Noise Suppression using Weighted Median Filter for Improved Edge Analysis in Ultrasound Kidney Images

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Abstract- Due to the characteristic speckle noise of ultrasound(US) kidney images, a noise reducing filter must be first applied before image processing stages like segmentation, registration etc. In addition the speckle noise suppression methods are highly required to improve the quality of the ultrasound image in retaining the edge features of the kidney images. The effect of this stage increases the dynamic range of gray levels which in turn increase the image contrast. The proposed system develops Weighted Median filter speckle noise suppression method for ultrasound kidney images. This paper designs intensity invariant local image phase features, obtained using improved Circular Gabor filter banks, for extracting edge texture features that occur at core and intermediate layer interfaces. The proposed model does the extension of phase symmetry features to modified circular gabor mode for use in automatic extraction of kidney edge texture features from US normal and diseased patient images. The system functionality is proved qualitatively and quantitatively through experimentation for synthetic and real data sets. The speckle noise error ratio with respect to the standard US images are compared and experimented

Keywords – Improved Circular Gabor filters, Kidney ultrasound images, Noise Suppression, Texture Analysis

I. Introduction

Ultrasound (US) imaging is non-ionizing, fast, portable, inexpensive and capable of real time imaging, but unfortunately, US images typically contain significant speckle and other artifacts which complicate image interpretation and automatic processing [3]. If anatomical structures of interest could be visualized and localized with sufficient accuracy and clarity, US may in fact become a strong practical alternative imaging modality for selected applications in Kidney disease diagnosis, particularly for computer-assisted applications where the image can be processed to provide quantitative information on the kidney structures.

The proposed filtering procedure can be stated as follows: sort the samples inside the filter window, duplicate each sample to the number of the corresponding weight, and choose the median value from the new sequence. The texture is very important cue in region based segmentation of images. Texture features play a very important role in computer vision and pattern recognition. Texture applications include industrial inspection, estimation of object range and orientation, shape analysis, satellite imaging, and medical diagnosis. In this paper, we study different definitions of texture that applied to US kidney images. The time- frequency transformed based method of texture discrimination, which is in turn based on Circular Gabor filters is done. In Gabor transform, a signal can be represented in terms of sinusoids that are modulated by translated Gaussian windows. The resulting time frequency decomposition is a suite of local Fourier transforms which displays any non stationary spectral trends. Here the interrelationship between individual transforms is well-understood and studied.

There are several research focuses in the field of texture analysis, mainly including texture classification, texture segmentation, texture synthesis, shape from texture, etc. Texture segmentation aims at localizing the boundaries between different textures on one textured image plane by classifying pixels based on their texture properties. In recent years, invariant texture analysis has been paid more and more attention due to its increasing importance. A great deal of wok has been done on this topic. However most of the existing methods focus on invariant texture classification. Efforts on invariant texture segmentation are still very limited, though invariant texture segmentation is highly desirable. Multichannel Gabor function has been recognized to be a very useful tool in computer vision and image processing, especially for texture analysis. The increasing research on Gabor analysis is motivated by biological findings. Numerous papers have been published on Gabor analysis since Gabor proposed the one dimensional Gabor function. Researchers have agreed that Gabor-like linear spatial filtering plays a crucial role in the function of mammalian biological vision systems, particularly with regard to textures. In this paper, we discuss edge texture extraction of ultrasound kidney images based on mutichannel analysis. The traditional Gabor filter is modified into a circular symmetric version. A very important property of this new version is that it is rotation invariant. Texture images are decomposed into several channel outputs. Texture features are computed from each channel output. Thus the feature space of each pixel is constructed. We also study the selection of Gabor parameters that is a very important problem. A new selection scheme is proposed for texture segmentation.

