward Fast Curvelet Transform which is also called as Second generation Curvelet Transform which is easily understandable and simple in 2005[7] .This paper is used to obtain the more informative fused image

I. WAVELET TRANSFORM

The word *wavelet* has been used for decades in digital signal processing and image processing. A **wavelet** is a wave-like oscillation with amplitude that starts out at zero, increases, and then decreases back to zero. It can typically be visualized as a "brief oscillation" like one might see recorded by a seismograph or heart monitor. Generally, wavelets are purposefully crafted to have specific properties that make them useful for signal processing. Wavelets can be combined, using a "revert, shift, multiply and sum" technique called convolution, with portions of an unknown signal to extract information from the unknown signal.

A. Continuous Wavelet Transform

In continuous wavelet transforms, a given signal of finite energy is projected on a continuous family of frequency bands (or similar subspaces of the L^p function space L^2 (R). For instance the signal may be represented on every frequency band of the form [*f*, 2f] for all positive frequencies *f>0*. Then, the original signal can be reconstructed by a suitable integration over all the resulting frequency components.

The frequency bands or subspaces (sub-bands) are scaled versions of a subspace at scale *1*. This subspace in turn is in most situations generated by the shifts of one generating function Ψ € $L^2(R)$, the *mother wavelet*. For the example of the scale one frequency band [1,2] this function is

$\Psi(t) = 2\mathrm{Sinc}(2t) - \mathrm{Sinc}(t) = [\mathrm{Sin}(2\pi t) - \mathrm{Sin}(\pi t)] / \pi t$

With the normalized Sinc function

The subspace of scale *a* or frequency band [1/a,2/a] is generated by the functions (sometimes called *child wavelets*)

$$\Psi_{a,b}(t) = \frac{1}{\sqrt{a}}\Psi\left(\frac{t-b}{a}\right)$$

Where *a* is positive and defines the scale and *b* is any real number and defines the shift. The pair *(a,b)* defines a point in the right half plane $\mathbb{R}_+ \times \mathbb{R}$.

The projection of a function *x* onto the subspace of scale *a* then has the form

$$x_a(t) = \int_{\mathbb{R}} WT_\psi\{x\}(a,b) \cdot \psi_{a,b}(t)\, db$$

With wavelet coefficients .

B. Discrete Wavelet Transform

It is computationally impossible to analyze a signal using all wavelet coefficients, so one may wonder if it is sufficient to pick a discrete subset of the upper halfplane to be able to reconstruct a signal from the corresponding wavelet coefficients. One such system is the affine system for some real parameters *a>1, b>0*. The corresponding discrete subset of the halfplane consists of all the points $(a^m, na^m b)$ with integers(m,n € ž). The corresponding *baby wavelets* are now given as

$\psi_{m,n}(t) = a^{-m/2}\psi(a^{-m}t - nb)$.

A sufficient condition for the reconstruction of any signal *x* of finite energy by the formula

$$x(t) = \sum_{m\in\mathbb{Z}}\sum_{n\in\mathbb{Z}} \langle x,\, \psi_{m,n}\rangle \cdot \psi_{m,n}(t)$$

is that the functions $\Psi_{m,n}$: m,n € ž form a tight frame of $L^2(R)$

C. *Wavelet decomposition*

Wavelet decomposition can be regarded as projection of the signal on set of wavelet basis vectors. Each wavelet coefficient can be computed as the dot product of the signal with corresponding basis vector. Wavelet decomposition is similar to the sub band coding of the input image. i.e an image is decomposed into set of band limited components called sub bands which can be reassemble to reconstruct the original image without any data loss.

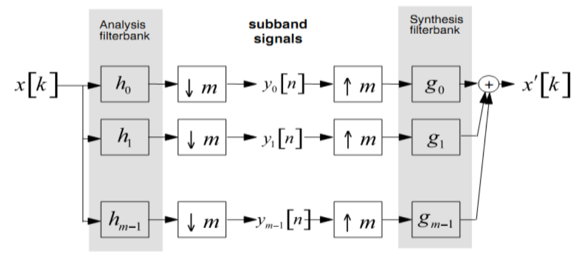

Fig 1: Image decomposition using sub band coding

Analysis filter: Decomposition filter is also called as analysis filter.

Synthesis filter: Reconstruction filter is also called as synthesis filter.

Decimation: Suppress the lowest samples by a factor 'm' is called decimation or down sampling. It is the process of reducing the samples.

