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Image Segmentation Based on Inhomogeneity Pixel Using Complex Wavelet Transform for Medical Image

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Abstract— **Abstract—The most widely used image segmentation algorithm are region based and typically rely on the homogeneity of the image intensities in the region of interest which is fail to provide accurate segmentation results due to the intensity of inhomogeneity. In this paper we have proposed novel region wavelet based method for image segmentation which is able to deal with intensity inhomogeneous. In segmentation the intensity inhomogeneity is identified by the efficient threshold technique in wavelet domain. This paper uses complex wavelet transform to segment the image based on inhomogeniety. Experiments demonstrate that the** Neighsureshrink **threshold method using the complex wavelet transform achieves better results than discrete wavelet transform in the terms of SSIM and CWSSIM.**

Index ***Terms—Segmentation, Inhomogeneity, Neighsureshrink, SSIM, CWSSIM***

I. INTRODUCTION

Intensity inhomogeneity often occurs in real world images due to various factors, such as spatial variation in illumination and imperfections of imaging devices, which complicates many problems in image processing and computer vision. In particular image segmentation may be considerably difficult for images with intensity inhomogeneities due to the overlaps between the ranges of the intensities in the regions to segment. This makes it impossible identify these regions based algorithm usually rely on intensity homogeneity and therefore are not applicable to images with intensity inhomogeneities.

Existing level set methods [5] for image segmentation can be categorized into two major classes, region based models, and edge based models. Region based models aim to indentify each region of interest by using a certain region descriptor to guide the motion of the active contour [7], but it is difficult to define a region based models. This model already implemented assumption of homogeneity intensities. The proposed method used to identify the intensities with wavelet domain. There are two basic approaches to processing the image namely spatial methods and transform methods. Spatial methods try to identify the inhomogeneity pixels by manipulating the image in the spatial domain itself whereas transform methods are using some transform to manipulate the image in transform domain. In transform domain, Wavelets the essential signal the image in transform domain. In transform domain, Wavelets give a superior performance in image segmentation due to its properties such as sparsity, energy compaction and multi-resolution structure. So, the focus was shifted from the spatial and Fourier domain to the wavelet transform domain.

Thresholding is a simple non-linear technique, which operates on one wavelet coefficient at a time. In its most basic form, each coefficient is thresholded by comparing against threshold, if the coefficient is smaller than threshold, set to zero; otherwise it is kept or modified. Replacing the small coefficients by zero and inverse wavelet transform on the result may lead to reconstruction with the essential signal characteristics and with less co-efficient [2]. But, wavelet transform suffers due to poor directionality and does not provide a geometrically oriented decomposition in multiple directions. One way to generalize the discrete wavelet transform so as to generate a structured dictionary of base is given by the Discrete Wavelet Packet Transform (DWPT). This benefit comes from the ability of the wavelet packets to better represent high frequency content and high frequency oscillating signals in particular. However, it is well known that both DWT and DWPT are shift varying. The Dual Tree Complex Wavelet Transform (DTCWT) introduced by Kingsbury is approximately shift-invariant and provides directional analysis. In this paper, it is proposed to combine two thresholding techniques namely Neighshrink and Sureshrink to identify the inhomogeneity.

II. DISCRETE WAVELET TRANSFORM

Wavelet transforms provide a framework in which a signal is decomposed, with each level corresponding to a coarser resolution, or lower frequency band. There are two main groups of transforms, continuous and discrete. Discrete transforms are more commonly used and can be subdivided in various categories. Although a review of the literature produces a number of different names and approaches for wavelet transformations, most fall into one of the following three categories: decimated, un-decimated, and non-separated. A continuous wavelet transform is performed by applying an inner product to the signal and the wavelet functions [3]. The dilation and translation factors are elements of the real line.