In this paper we propose a propose a technique for texture edge detection using Circular Gabor filter and the self-organizing map (SOM). The overall methodology followed for texture edge detection is shown in Fig. 1. The texture features are first extracted as n-dimensional vectors by using Circular Gabor filter bank in both directions (horizontal and vertical parallel lines of an image). The variation of prediction errors are smoothed using a Gaussian filter to suppress local fluctuations. They are then smoothed using asymmetric Gaussian filter and are projected onto one dimensional feature map using SOM. The feature map is smoothed with a two dimensional symmetric Gaussian filter, and the final map is obtained by Canny's edge detection

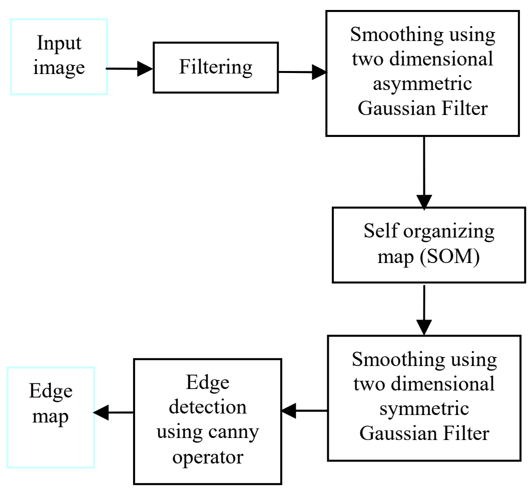

Fig.1. Block diagram of the proposed method

II. METHODOLOGY

Median based filters have been widely used in image processing because some important image details, e.g. edges, can be retained while noise can be effectively removed by the filters. Weighted median (WM) filters are a natural extension of median filters, which exploit not only rank-order information but also spatial information of input signal.

A. Weighted Median Filters

The weighted median (WM) filter was first introduced as a generalization of the standard median filter, where a nonnegative integer weight is assigned to each position in the filter window. For real-valued signals, WM filters can be defined in two different but equivalent ways. The first definition can be used in the common case of positive integer weights.

Definition: For the discrete-time continuous-valued input vector $X=[X_1,X_2,\ldots,X_N]$ the output Y of the WM filter of span N associated with the integer weights

$$W= [W_1,W_2,...,W_N] \quad (1)$$

is given by

$Y = MED [W_1 \lozenge X_1 , W_2 \lozenge X_2 , W_N \lozenge X_N]$ (2)

where MED[.] denotes the median operation and ◊ denotes duplication.

This filtering procedure can be stated as follows: sort the samples inside the filter window, duplicate each sample X_i, to the number of the corresponding weight W_i , and choose the median value from the new sequence.The second definition of the WM operation also allows positive noninteger weights to be used. Definition: The weighted median of X is the value β minimizing the following expression

$$L(\beta) = \sum_{i=1}^{N} W_i \mid X_i - \beta \mid \quad (3)$$

Here, β is guaranteed to be one of the samples X_i because L (β) is piecewise linear and convex, if $W_i \geq 0$ for all i.

The output of the WM filter for real positive weights can be calculated as follows: sort the samples inside the filter window; add up the corresponding weights from the upper end of the sorted set until the sum just exceeds half of the total sum of weights (i.e. $\geq \frac{1}{2} \sum_{i=1}^{N} W_i$ *);* the output of the WM filter is the sample corresponding to the last weight added.

B. Local Phase Symmetry Feature

The purpose of edge detection is to capture the major axis of symmetry of a feature at some specified spatial scale. Local phase information of a one dimensional signal can be obtained by convolving the signal with a pair of band-pass quadrature filters (an odd filter and an even filter). Using two filters in quadrature enables the calculation of signal amplitude and phase at a particular scale (spatial frequency) at a given spatial location. The selection quadrature filters is the Circular Gabor filter which can be constructed with arbitrary bandwidth. In order to obtain simultaneous localization of spatial and frequency information, analysis of the signal must be done over a narrow range (scale) of frequencies at different locations in the signal. This can be achieved by constructing a filter bank using a set of quadrature filters created from rescaling of the Circular Gabor filter. Each scaling is designed to pick out particular frequencies of the signal being analyzed.