Interpolation: Insert the zeros between the samples of the process of lengthening the signal component by inserting zeros is called up sampling or interpolation

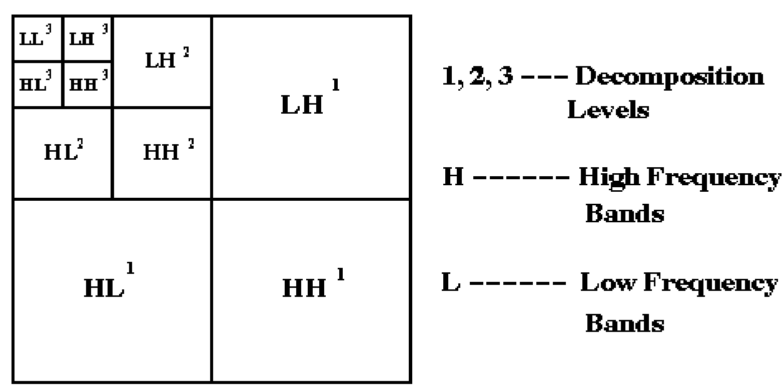

Fig 2: Wavelet decomposition

After one level of decomposition, there will be four frequency bands, namely Low-Low (LL), Low-High (LH), High-Low (HL) and High-High (HH). The next level decomposition is just apply to the LL band of the current decomposition stage, which forms a recursive decomposition procedure. Thus, an N-level decomposition will finally have 3N+1 different frequency bands, which include 3N high frequency bands and just one LL frequency band.

D Multi Resolution Analysis

The idea behind the multi resolution analysis is fairly simple. Let's define a function φ(t) that we call a scaling function. By taking the linear combination of scaling function and its translates we can generate a large number of functions

$F(t) = \quad k\,\varphi(t-k)$

The scaling function has the property that a function that can be represented by the scaling function can also be represented by the dilated versions of the scaling functions.For example, one of the simplest scaling functions is the haar scaling function:

$$\Phi(t) = \begin{cases} 1 & 0 \le t < 1 \\ 0 & \text{Otherwise} \end{cases}$$

Then f(t) can be any piecewise continuous function that is constant in the interval [k,k+1] for all k.Let's define

$$\Phi k(t) = \varphi(t - k)$$

The set of all functions that can be obtained using a linear combination of the set [φk(t)]

$$f(t) = \Sigma_k a_k \varphi(t)$$

is called the span of the set { φk(t) }. If we now add all functions that are limits of sequences of functions in span { φk(t) }, this is referred to as the closure of span { φk(t) } and denoted by span { φk(t) }.

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II CURVELET TRANSFORM

Curvelets are non-adaptive technique for multi-scale object representation. Being an extension of the wavelet concept, they are becoming popular in similar fields, namely in image processing and scientific computing. Wavelets generalize the Fourier transform by using a basis that represents both location and spatial frequency. For 2D or 3D signals, directional wavelet transforms go further, by using basis functions that are also localized in *orientation*. A curvelet transform differs from other directional wavelet transforms in that the degree of localization in orientation varies with scale. In particular, fine-scale basis functions are long ridges; the shape of the basic functions at scale *j* is 2^{-j} by $2^{-j/2}$ so the fine-scale bases are skinny ridges with a precisely determined orientation.

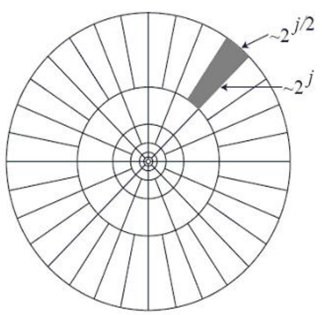


Fig 3: Image with acceptable resolution

Curvelets are an appropriate basis for representing images (or other functions) which is smooth apart from singularities along smooth curves, where the curves have bounded curvature. Curvelets take advantage of this property, by defining the higher resolution curvelets to be skinnier the lower resolution curvelets. However, natural images (photographs) do not have this property; they have detail at every scale. Therefore, for natural images, it is preferable to use some sort of directional wavelet transform whose wavelets have the same aspect ratio at every scale.

When the image is of the right type, curvelets provide a representation that is considerably sparser than other wavelet transforms. This can be quantified by considering the best approximation of a geometrical test image that can be represented using only *n* wavelets, and analysing the approximation error as a function of *n*. For a Fourier transform, the error decreases only as $O(1 / n^{1/2})$. For a wide variety of wavelet transforms, including both directional and non-directional variants, the error decreases as $O(1 / n)$. The extra assumption underlying the curvelet transform allows it to achieve $O((log(n))^3 / n^2)$.

