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

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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 study 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.

Key words: Improved circular Gabor filters, kidney ultrasound images, noise suppression, texture analysis, speckle noise error

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 (Daanen *et al*., 2004). 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. Imaging speckle is a phenomenon that occurs when a coherent source and a non-coherent detector are used to interrogate a medium which is rough on the scale of the wavelength. Speckle occurs, especially in images of the liver and kidney whose underlying structures are too small to be resolved by large wavelength ultrasound. 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. Texture is a 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 study, researchers study different definitions of texture that apply to US kidney images. The time-frequency transform based method of texture discrimination, based on circular Gabor filters is done in the research. 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 (Gupta and Das, 2006) like 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

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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. Previous studies related to wavelet shrinkage using Bayesian theory have underlined the need for a prior model that accurately approximates the probability density function of the signal and noise wavelet coefficients (Zong *et al*., 1999). More importantly, the 2D nature of fluoroscopic images makes it difficult to obtain accurate measurements of the shape and relative position of 3D anatomical structures. Therefore, there is considerable interest in trying to replace the radiation based intraoperative imaging modalities with safer non ionizing real time imaging modalities and Ultrasound (US) is the leading alternative (Popescu *et al*., 1999). Amin *et al*. (2003), the researcher presented a local phase-based method of endocardial and epicardial boundary feature detection from Feature Asymmetry (FA) measure which also took notice of the spatio-temporal characteristics of the images. They assumed that endocardial or epicardial boundaries have step edge characteristics (thus asymmetry). Intraoperative freehand 3-Dimensional (3-D) Ultrasound (3D-US) has been proposed in Mulet-Parada and Noble (2000) as a non-invasive method for registering bones to a preoperative computed tomography image or computer-generated bone model during Computer-Aided Orthopedic Surgery (CAOS). The transfer function (G) of a 3D Log-Gabor filter in thefrequency domain is constructed as the product of 2 components: A one dimensional Log Gabor function that controls the frequencies to which the filter responds and a rotational symmetric angular Gaussian function that controls the orientation selectivity of the filter (Barratt *et al*., 2006). Thresholding methods have 2 main drawbacks: The choice of the threshold, arguably the most important design parameter is done in an ad hoc manner and the specific distributions of the signal and noise may not be well matched at different scales.

To address these disadvantages, Simoncelli and Adelson (1996) developed nonlinear estimators, based on formal Bayesian theory which out perform classical linear processors and simple thresholding estimators in removing noise from visual images (Dosil *et al*., 2006). Simoncelli and Adelson (1996), researchers proposed a methodology in which the wavelet coefficients are assumed to be conditionally independent zero-mean Gaussian random variables with variances modeled as identically distributed, highly correlated random variables. Simoncelli and Adelson (1996) used a 2 parameter generalized Laplacian distribution for the wavelet coefficients of the image which is estimated from the noisy observations. The images produced by commercial ultrasound systems are usually optimized for visual interpretation, since they are mostly used in real-time diagnostic situations. However, the main disadvantage of medical ultrasonography is the poor quality of images which are affected by multiplicative speckle noise (Tamilselvi and Thangaraj, 2010). The general structure and computational framework of the Discrete Wavelet Transform (DWT) are similar to sub and coding systems. The main difference lies in filter design where wavelet filters are required to be regular. In this study, researchers considered 2 methods of multi scale analysis: Discrete Wavelet Transform (DWT) (Jain, 1989) which corresponds to an octave-band filter bank.

The increasing research on Gabor analysis is motivated by biological findings (Jain and Bhattacharjee, 1992). Numerous study 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 study, researchers 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. A feature map is constructed using Self-Organizing Map (SOM). Researchers also study the selection of Gabor parameters which is a very important problem. A new selection scheme is proposed for texture segmentation.