Symmetry information is investigated by looking at the points where the response of the even filter dominates the response of the odd filter taking the difference of their absolute values. Traditional Gabor filters are mostly used for detection of texture direction. But in rotation invariant analysis the orientation of the texture is ignored. Thus traditional Gabor filters are less suitable for this purpose. The sinusoid of the Traditional Gabor function (TGF) varies in one direction . If the sinusoidal varies in all directions, it is circular symmetric. This results in a new type of Gabor filter known as Circular Gabor filter(CGF). It is represented as

$G(x , y)=g(x , y) * \exp(2\pi jF(\sqrt{x^2 + y^2}))$ (4)

where $g(x , y) = (1/2\pi\sigma^2) * \exp(-(x^2+y^2)/2\sigma^2)$ (5)

g(x , y) represents the Gaussian function which is symmetric along the vertical axis. F is the central frequency of a circular Gabor filter. σ is the scale parameter. Gabor filters can achieve the optimal location in both the spatial and frequency domain.

C.Texture edge detection of Ultrasound Kidney Images

The stages of texture edge detection (Fig. 1) are described below. The outputs of intermediate stages of processing are shown for each step for the image in Fig.3.

Step 1 (Filtering). A one dimensional Circular Gabor filter is applied along the set of all parallel lines of an image I in one direction (say, along all the vertical lines of the image). For a Circular Gabor filter, the output is given as

$$H_k (x_c , y) = I (x_c , y) * g_k \qquad (6)$$

where * indicates the one dimensional convolution operator, g_k represents one dimensional Circular Gabor filter with the parameter set $k = (\omega_k, \sigma_k)$, $I(x_c, y)$ represents the x_c^{th} column of the image I, and H_k denotes the k^{th} filter response.

Step 2 (smoothing).Filtered images obtained in step 1 are smoothed with asymmetric Gaussian filter.

$$V(x, y) = H(x, y) * L(x, y) \qquad (7)$$

where, L(x, y) denotes a Gaussian filter with σ_x=8x σ_y if images are filtered along parallel vertical lines and σ_y=8x σ_x if images are filtered along parallel horizontal lines $V_i(x, y)$ denotes the convolved output of i^{th}image where i = 1, ..., 8.

Step 3: Steps 1 and 2 are repeated to obtain filtered images in orthogonal direction. Let F_i (x ,y) denote all the filtered images, where i = 1, ...,16. Thus a 16-dimensional vector F(x, y) is obtained as:

$$F(x,y)= [F_1(x, y), ..., F_{16}(x, y)] \qquad (8)$$

Step 4: A one dimensional feature map Γ over the vectors {F(x, y)} is generated using the texture edge detection. For each pixel (x, y), the scalar index M(x, y) of the reference vector closest to {F(x, y)} is assigned

$$M(x, y)=\arg\min\|F(x, y)-w_i\| \text{ for all } w_i \in \Gamma \qquad (9)$$

In this way we transform the vector image to a scalar image. Feature map M is smoothed with a symmetric Gaussian

$$E(x, y) = M(x, y) * L(x, y) \qquad (10)$$

where, L(x, y) denotes Gaussian filter and E denotes a smoothed image.

Step 5 (canny edge detection): Canny's edge-detection method is applied to the smoothed feature map image E obtained in previous step to obtain the edge map.

