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4D Ultrasound Adaptive Image Pre-processing

Ahmed F. Elnokrashy[1], *Yasser M. Kadah*[2]
[1]Electrical Engineering, Benha University, Benha, Egypt,
ahmed.elnokrashy@bhit.bu.edu.eg
[2]Electrical and Computer Engineering, King Abdulaziz University, Jeddah, Saudi Arabia,
ymk@k-space.org

ABSTRACT

4D ultrasound is one of the most advancing visualization techniques of the ultrasound dataset. it is subdivided into main five visualization modes volume render, maximum, minimum, mean, and the surface render. The surface render visualization mode is the most realistic mode among the five modes of visualizing the ultrasound 3D dataset.

We enhance the rendered image quality of the surface render mode by enhancing the pre-processing of the 2D ultrasound image. Surface render is subdivided into four major stages, 2D image pre-processing, volume render with surface detection, surface shading and finally post-processing.

Surface render mode gives a low rendered image quality because of the speckle noise nature of the ultrasound, which is the reason for the coherent nature of the ultrasound imaging. And so, pre-processing of the 2D image is needed to remove the speckle noise keeping and enhancing the surface edges.

Our processing meets the Three major challenges which must be concerned when designing the pre-processing of the 2D ultrasound image. Firstly, robustly smooth the speckle noise. Secondly, preserves and enhances the organs edges. and finally, the time constrains must be met that is because of this processing is part of many intensive processing stages. in addition, the processing implemented on the current GPUs platform, which shows a very high processing power with significant low coast value.

A recent review of the literature, on this topic found that, a vast publication in the area of the 4D rendering pipeline [1] and 2D image enhancement each separately, despite this interest, no one to the best of our knowledge has studied the suitable 2D image pre-processing to get the best 4D data visualization [2], considering the nature of the ultrasound image [3] and the time constrains of the ultrasound physics.

Our processing is a merge between local statistics and non-linear filters. It guarantees the required suitable quality of the 2D ultrasound image and performance constrains.

Keywords: 4D Ultrasound; Speckle noise; Lee-Sigma Filter; Surface rendering; GPU Processing;

I. INTRODUCTION

4D ultrasound surface rendering reconstruction contains a number of processing stages. The major critical and most important stage is the surface detection process, which is included in the volume rendering stage in most rendering techniques. Erroneous detection of the surfaces will occur, because of the speckle noise of the ultrasound image, and so 2D image de-speckling and edge enhancement must be included in a pre-processing stage before the surface detection [4] [5].

Speckle noise is generated due to the out of phase constructive and destructive interference between the scattered ultrasound waves, which occurs when the ultrasound waves interact with tissue particles smaller in size than the ultrasound wavelength, these interference patterns will show a texture in the soft tissue known as speckle or speckle noise [6], by the way, speckle noise gives the organ a texture pattern, which is different based on the tissue composition and characteristics, and so it is used in some cases for diagnoses, example of that is, the liver fibrosis, which shows a speckle texture pattern differed than that of the normal liver, in more general terms, the speckle texture is important when studying the tissue characteristics [7], While in other cases the speckle texture is considered as unwanted noise of the ultrasound image: for example, when diagnosis the fetus anomalies and in our case when trying to form the 3D ultrasound image of the fetus body or face.

Ultrasound speckle noise is a multiplicative noise in nature follow Raleigh distribution [8] [9] [10]. Logarithmic mapping is an essential processing stage of the ultrasound image formation, which transform the multiplicative noise into additive noise, leads to the de-speckling processing become more easer, in addition Gaussian assumption of the noise become valid [6].

Ultrasound visualization has time constrain due to the ultrasound physics and imaging topology, and thus any visualization must guarantee to not limits the achievable frame rate due to the processing requirements. 4D surface render needs exhaustive processing power as well, which must be considered in the design of the 2D image pre-processing to guarantee the usability of that processing stage. In addition, the advancements of the GPUs technology with very large number of concurrent processing cores makes it the most suitable processing platform for the 4D ultrasound data visualization, and so pre-processing must be optimized to the GPUs platform.