An easy way to comply with the conference paper formatting requirements give a superior performance in image segmentation due to its properties such as sparsity, energy compaction and multi-resolution structure. So, the focus was shifted from the spatial and Fourier domain to the wavelet transform domain. Thresholding is a simple non-linear technique, which operates on one wavelet coefficient at a time. In its most basic form, each coefficient is thresholded by comparing against threshold, if the coefficient is smaller than threshold, set to zero; otherwise it is kept or modified. Replacing the small coefficients by zero and inverse wavelet transform on the result may lead to reconstruction with is to use this document as a template and simply type your text into it. For a particular dilation a and translation b, the wavelet coefficient W f (a,b) for a signal f can be calculated as

$$W_f(a,b) = \langle f, \psi_{a,b} \rangle = \int f(x)\psi_{a,b}(x)dx \qquad (1)$$

Wavelet coefficients represent the information contained in a signal at the corresponding dilation and translation. The original signal can be reconstructed by applying the inverse transform:

$$f(x) = \frac{1}{c_w}\int_{-\infty}^{\infty}\int_{-\infty}^{\infty} W_f(a,b)\psi_{a,b}(x)db\frac{da}{a^2} \qquad (2)$$

where Cψ is the normalization factor of the mother wavelet. Although the continuous wavelet transform is simple to describe mathematically, both the signal and the wavelet function must have closed forms, making it difficult or impractical to apply.

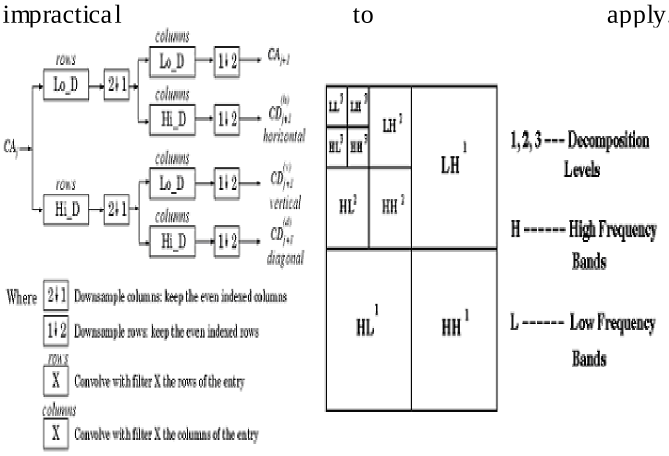

Fig. 1. 2D-Discrete Wavelet Transform

The discrete wavelet is used instead. The term discrete wavelet transform (DWT) is a general term, encompassing several different methods. It must be noted that the signal itself is continuous; discrete refers to discrete sets of dilation and translation factors and discrete sampling of the signal. For simplicity, it will be assumed that the dilation and translation factors are chosen so as to have dyadic sampling, but the concepts can be extended to other choices of factors. At a given scale J, a finite number of translations are used in

The conventional DWT can be applied using either a decimated or an un-decimated algorithm. In the decimated algorithm, the signal is down sampled after each level of transformation. In the case of a two-dimensional image, down-sampling is performed by keeping one out of every two rows and columns, making the transformed image one quarter of the original size and half the original resolution. The decimated algorithm can therefore be represented visually as a pyramid, where the spatial resolution becomes coarser as the image becomes smaller. The decimated algorithm is not shift-invariant, which means that it is sensitive to shifts of the input image. The decimation process also has a negative impact on the linear continuity of spatial features that do not have a horizontal or vertical orientation. These two factors tend to introduce artifacts when the algorithm is used in applications

applying multi resolution analysis to obtain a finite number of scaling and wavelet coefficients. The signal can be represented in terms of these coefficients as

$$f(x) = \sum_k C_{Jk}\phi_{Jk}(x) + \sum_{j=1}^{J}\sum_k d_{jk}\psi_{jk}(x) \qquad (3)$$

where cJk are the scaling coefficients and djk are the wavelet coefficients. The first term in Eq. (3) gives the low-resolution approximation of the signal while the second term gives the detailed information at resolutions from the original down to the current resolution J. The process of applying the DWT can be represented as a bank of filters. In case of a 2D image, a single level decomposition can be performed resulting in four different frequency bands namely LL, LH, HL and HH sub band and an N level decomposition can be performed resulting in 3N + 1 different frequency bands and it is shown in figure 1. At each level of decomposition, the image is split into high frequency and low frequency components; the low frequency components can be further decomposed until the desired resolution is reached. When multiple levels of decomposition are applied, the process is referred to as multi-resolution decomposition. In practice when wavelet decomposition is used for image fusion, one level of decomposition can be sufficient, but this depends on the ratio of the spatial resolutions of the images being fused.