III. Results

The experimentation of the ultrasound kidney images is conducted to quantitatively evaluate the performance of the proposed local phase and edge texture extraction for future kidney segmentation. The proposed algorithm was implemented in MATLAB. In addition to the quantitative speckle noise removal, the proposed model also present qualitative results for the texture extraction of the kidney image edges. The localization accuracy of kidney surface detection technique and assessing the accuracy of measuring relative inner layers of separation is a clinically relevant

Table I Speckle noise suppression with multiple filters in us kidney images

Noise Density (%)	PSNR value of Median filter in dB	PSNR value of DWM filter in dB	PSNR valueof WM filter in dB
10	24.32	24.70	25
20	23.55	23.77	24.77
30	22.47	22.89	23.62
40	21.17	21.42	22.45
50	20.04	20.58	21.67
60	19.76	20.06	20.43
70	18.45	18.92	19.36
80	17.57	17.78	18.19
90	15.28	15.66	17.06

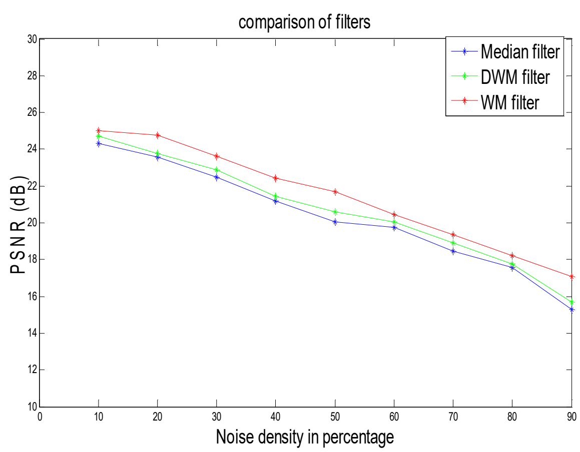

Fig. 2. PSNR performance comparison using median filter, directional weighted median filter and weighted median filter on US kidney images.

Task for which the system uses two dimensional US imaging.

The weighted median filter under a quadratic cost function minimizes the mean square error (MSE). To quantify the achieved performance improvement the standard signal to noise ratio (SNR) is not adequate due to the multiplicative nature of speckle noise. Instead, a common way to achieve this in coherent imaging is to calculate the Peak signal-to-noise ratio (PSNR). The results are shown in table I.

(a) (b)

(c) (d)

Fig. 3. (a)Original Ultrasound kidney image;(b)Denoised image; (c)Circular Gabor filter output; (d) Final edge map obtained after applying Canny's edge detecto

IV. DISCUSSION

For the implementation of the supervised texture segmentation algorithm, textured images from the Kidney dataset are used. Every textured image is preprocessed by weighted median filter to minimize the effect of noise. If content of noise increases to the extent that image turns to be perturbed, then the Circular Gabor filter scheme may not give optimum results. It has to be noted that Circular Gabor filters are very sensitive to scale, orientation and frequency of the texture. If any of these are affected due to noise, then Circular Gabor filter bank may not even detect the particular texture.

The filter bank parameter tuning, texture feature extraction and texture classifier design are performed as discussed in the previous sections. The multi-textured US kidney image is processed by the tuned filter bank and the textural features are extracted for each pixel position. The pixels are labeled to be belonging to certain texture classes as classified for further segmentation using seeded region growing method. The classified image is further processed where the pixel label is set to that which occurs maximum times in its 3 x 3 neighborhood. This ensures the removal of classification noise thereby enhancing the segmented image.

V. CONCLUSIONS

The proposed approach for accurate and fully automatic extraction of kidney surfaces directly in ultrasound volumes is based on local phase symmetry image features that employ improved filters. The errors were relatively independent of the depth of the edges of the kidney internal segment interface and of the inclination of the probe relative to the outer kidney surface.

The phase method has high localization accuracy even when the US beam is not perfectly normal to the kidney surface. The obtained results are encouraging for using local phase processed images in kidney assessment since the average accuracy required for such application is typically in the range of 1-2mm. The true analysis produced a noticeably smoother image of the kidney surface than previously reported two dimensional analysis. The image processing will be of special importance during the assessment of kidney disease diagnosis where good accuracy is needed to avoid elimination or redundant kidney inner layers. Furthermore, since there is no need to align the imaging plane with the anatomical area of interest, evaluation of the surface area can likely be performed more rapidly.

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