We propose a Pre-processing stage for the surface render mode of the 4D ultrasound visualization. The processing removes the speckle noise and enhances the edges of 2D image. All the processing is implemented and tested on the available GPUs. The processing is based on the assumption that the speckle noise is a Gaussian distribution after the log-transformation. It makes a moving average of all the pixels using the two-sigma range of the pre-estimated center pixel. More details about the estimation of the center pixel value will be mentioned later, adaptive kernel size is used. The proposed processing meets the required image quality for the surface rendering, enhances the edges, and meets the time constrains of the ultrasound physics.

II. RELATED WORK

2D Image pre-processing enhancement for the 4D ultrasound did not got the attention of a large number of researcher because most of them concentrate mainly on the rendering pipeline of the 3D dataset, and trying to test different rendering techniques. so, we will give an overview of the most known 2D image enhancement filters, then develop our own based on the local statistics nonlinear filter approach with adaptive kernel size.

There are two major classifications of image enhancement filters. single scale spatial filters and transform domain multiscale filters [11] [12]. The transform domain filters are out of scope of this work, because it needs a heavy processing power, in addition it's not suitable for the current GPUs. On the other hand, spatial filter which reduces the variation between adjacent pixels, and could be sub classified to Linear and nonlinear filters.

The most general form of the linear filters the Kuan filter [13], Lee and Frost filters have the same structure whereas Kuan filter is the generalization form [10]. these types of filters generate the output image based on computing the central pixel intensity inside the filter window, which is calculated with different methods, one of them is the average intensity value of the window(box) pixels.

Nonlinear filter [14], Median, homogeneous [15], geometric filters [16] are the well-known examples, median is the most traditional one which is perfect for salt and paper noise, homogenous filter [17] [18] chooses the filtered window values as the most homogenous neighborhood in the filter kernel window while the geometric filter go through iterative repetition to gradually tears down the narrow walls and fills up the narrow valleys this synonym started on the SAR images and tested with the ultrasound images [19].

One of the known nonlinear filter is the Sigma filter which is known as Lee Filter as well. It's considered as an adaptive filter, it uses the standard deviation(two-sigma) of those pixels within a local filter window surrounding each pixel to calculate a new pixel value. Typically, the pixel value is replaced with a new value calculated based on the surrounding pixels (those that satisfy two-sigma range criteria). Unlike the linear filter, the adaptive filters keep the edges and the fine details suppressing the speckle noise. Biasing is the major disadvantage of the original Sigma filter, the filter shows better smoothing at the homogenous regions, also it does not remove the spike noise as well, thus Lee added an additional stage in his original algorithm to smooth the spike noise. Lee et. al. [20] [21] , Lopes et. al. [22] and Lu et. al. [23] proposed many solutions for the original Sigma filter, (Lopes et al, 1990) [22] developed the enhanced Lee filter, it statistically subdivides the filter window into three classes: Homogeneous, Heterogeneous, and Point target, (Lu et al, 1996) [23] developed the modified Lee filter and (Lee et al, 2009) [24] developed the improved sigma filter. Lu performs speckle reduction at the edges and Lopes uses three classes mean filter for homogenous area, Lee's filter for heterogeneous area and finally the pixel value for the strong heterogeneous areas. The improved sigma filter by Lee solved the deficiencies were discovered in producing biased estimation and in blurring and depressing strong reflected targets by redefining the sigma range based on the speckle probability density functions of the filter kernel. even these solutions showed a better quality, it needs more strength processing.

Based on the original Sigma filter we propose our filter i.e. 2D pre-processing stage. Firstly, to solve the biasing problem we designed the filter with dynamic expanding window. and Secondly, spike noise removed using pre-estimate of the center pixel based on median of the closest neighbor pixels, as we will be demonstrated.

The most common assumption of the ultrasound noise is that it's Normally distributed [21]. i.e. the two-sigma range guarantees that 95% of the pixels of the same distribution will share in the kernel window average(smoothing) and any pixel outside this range is expected to be due to changes in the statistical properties which in our case most probably due to an edge in the image and so will not contribute in the smoothing(averaging). The major disadvantage of the two-sigma range is the spike noise, which is in some cases will be out of the two-sigma range and so it will not be smoothed. To overcome this drawback Lee calculate the number of pixels sharing in the smoothing(averaging) and based on a predefined threshold replaces the two-sigma range method by taking the average of the pixels immediate to the center pixel.