Efficient numerical algorithms exist for computing the curvlet transform of discrete data. The computational cost of a curvlet transform is approximately 10–20 times that of an FFT, and has the same dependence of $O(n^2 log(n))$ for an image of size n x n.

A Steps involved in curvelet transform:

1) Sub-band decomposition
2) Smooth partitioning
3) Renormalization
4) Ridgelet analysis

1. Sub band decomposition: The image is filtered into sub bands

$$f \rightarrow (P_0 f, \Delta_1 f, \Delta_2 f, \cdots),$$

Where the filter Po deals with frequencies |ε|≤ 1 and the band pass filter s is concentrated near the frequencies $[2^s, 2^{2s+2}]$, for example

$$\Delta_s = \Psi_{2s} * f, \hat{\Psi}_{2s}(\xi) = \hat{\Psi}(2^{-2s}\xi)$$

2. Smooth partitioning: Each sub band is smoothly windowed into "squares" of an

appropriate scale

$$\Delta_s f \rightarrow (w_Q \Delta_s f)_{Q \in Q_s}$$

3. Renormalization: Each resulting square is renormalized into unit scale

$$g_Q = (T_Q)^{-1}(w_Q \Delta_s f), Q \in Q_s;$$

4. Ridgelet Analysis: Each square is analyzed via the discrete ridgelet transform.

For improved visual and numerical results of the digital curvelet transform, the following curvelet transform algorithm should be followed.

- Apply the á trous algorithm with J scales:

$$I(x,y) = C_J(x,y) + \sum_{j=1}^{J} w_j(x,y),$$

Where Cj is the coarse or smooth version of the original image I and Wj represents the details of I at scale 2^{-j}

- Set $B_1 = B_{min}$
- For j=1,2,…. J do

a) Partition the sub band Wj with a block size Bj and apply the ridgelet transform to each block

b) else $B_{j+1} = B_j$

B *Point and Curve Discontinuities*

A discontinuity point affects all the Fourier coefficients in the domain. Hence the FT doesn't handle point's discontinuities well. Using wavelets, it affects only a limited number of coefficients.

➢ Hence the WT handles point discontinuities well. across a simple curve affect all the wavelets coefficients on the curve.

➢ Hence the WT doesn't handle curves discontinuities well. Curvelets are designed to handle curves using only a small number of coefficients. Hence the CvT handles curve discontinuities well.

III IMAGE FUSION

Multi sensor **Image fusion** is the process of combining relevant information from two or more images into a single image. The resulting image will be more informative than any of the input images.In remote sensing applications, the increasing availability of space borne sensors gives a motivation for different image fusion algorithms. Several situations in image processing require high spatial and high spectral resolution in a single image.

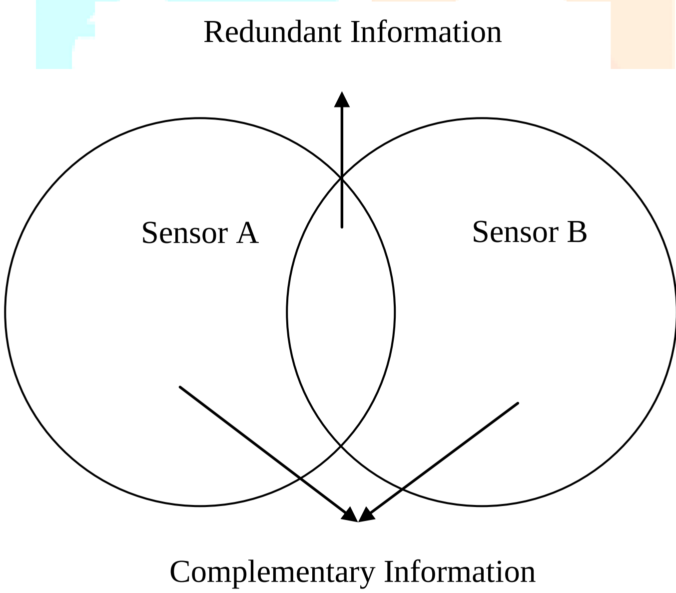


Fig4: Image fusion

Most of the available equipment is not capable of providing such data convincingly. The image fusion techniques allow the integration of different information sources. The fused image can have complementary spatial and spectral resolution characteristics. However, the standard image fusion techniques can distort the spectral information of the multispectral data while merging.