III. DUAL TREE COMPLEX WAVELET TRANSFORM

The Dual Tree Wavelet Transform (DTWT) overcomes the limitations of DWT like poor directionality and shift invariance. It can be used to implement 2D wavelet transforms that are more selective with respect to orientation than the separable 2D DWT. For example, the 2D DTWT transform produces six subbands at each scale, each of which is strongly oriented at distinct angles. There are two versions of the 2D DTWT transform namely Dual Tree Discrete Wavelet Transform (DTDWT), and Dual Tree Complex .

IV. DUAL TREE DISCRETE WAVELET TRANSFORM

The DTDWT of an image is implemented using two critically sampled separable DWT in parallel. Then for each pair of sub bands, the sum and difference are taken. The six wavelets associated with DTDWT are illustrated in figure 2 as gray scale images. Note that each of the six wavelets is oriented in a distinct direction. Unlike the critically-sampled separable DWT, all of the wavelets are free of checker board artifact. Each subband of the 2-D dual-tree transform corresponds to a specific orientation.

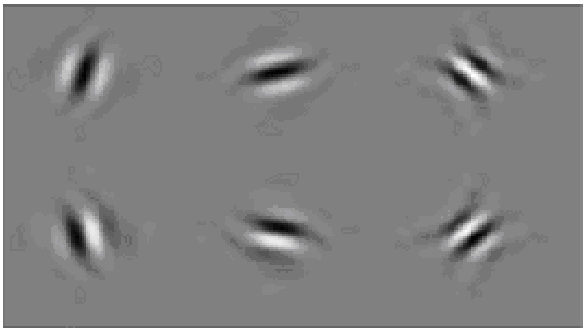

Fig. 2. Directionality of DTDWT

A. VisuShrink

VisuShrink is thresholding by applying the Universal threshold proposed by Donoho and Johnstone. This threshold is given by σ√2logM where σ is the variance and M is the number of pixels in the image. It is proved that the maximum of any M values iid as N(0,σ2) will be smaller than the universal threshold with high probability, with the probability approaching 1 as M increases. Thus, with high probability, a pure inhomogeneity signal is estimated as being identically zero.

B.. Neighshrink

For each inhomogeneity wavelet coefficient Wi, j to be shrinked, it incorporates a square neighboring window Bi, j centered at it. The neighbouring window size can be represented as LXL, where L is a positive odd number. The Neighshrink shrinkage formula can be represented as.

$$S_{i,j}^2 = \sum k, I\varepsilon B_{i,j} W_{kl}^2$$
$$\bar{\theta}_{i,j} = W_{i,j} B_{i,j} \qquad (4)$$

Where $\bar{\theta}_{i,j}$ is the estimator of the unknown homogeneity coefficient, and λ is the universal threshold. (g)+ is defined as (g)+ = max (g, 0). Different wavelet coefficient subbands are shrinked independently, but the threshold λ and neighbouring window size L keep unchanged in all subbands. When $S_{i,j}^2$ summation has pixel indexes out of the wavelet subband range, the corresponding terms in the summation are omitted. The shortcoming of this method is that using the same universal threshold λ and neighbouring window size L in all subbands is suboptimal.

C .SureShrink

SureShrink is a thresholding technique in which adaptive threshold is applied to subband, a separate threshold is computed for each detail subband based upon SURE (Stein's unbiased estimator for risk), a method for estimating the loss in an unbiased fashion. The optimal λ and L of every subband should be data-driven and minimize the mean squared error (MSE) or risk of the corresponding subband. Fortunately, Stein has stated that the MSE can be estimated unbiasedly from the observed data. NeighShrink can be improved by determining an optimal threshold and neighbouring window size for every wavelet subband using the Stein's unbiased risk estimate (SURE). For ease of notation, the wavelet coefficients from subband 's' can be arranged into the 1-D vector. Similarly, we combine the Ns unknown coefficients from subband 's' into the corresponding 1-D vector. Stein shows that, for almost any fixed estimator θs based on the data ws, the expected loss (i.e. risk) $E\left\{\left\|\bar{\theta}_{s-\theta}\right\|_2^2\right\}$ can be estimated unbiasedly. Usually, the standard deviation σ is set at 1, and then

$$E\left\{\left\|\bar{\theta}_{s-\theta s}\right\|_2^2\right\} = E\{SURE(w_s, \lambda, L\} \qquad (5)$$