4D ultrasound surface rendering pre-processing concerning mainly with the true edges, so suppressing the white noise in front of fetus face (amniotic fluid). Enhancing the surface/edges to enhances the detection of the surface/ edge in post-processing stages and to make the rendered surface photogenic.

Ultrasound despeckling algorithm must be adaptable because of the difference in ultrasound images due to number of factors like (TGC, Gain, acoustic power, frequency, logarithmic scale and gray mapping).

Finally, the time constrains of the despeckle filter must meet the ultrasound 4D physical constrains also the algorithm must be GPU processing friendly, viz, the algorithm must be fragment based implementable. In addition, the algorithm must be CG compatible, the shader program written in CG has some limitation [25].

III. Methodology

The algorithm is based on the approach that taking the average of all the pixels within the filter kernel that lies in the two-sigma range. The Two-sigma range for Gaussian distribution interpreted as 95.5% of the random samples lies within it. Any pixel outside this range means it comes from a different distribution i.e. edge pixel or different region characteristic. *First*, the algorithm estimates the mean of the distribution based on the median of the immediate of the center pixels of the filter window(box), *Then,* generate the two-sigma range, it then takes the average of all the pixels within the two-sigma range in the window. we start the window size with the minimum size that achieves the smoothing at the homogenies region, in the case of not all the pixels shared in the average we increase the kernel size in all dimensions and continue tell the number of pixels shared in the average equal the minimum acceptable size.

A. Despeckle Algorithm

Step1. Establish an estimate of the center pixel value ($\bar{x}$) based on Median of ($x_{i-1,j}$, $x_{i,j}$, $x_{i+1,j}$,$x_{i,j-1}$, $x_{i,j+1}$).

Step2. Establish an intensity range ($\bar{x}$ + Δ, $\bar{x}$ - Δ) where Δ = 2σ.

Step3. Take the average of all the pixels which lies in the calculated range of step2 in the filter moving window.

Step4. If the number of pixels contributed in the average are less than (M x M) Continue step (3) with greater windows size by (2 x 2).

Step5. Normalize the average by dividing the sum by the number of contributed pixels.

Mathematically,

Let: ($\delta_{k,l}$) is the condition of each pixel in the kernel windows, is it within the two Sigma range or not.

($\bar{x}$) is the estimation of the center pixel of the kernel window based on the median.

(Δ) is the two sigma range.

$$\delta_{k,l} = 1 \qquad if\ (\bar{x} - \Delta) \leq x_{k,l} \leq (\bar{x} + \Delta) \qquad (1)$$

$$= 0 \qquad \text{otherwise.}$$

$$\hat{x}_{i,j} = \frac{\sum_{k=i-n}^{n+i} \sum_{l=j-m}^{m+j} \delta_{k,l}\ x_{k,l}}{\sum_{k=i-n}^{n+i} \sum_{l=j-m}^{m+j} \delta_{k,l}} \qquad (2)$$

IV. Results and Discussions

Assessment of the proposed method is based on two stages, 2D image assessment and rendered 3D image Assessment. Simulated and real ultrasound image will be used. Finally, the rendered 3D images assessment will be done visually, because the surface rendered image has many visualization effects which makes the regular image quality assessments not applicable. We will illustrate the rendered 3D images after our proposed processing technique and compare it with many other well know techniques.

the mainly filter that we are interested to compare our method with is the Lee [21] filter because it's the most closed filter to our method, in addition we used the simple Box filter.

Simulated ultrasound images will be generated using Field-II program [26] "MATLAB program simulate the ultrasound images". A kidney image is chosen to assess the method for the heterogamous images.

Real ultrasound image for fetal phantom will be used also, to test the homogenous images. By this two images we guarantee to test the two major types of the ultrasound images homogenous and heterogenous images.

About the reference images(noise free images or low noise images) which we need to assess the new method, Two methods are presented, first, for the simulated US images we used the original noise free image, on the other hand the real ultrasound images for the 3D phantom, we do not have the original(noise free) images, so we used Perona-Malek [27] filter with aggressive parameters to get reference image close to the original image Fig. 2., shows the generated reference image and real scan US image for the 3D phantom.