The overall methodology followed for texture edge detection is shown in Fig. 1. As mentioned before, raw US images contain significant speckle noise causing disturbance in edge detection. Therefore, the first step is the suppression of this noise. Next the texture features are extracted as n-dimensional vectors by using circular Gabor filter bank in both directions (horizontal and vertical parallel lines of an image). The variations 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. This feature map is

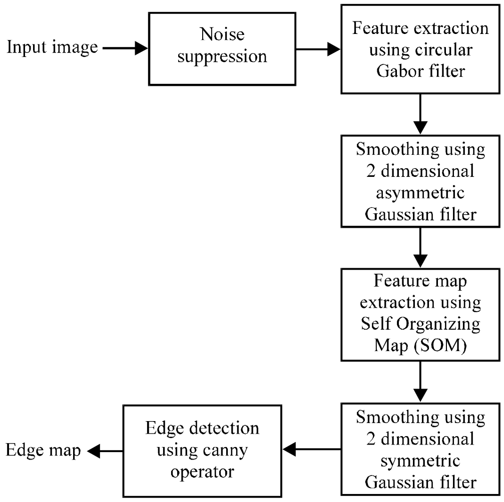

Fig.1: Block diagram of the proposed method

then smoothed with a 2 dimensional symmetric Gaussian filter and the final map is obtained by applying Canny's edge detection operator.

MATERIALS AND METHODS

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.

Weighted median filters: The Weighted Median (WM) filter (Yin *et al*., 1996) 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 2 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 = [X1, X2, ..., XN] the output Y of the WM filter of span N associated with the integer weights:

$$W = \left[W1, W2, \ldots, WN\right] \quad (1)$$

Is given by:

$$Y = MED\left[W1 + X1, W2 + X2, WN + XN\right] \quad (2)$$

Where:

MED [.] = The median operation
\+ = Duplication

Table 1: Speckle noise suppression with multiple filters in us kidney images

Noise density (%)	PSNR value of median in filter dB	PSNR value of WM filter in dB
10	24.32	25.00
20	23.55	24.77
30	22.47	23.62
40	21.17	22.45
50	20.04	21.67
60	19.76	20.43
70	18.45	19.36
80	17.57	18.19
90	15.28	17.06

This filtering procedure can be stated as follows: Sort the samples inside the filter window, duplicate each sample Xi to the number of the corresponding weight Wi 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 equation:

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

Here, β is guaranteed to be one of the samples Xi because L (β) is piecewise linear and convex, if Wi≥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.

Table 1 represents the comparison of the result of noise suppression using median filter and weighted median filter. Figure 2 represents the graphical comparison of the earlier. Figure 3 represents the result obtained on a sample of US image.

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 2 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

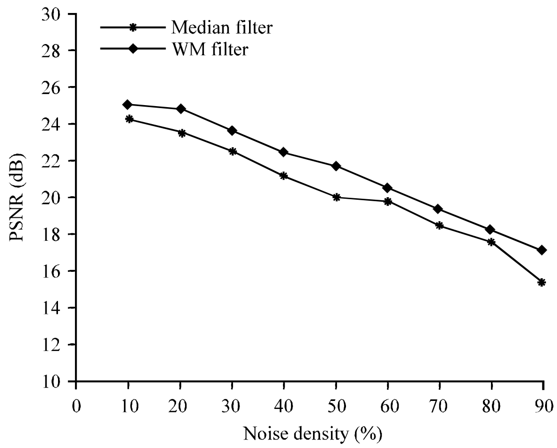

Fig. 2: PSNR performance comparison using median filter and weighted median filter on US kidney images