Satellite imaging, two types of images is available. The panchromatic image acquired by satellites is transmitted with the maximum resolution available and the multispectral data are transmitted with coarser resolution. This will usually be two or four times lower.

At the receiver station, the panchromatic image is merged with the multispectral data to convey more information. Many methods exist to perform image fusion. The very basic one is the high pass filtering technique. Later techniques are based on DWT, uniform rational filter bank, and laplacian pyramid.

***A Steps involved in fusion of two images*:**

Resample and registration:

Through RESAMPLE and registration of original images, we can correct original images and distortion so that both of them having similar probability of distribution. Then, wavelet coefficients of similar components will stay in the same magnitude.

Decomposition:

(i) Using wavelet transform to decompose original images into proper levels. One low frequency approximate component and three high frequency detail components will be acquired in each level

(ii) Curvelet transforms of individual acquired low frequency approximate coefficient and high frequency detailed components from both of images, neighborhood interpolation method is used and then the details of gray can't be changed

Choose local area variance:

According to definite standard to fuse two images, local area variance is choose to measure definition for low frequency component. First divide low frequency Cj0 (k1,k2) into individual four square sub-blocks which are N1 M1 (3×3 or 5×5), then calculate the local area variance of the current sub-block

Inverse Transformation:

Inverse transformation of coefficients after fusion, the reconstructed images will be fusion images

B ***Feature based image fusion technique***

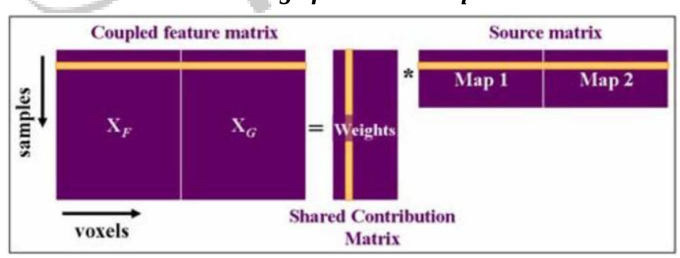


Fig 5: Block diagram of Feature based imag fusion

The figure illustrates of model in which loading parameters are shared among features. The feature matrix is organized by placing the features (e.g., SPM map and GM map) from the two modalities side by side (with one row containing data collected from the same subject for both modalities). CA is a statistical method used to discover hidden factors (sources or features) from a set of measurements or observed data such that the sources are maximally independent., ICA works with higher order statistics to achieve independence. A typical ICA model assumes that the source signals are not observable, statistically independent, and non-Gaussian, with an unknown, but linear, mixing process. Consider an observed M-dimensional random vector denoted by $\mathbf{x} = [x_1, \cdots, x_M]^T$ that is generated by the ICA model:

$$X = As \;\ldots\ldots\ldots\ldots\ldots\ldots (1)$$

where $\mathbf{s} = [s_1, s_2, \cdots, s_N]^T$ is an N-dimensional vector whose elements are assumed to be independent sources and $\mathbf{A}_{M \times N}$ is an unknown mixing matrix. Typically, $M \geq N$, so that $\mathbf{A}$ is usually of full rank. The goal of ICA is to estimate an unmixing matrix $\mathbf{W}_{N \times M}$ such that $\mathbf{y}$ [defined in (4)] is a good approximation to the "true" sources $\mathbf{s}$:

$$y = Wx \ldots\ldots\ldots\ldots.. (2)$$

ICA has been shown to be useful for fMRI analysis for several reasons. Spatial ICA finds systematically nonoverlapping, temporally coherent brain regions without a specific assumption about the shape of the temporal response. The temporal dynamics of many fMRI experiments are difficult to study with fMRI due to the lack of a well-understood brain-activation model. ICA can reveal intersubject and interevent differences in the temporal dynamics. A strength of ICA is its ability to reveal dynamics for which a temporal model is not available . Spatial ICA also works well for fMRI as it is often the case that one is interested in spatially distributed brain networks.