A. Assessment indexes

The quality assessment matrices which will be used are the PSNR, SSIM.
The traditional assessment Peak Signal to Noise Ratio (PSNR) index is used

$$PSNR = 10 * log_{10} \frac{{MAX_I}^2}{\left(\frac{1}{n * m} \sum_{i=1}^{n} \sum_{j=1}^{m} [I(i,j) - K(i,j)]^2\right)} \quad (3)$$

Here, MAX_I the maximum pixel value, I, K are the reference and processed image respectively. n,m are the image number of pixels in both direction, i,j are the pixel row and column index. Higher values of the *PSNR* means higher signal to noise ration and so better performances.

In addition the Structural Similarity *SSIM* is used, it is closer to the human visual perception [28].

$$SSIM(x,y) = \frac{(2\mu_x\mu_y + c_1)(2\sigma_{xy} + c_2)}{(\mu_x^2 + \mu_y^2 + c_1)(\sigma_x^2 + \sigma_y^2 + c_1)} \quad (4)$$

μ_x, μ_y *Average in x and y direction*
σ_x^2, σ_y^2 *Average in x and y direction*
σ_{xy} *covariance of x and y,* $c_1 = (k_1L)^2$, $c_2 = (k_2L)^2$, *L pixel dynamic range*
$k_1 = 0.01$ *and* $k_2 = 0.03$ *small values by defualt*

B. Experiment I

A real ultrasound scan using IBETECH "Digison-Q" [29] machine with 3D fetal ultrasound biometrics phantom CIRS "model 068" [30], Fig. 2(a)., shows the real ultrasound image, generated reference image and the processed images using different methods. The used image is gray scan image of 512x512 resolution, two methods are used for assessment, Lee and box filters with the following configuration:

Box filters: kernel size 9x9;
Lee's filter: 9x9 kernel, 0.2 σ;
Proposed filter: 9x9 kernel, 0.2 σ;

Fig. 2(b)., The reference image which is generated using Perona-Malik anisotropic diffusion filter [27] using the following parameters: Number of iteration 35, Delta 1/7, kappa 13, the second configuration. Then the Box, Lee and the new method image results are show in Fig. 2(c,d,e)., subsequently.

Fig. 1(a,b)., shows the SSIM and PSNR with respect to the kernel size for the three methods: Box, Lee and the new method.

It's clear that the proposed filter shows slightly better performance than the Lee filter, the use of homogenous phantom image makes the differentiation so difficult. Because any simple method could show a good result.