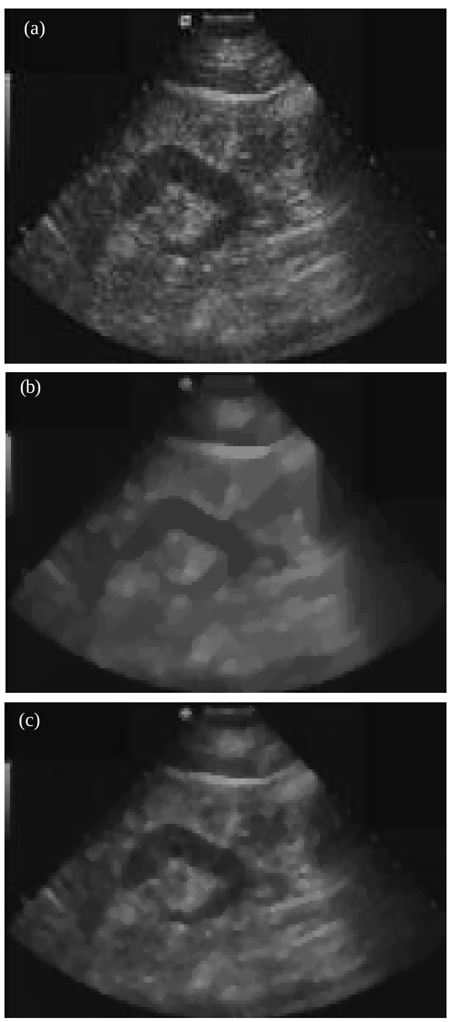

Fig. 3: a) Original ultrasound kidney image; b) Denoised image using weighted median filter; c) Denoised image using median filter

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 (Popescu *et al*., 1999). 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:

$$G(x,y) = g(x,y)^{*} \exp\left(2\pi jF\left(\sqrt{x2+y2}\right)\right) \quad (4)$$

Where:

$$g(x,y) = (1/2\pi\sigma 2)^{*} \exp\left(-(x2+y2)/2\sigma 2\right) \quad (5)$$

Where, 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. For a circular Gabor filter, the output is given as:

$$H(xc,y) = I(xc,y)^{*} gk \quad (6)$$

Where:
* = The one dimensional convolution operator
gk = One dimensional circular Gabor filter with the parameter set
k = (F, σ)
I (xc, y) = The xcth column of the image I
H (xc, y) = The filter response

Feature extraction for various frequencies and scaling parameters ranging from 0.1-0.9 and 0.01-1, respectively has been carried out in the experiments. The results obtained are shown in Fig. 4.

Post processing of symmetric features: The Gaussian filter blurs objects. The filter creates an output image by using a Gaussian weighted average of the input pixels around the location of each corresponding output pixel.

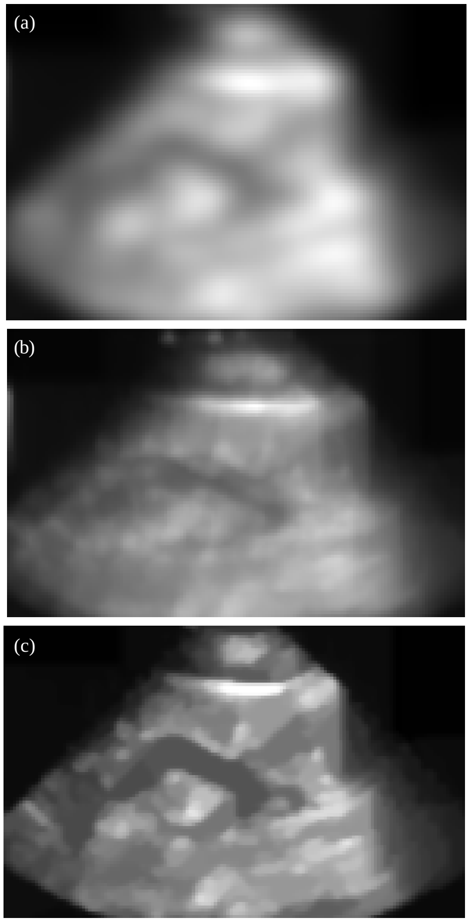

Fig. 4: Circular Gabor filtered US kidney images for: a) F = 0.1, σ = 0.65; b) F = 0.6, σ = 0.77; c) F = 0.4, σ = 0.0884

Filtered images are smoothed with asymmetric Gaussian filter. Mathematically, applying a Gaussian smoothing to an image is the same as convolving the image with a Gaussian function:

$$v(x,y) = H(xc,y)^{*} L(x,y) \tag{7}$$

Where:

L (x, y) = A Gaussian filter with images filtered along parallel vertical lines and filtered along parallel horizontal lines

V (x, y) = The convolved output of image

Figure 5 shows the asymmetric Gaussian smoothing of filtered images for F = 0.4 and σ = 0.0884 in horizontal and vertical directions.