ICA has demonstrated considerable promise for the analysis of fMRI , EEG and sMRI data. In this section, we present a data fusion framework utilizing ICA, which we call the joint ICA (jICA). Note that the ICA approach we described earlier for fMRI data is a first-level analysis (i.e., is applied directly to the 4-D data without reduction into a feature, and though the basic algorithm is similar, with the same basic assumptions, the application details are different from the ICA we propose to utilize at the second level, on the generated features). An amplitude map generated by ICA at the first level would be considered a feature similar to an amplitude map generated by the GLM approach

Given two sets of data (can be more than two, for simplicity, we first consider two), $\mathbf{X}_F$ and $\mathbf{X}_G$, we concatenate the two datasets side-by-side to form $\mathbf{X}_J$ and write the likelihood as

$$L(\mathbf{W}) = \prod_{n=1}^{N}\prod_{v=1}^{V} pJ,n(uJ,v) \qquad \ldots\ldots.. (3)$$

where $\mathbf{u}_J = \mathbf{W}\mathbf{x}_J$. Here, we use the notation in terms of random variables such that each entry in the vectors $\mathbf{u}_J$ and $\mathbf{x}_J$ correspond to a random variable, which is replaced by the observation for each sample $n = 1, \cdots, N$ as rows of matrices $\mathbf{U}_J$ and $\mathbf{X}_J$. When posed as a maximum likelihood problem, we estimate a *joint* demixing matrix $\mathbf{W}$ such that the likelihood L ($\mathbf{W}$) is maximized.

Let the two datasets $\mathbf{X}_F$ and $\mathbf{X}_G$ have dimensionality $N \times V_1$ and $N \times V_2$, then we have

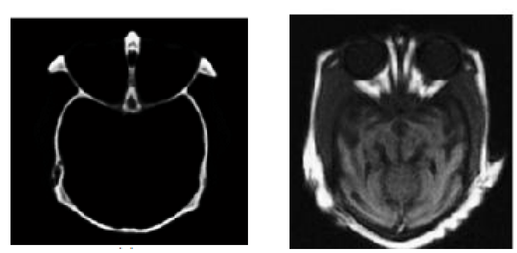
$$L(\mathbf{W}) = \prod_{n=1}^{N}\left(\prod_{v=1}^{V_1} pF,n(uF,v) \prod_{v=1}^{V_2} pG,n(uG,v)\right). \qquad \ldots\ldots.. (4)$$

This formulation assumes that the sources associated with the two data types (F and G) modulate the same way across N samples (usually subjects). This is a strong constraint; however, it has a desirable regularization effect to the problem simplifying the estimation problem significantly, which is important especially when dealing with different data types. Also, the framework provides a natural link to two types of data by constraining the contributions to be similar. In addition, it is important to normalize the two data types independently so that they have similar contributions to the estimation and that $V_1 \approx V_2$. The normalization process is important and should be modality specific (see examples in and.

The underlying assumptions for the form given in depend on the data types used for F and G. For example, when the two data types belong to the same data type but different tasks, the assumption of $p_J = p_F = p_G$ is more plausible than when dealing with different data types. On the other hand, when little is known about the nature of the source distributions in a given problem, imposing a distribution of the same form provides significant advantages yielding meaningful results as we demonstrate with an fMRI-ERP fusion exampleHence, there are different ways to relax the assumptions made in the earlier formulation, such as instead of constraining the two types of sources to share the same mixing coefficients, i.e., to have the same modulation across N samples, we can require that the form of modulation across samples for the sources from two data types are correlated but not necessarily the same. We have implemented such an approach, called parallel ICA

Experimental Analysis:

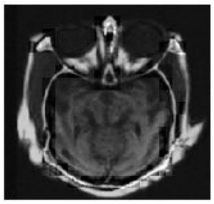
In order to verify the performance of the proposed fusion algorithm, we have designed the experiments on two images using Matlab. Each set image has different focuses and is partly blurring, they have done registration strictly with the size 256 ×256 pixels. The proposed method compared with other fusion methods such as average method, PCA method, neighbor variance method, wavelet transform method and pyramid method.



(a) (b)

Fig 6:

Images and their fused image (a) CT image (b) MRI image (c) Fused image



(c)

We know that CT and MRI images are tomographic images. They are having variety of features/. Fig 6(a) shows the CT image,in which image brightness are related to tisue density.Since,brightness of bones are higher, and some soft tissues cant seen in CT scan images.Fig 6(b) shows the MRI image,here image brightness are related to amount of hydrogen atoms in tissue,thus brightness of soft tissue is higher and bones can't be seen. There are some complementary information in these images. So the method of fusiion is used to combine the high spatial and spectral information from two images into a single image. Fig 6(c) shows the fused image

FUTURE SCOPE:

Based on multi modality image fusion we can fuse Pet, SPECT and satellite images also

CONCLUSION:

Image fusion is the process of combining relevant information from two or more images into a single image. The fused image is more informative than the original image. If one image is acquired from a single patient and the other image is taken from an image information data base, the mono modal images for comparison of several images of the same object to analyze the development of the disease.

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