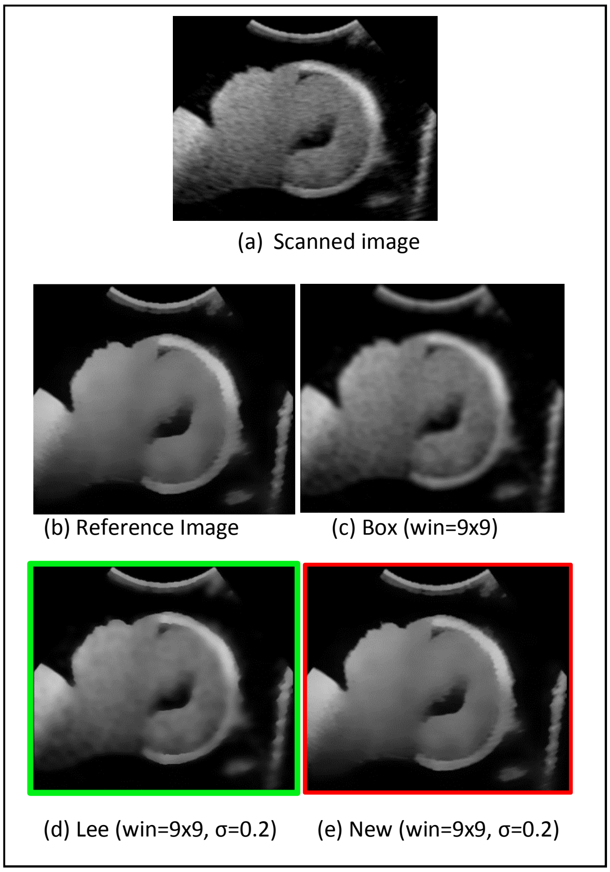

Fig. 2: Results for 3D biometrics phantom using real scan image

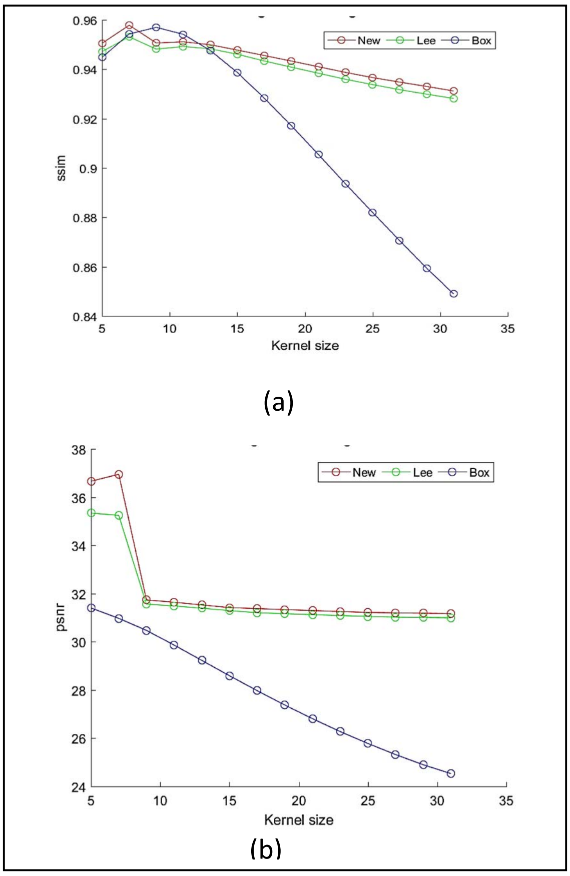

Fig. 1: Behavior of (a) SSIM and (b) PSNR both versus the kernel size

C. Experiment II

Fig.4 (b)., Simulated image is used using Field II [26]. Fig.4 (a)., A reference 'kidney' image is chosen, with size 256x256 and gray scale. The used parameters for generating the kidney image are: 106 randomly distributed scatterers, 7 MHz 128 element convex array transducer, Single focal point at 6cm. we preferred to choose highly detailed image in comparison to the 3D phantom image which shows less details.

Lee filter is used to be comparted to our method with the following configurations:

- Lee's filter: 9x9 kernel, 0.2 σ;
- Proposed filter: 9x9 kernel, 0.2 σ;

Fig. 4 (b)., The reference image with the following parameters: Number of iteration 35, Delta 1/7, kappa 13, using the second configuration. Then the Box, Lee and the new method images are show in Fig.4 (c,d,e)., subsequently. Fig. 3 (a,b)., shows the SSIM and PSNR with respect to the kernel size for the three methods: Box, Lee and the new method.

the proposed filter shows a great performance over the Lee filter specially with the heteronymous images, which is the case for the fetus images.