Feature map using SOM: A simple modification to the competitive learning model gives rise to a powerful new

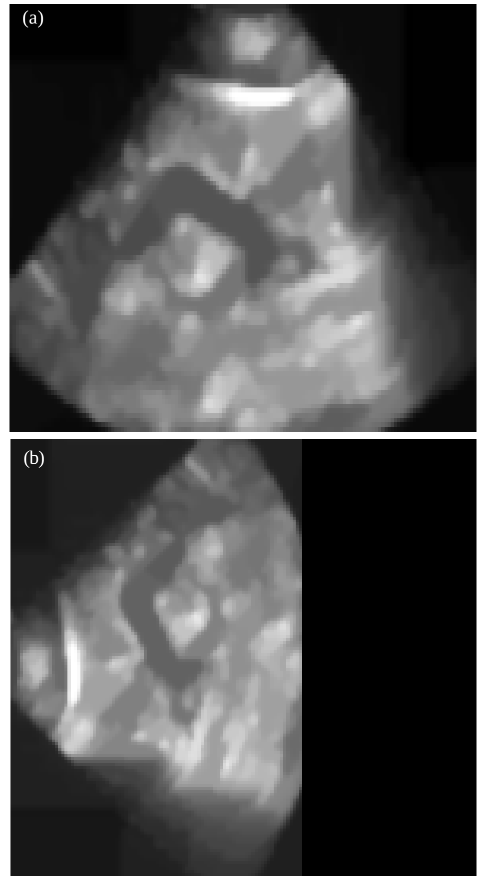

Fig. 5: Images obtained by smoothing using asymmetric Gaussian filter in: a) Horizontal direction; b) Vertical direction

class of models called the Self-Organizing Map (SOM). These models were pioneered by Kohonen and are also referred to as Kohonen maps.

The SOM can be thought of as the simple competitive learning model with a neighborhood constraint on the output units. The output units are arranged in a spatial grid, for instance 100 output units might form a 10×10 square grid. Sticking with the hyper sphere analogy instead of just moving the winning output unit weights towards the input pattern, the winning unit and its neighbors in the grid are adjusted. The amount of adjustment is determined by the distance in the grid of a given output unit from the winning unit. The effect of this constraint is that neighboring output units tend to respond to similar input pattern, producing a topology preserving map (also called a topographic map) from input space to the output space. This property can be used to visualize structure in high-dimensional input data.

Let, Fi (x, y) denote all the filtered images where i = 1, 2. Thus, a two-dimensional vector F(x, y) is obtained as:

Fig. 6: Feature map of US kidney image

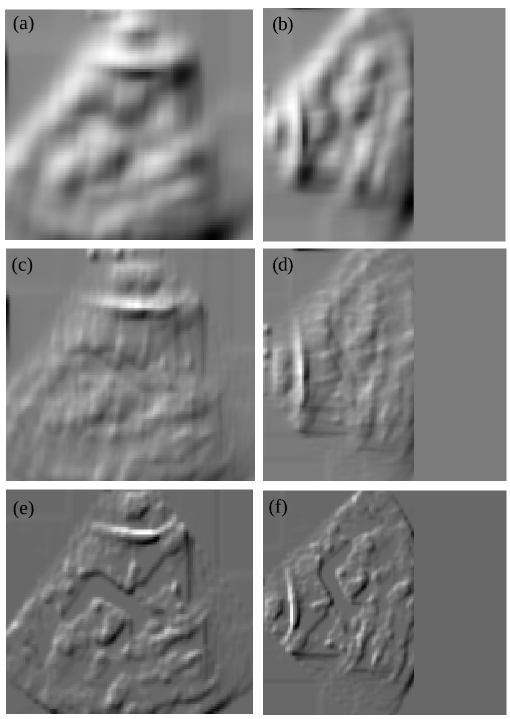

Fig. 7: Smoothed feature map obtained by smoothing using symmetric Gaussian filter using: a) F = 0.1, σ = 0.77 in horizontal direction; b) In vertical direction; c) F = 0.6, σ = 0.65 in horizontal direction; d) in vertical direction; e) F = 0.4, σ = 0.0884 in horizontal direction; f) in vertical direction