***D.** Neighsureshrink*

The quantity

$$SURE(w_s, \lambda, L) = N_s + \sum_n \left\|g_n(w_{n)}\right\|_2^2 + 2\sum_n \frac{\partial g_n}{w_n} \qquad (6)$$

is an unbiased estimate of the risk on subband s where L is the neighbourhood window size (L is an odd number and greater than 1, for example, 3, 5, 7, 9, etc.):

$$E\left\{\left\|\bar{\theta}_{s-\theta s}\right\|_2^2\right\} = N_s + E\left\{\left\|g(w_s)\right\|_2^2 + 2\nabla . g(w_s)\right\} \qquad (7)$$

Then, it can be chosen the threshold λs and neighbouring window size Ls on subband 's' which minimizes SURE(ws, λ, L).

V.EXPERIMENTAL WORK

Quantitatively assessing the performance in practical application is complicated issue because the ideal image is normally unknown at the receiver end. So this paper uses the following method for experiments. It takes one cardiact MRI medical image. The methods proposed for implementing image segmentation using wavelet transform take the following form in general. The image is transformed into the orthogonal domain by taking the wavelet transform. The detail wavelet coefficients are modified according to the shrinkage algorithm. Using region based method to fix the contour for our interested region .Subsequently applied threshold methods to the decomposed image for identify the inhomogeneity pixels. Finally, inverse wavelet is taken to reconstruct the segmented image.

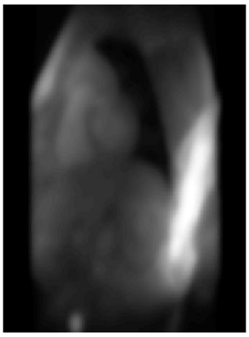

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Fig. 3. MRI cardiac image Initial contour identification for segmentation

Fig. 4. MRI cardiac image with Different region identification

Fig. 5. MRI cardiac segmented image

For taking the wavelet transform of the image, readily available MATLAB routines are taken. In each sub-band, individual pixels of the image are shrinked based on the threshold selection. A segmented wavelet transform is created by shrinking pixels. The inverse wavelet transform is the-segmented image.

VI. EVALUATIONCRITERIA

There are two evaluation measures used for comparing the segmented image based on inhomogeneity pixels with threshold methods. The SSIM value is evaluated from the following equation(8s)

$$SSIM(x,y) = l(x,y)^{\alpha} c(x,y)^{\beta} s(x,y)^{\gamma} \quad (8)$$

Where $l(x,y)^{\alpha}$, $c(x,y)^{\beta}$ *and* $s(x,y)^{\gamma}$ luminance, contrast and structure comparison are functions respectively. The second evaluation measure is CWSSIM and is found out from the equation given below:

$$CWSSIM(c_x, c_y) = \frac{2\left|\sum_{i=1}^{N} c_{x,i} * c_{y,i}\right| + k}{\sum_{i=1}^{N}\left|c_{x,i}\right|^2 + \sum_{i=0}^{N}\left|c_{y,i}\right|^2 + k} \quad (9)$$

where k is a small positive constant and cx, cy are complex wavelet co-efficient that correspond to image patches x and y. The valueα, β and Υ are positive constants. The results of SSIM and CWSSIM are tabulated in Table-I.

TABLE I

PERFORMANCE COMPARISON WITH SSIM AND CWISS FOR MRI HEART IMAGE

Method	SSIM	CWISS
Visushrink	0.974579	0.965714
Neighshrink	0.930528	0.937505
Sureshrink	0. 857467	0.807307
Neighsureshrink	0.723838	0.744948

VII. CONCLUSION

In this Paper we have proposed and describes concept of image segmentation based on inhomogeneity pixels. The proposed method generally accepted model of medical images with intensity inhomogeneities and derived a discrete complex wavelet transform. The inhomogeneity pixels are indentified using efficient threshold technique in wavelet domain instead of clustering and energy function. The experiment results show that the proposed method gives the better identification of intensity inhomogeneity and contour The new threshold method **Neighsureshrink** with the domain of the complex wavelet transform achieves better results than discrete wavelet transform in the terms of SSIM and CWSSIM.

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