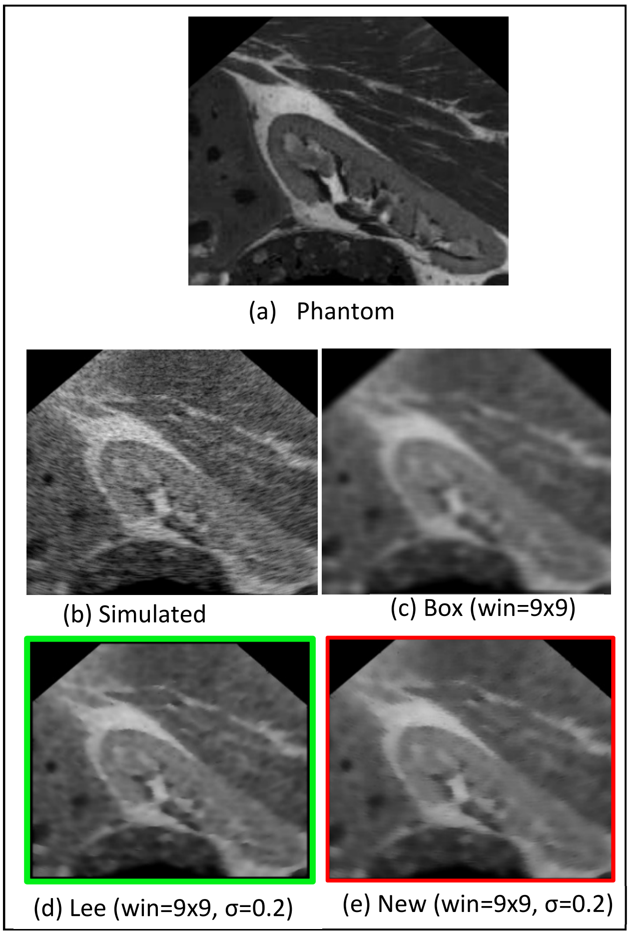

Fig. 4: Results for simulated kidney image

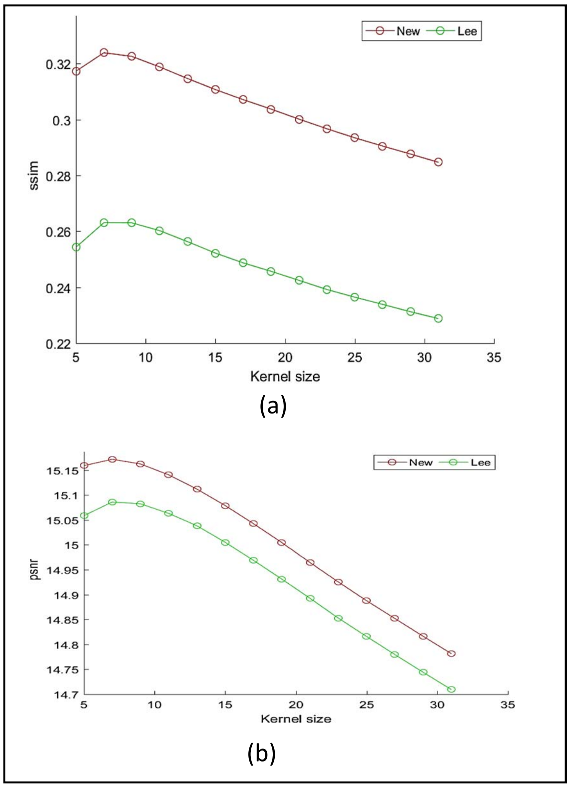

Fig. 3:Behavior of (a) SSIM and (b) PSNR both versus the kernel size

D. Ultrasound 4D Image Quality

Fig. 5,6,7., show 4D ultrasound surface rendered volume [1] with three different types of pre-processing of the input ultrasounds 2D image, even the box filter shows a good smoothed surface at large kernel size the rendered volume is blurred/smeared and surface/edges are lost, Fig. 6., Gaussian filter shows lower blurred volume but also lower surface quality. Finally, Fig. 7., shows the rendered 4D ultrasound volume with the proposed filter, the rendered volume shows better smooth surface with lower blurring. all the rendered volume does not have any 3D filters by the way any simple 3D filter with small kernel size will greatly enhances the rendered 3D image.

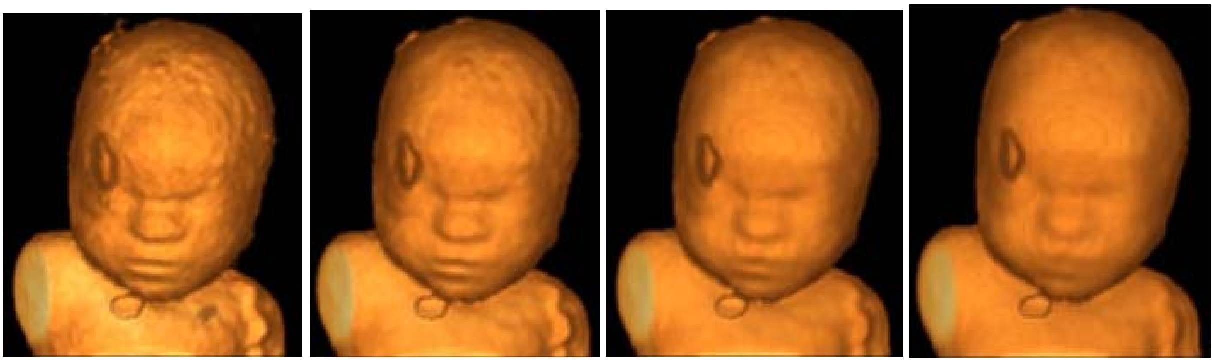

Fig. 5: Smoothing filter based on Box Filter Pre-processing, with different kernel size. (a) 5x5 (b) 11x11, (c) 17x17, (d) 21x21