$$F(x,y) = \left[F1(x,y),\ F2(x,y)\right] \tag{8}$$

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 as:

$$M(x,y) = \arg\min \left\| F(x,y) - wi \right\| \text{for all wi } \varepsilon\Gamma \tag{9}$$

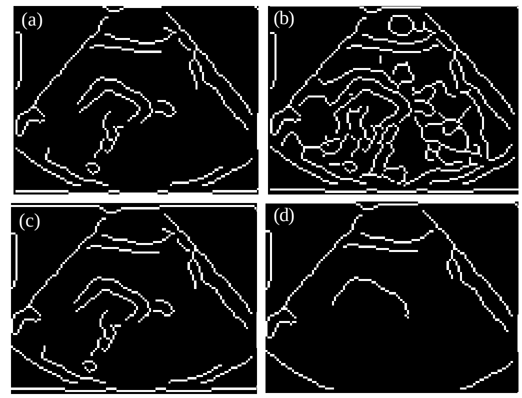

Fig. 8: Final edge map obtained after applying canny's edge detector for: a) σ = 0.1; b) σ = 0.2; c) σ = 0.3; d) σ = 0.4

In this way, researchers transform the vector image to a scalar image. Then applying this scalar image to a SOM algorithm researchers obtain a feature map. Figure 6 shows the feature map of US image.

Post processing of feature map: Feature map M is smoothed with a symmetric Gaussian filter:

$$E(x,y) = M(x,y)^{*} L(x,y) \tag{10}$$

Where:
L (x, y) = Gaussian filter
E = A smoothed image

Figure 7 shows the smoothed image using symmetric Gaussian filter in horizontal and vertical direction for various values of F and σ.

Edge detection: Canny's edge-detection method is applied to the smoothed feature map image E obtained in previous step to obtain the final edge map. Figure 8 shows the canny edge map of US image for various values of σ.

RESULTS AND DISCUSSION

Several US images obtained from the medical research institute were used for simulations. 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 speckle noise suppression in US images is done using median and weighted median filter. The weighted median filter under a quadratic cost function minimizes the Mean Square Error (MSE) as indicated in Fig. 2. 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). Table 1 clearly indicates the better performance of WM filter as evident from the PSNR values. Figure 3 shows that WM filter is better than median filter.

The denoised US image is applied to circular Gabor filter for various values of F and σ. From Fig. 4, it is evident that for $F = 0.4$ and $\sigma = 0.0884$, researchers get a good filtered output. Then the filtered output is smoothed using asymmetric Gaussian filter for $F = 0.4$ and $\sigma = 0.0884$ and then feature map is drawn using SOM algorithm. The feature map is smoothed using symmetric Gaussian filter. From Fig. 7, it is evident that for $F = 0.4$ and $\sigma = 0.0884$ researchers get a good smoothed output image in vertical and horizontal directions. The final step is the edge detection of this smoothed US image using canny operator. Figure 8 shows that for $\sigma = 0.3$ researchers get a good edge map of US kidney image.

CONCLUSION

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 proposed method of speckle noise suppression using weighted median filter is an effective method compared to median filter. The circular Gabor filter parameters F and σ are taken in the range from 0.1-0.9 and 0.01-1, respectively. The circular Gabor filter outputs and Gaussian smoothed outputs are good for $F = 0.4$ and $\sigma = 0.0884$ values. The final edge map of US kidney image obtained using canny operator is good for a value of $\sigma = 0.3$. Researchers can improve the US kidney image edge analysis by using other denoising methods and further filtering and smoothing using improved filters.

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