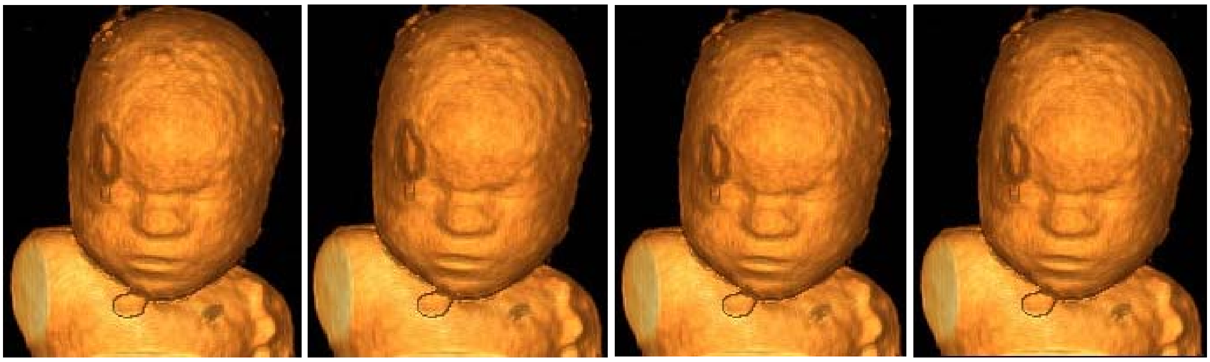

Fig. 6: Smoothing filter based on Gauss Filter Pre-Processing, with sigma = 1.5 and different kernel size (a)5x5, (b)11x11, (c)17x17, (d)21x21

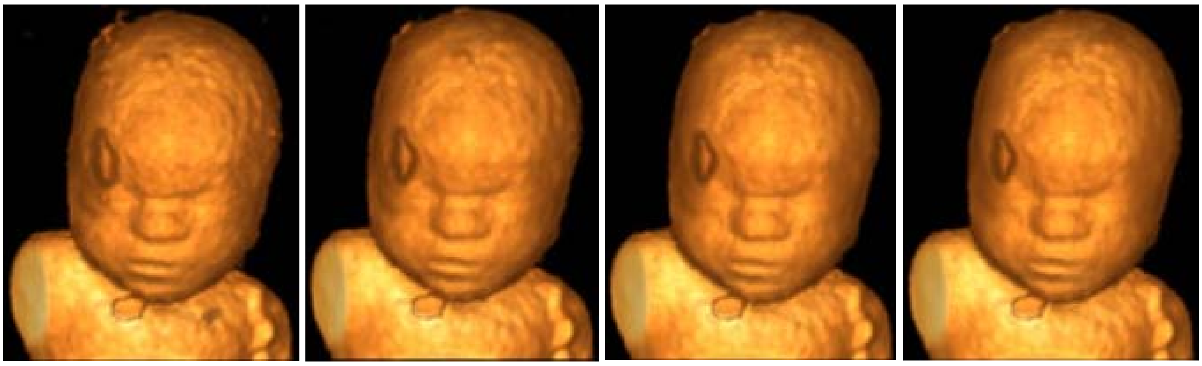

Fig. 7: Proposed Algorithm with Sigma = 1.5 with different kernel sizes, (a) 5x5, (b)11x11, (c)17x17, (d)21x21

V. CONCLUSION

Ultrasound 2D image pre-processing for 4D ultrasound surface rendering is proposed, the filter algorithm uses adaptive local statistical approach, the algorithm solves the biasing problem of the original Lee-Sigma filter, it also removes the spike noise, and finally it works non-iteratively. The developed filter designed to be suitable for modern GPUs. 2D image analysis shows reasonable quality of the ultrasound image and enhanced the edges as well, which is mainly required for surface detection of the fetal face. In addition, timing performance is measured with all the rendering pipeline working on, acceptable rendering performance were found. Even the study is made on a low-end GPUs, better time performance could be achieved with better GPU. Finally, the processing performance met the ultrasound time constrains.

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