Brief notes: Abs-Laplacian series kernels as a promising edge detection tool for real time imaging

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Abstract – **Conventional edge detection involves convolving images with the kernels as the 1st step, then followed by local orientation calculation, if required and thresholding to detect the edges. Where ever necessary the algorithm would also carry out some kind of image modification similar to pre-processing to enhance the image quality for better edge detection. In general, convolution is the preliminary and the most crucial step because the convolved images obtained may or may not retain all the details present in the original image. Abs-Laplacian is a newer technique and has been demonstrated to be better in comparison to Sobel and Prewitt. Here in the paper, I present recent developments that have been undertaken so far in terms of the advantage we have with the abs-Laplacian along with a comparative analysis carried over a set of 9 kernels/edge detection techniques. Edge quality determined by abs-Laplacian is clear and comparable to the best available technique. In addition the kernel requires a complexity of only 7 additions against 15 and 13 respectively for Sobel and Prewitt. While the Robert's cross operator performs the faster with a mere 3 additions, the previous and also the current analysis would show that the edge quality does not fare better in comparison to newer technique. In order to demonstrate the potential abilities of the technique to resolve fine details in the image, the edge detection was carried out on high-resolution complex images so that we can compare the edges together with its original image. I would like to conclude here saying that technique offer best in terms of edge quality and also in speed for real time imaging applications.**

Keywords – Abs-Laplacian

I. INTRODUCTION

Real time edge detection over an image is challenging esp. for tasks requiring automated surveillance where one needs to identify certain objects wandering over a complex area. There are lots of practical challenges involved; noisy data, blurring of image due to winds or rainfall or mist, poor quality imaging system, flexible and transparent object that bear no definite shape and many more. Edge detection [1] is the preliminary step we usually carry out to detect such objects and of course they would dictate further analysis that can be carried over the edge detected image. Poor edge quality means that we can only perform coarse detection while a better detection would provide miniscule details. Abs-Laplacian, a newly developed technique that is a slight modification over Laplacian offers high quality edges comparable to Sobel and Prewitt. Here, in the article I will discuss few development that has been undertaken so far with an example to demonstrate on how well the edges are detectable and even for complex image where the edges seems blurry. In addition, edge profiling analysis was done for a set of 10 kernels/edge detection techniques commonly used, for comparative analysis.

II. METHODOLOGY

Convolution technique was employed to determine an edge as follows. Convolution of an image is carried out on a pixel by pixel basis by multiplying the sub-image (I) with a kernel (K) and summing up the matrix elements (eq1 and eq2). Due to their filtering properties, they are used to smoothen, sharpen, intensity or enhance the image quality.

$$I_c = I \cdot K \tag{1}$$

$$I_c(i,j) = \sum_{k=1}^{m}\sum_{l=1}^{n} I(i+k-1,+l-1)\cdot K(k,l) \tag{2}$$

Table 1 provides list of kernels that have are used in image processing. Kernel selection depends on how we sample an image and calculate gradients along each dimension. Generally, two kernels are used, one for computing the convolution along x-axis (G_x) and other along y-axis (G_y). While there are some kernels e.g. Kirch and Robinson which takes advantage of 8 kernels For those methods utilizing more than one kernel final convoluted image is calculated as the root of the sum of the squares of the convolution results along all axes. Sometimes it is better that we reduce the amount of computation involved so that we can speed up our algorithm and perform high speed edge detection. In such cases, authors approximate the final convolution as a mere addition of the absolute of the convolution of along each direction [2, 3]. For example, Sobel technique involves two kernels one that performs convolution along x and the other along y direction and therefore final gradients would become the magnitude of two components which can be approximated as a mere sum. The direction of the normal to the edges or the orientation of the edge is given by inverse tangent of the 'x' component of the convolution upon the 'y' component.

Table1. List of kernels employed in image processing algorithms

Kernel	Gx	Gy
abs-Laplacian, with shift=1	0 1 0 1 -4 1 0 1 0	
Sobel	-1 0 1 -2 0 2 -1 0 1	-1 -2 -1 0 0 0 1 2 1
Prewitt	-1 0 1 -1 0 1 -1 0 1	1 1 1 0 0 0 -1 -1 -1
Kirch	-3 -3 5 -3 0 5 -3 -3 5	-3 5 5 -3 0 5 -3 -3 -3
	5 5 5 -3 0 -3 -3 -3 -3	5 5 -3 5 0 -3 -3 -3 -3
	5 -3 -3 5 0 -3 5 -3 -3	-3 -3 -3 5 0 -3 5 5 -3
	-3 -3 -3 -3 0 -3 5 5 5	-3 -3 -3 -3 0 5 -3 5 5
Robinson	-1 0 1 -2 0 2 -1 0 1	0 1 2 -1 0 1 -2 -1 0
	1 2 1 0 0 0 -1 -2 -1	2 1 0 1 0 -1 0 -1 -2
	1 0 -1 2 0 -2 1 0 -1	0 -1 -2 1 0 -1 2 1 0
	-1 -2 -1 0 0 0 1 2 1	-2 -1 0 -1 0 1 0 1 2
Laplacian, 3x3	0 1 0 1 -4 1 0 1 0	
Laplacian, 5x5	0 0 0 0 0 0 0 0 0 0 0 0 -4 0 0	

	0 0 0 0 0	
	0 0 0 0 0	
Laplacian of Gaussian	1 1 1 1 1	
	1 1 1 1 1	
	1 1 -24 1 1	
	1 1 1 1 1	
	1 1 1 1 1	
Canny's method apply Gaussian filter and then use sobel/prewitt or other kernels	2 4 5 4 2	
	4 9 12 9 4	
	5 12 15 12 5	
	4 9 12 9 4	
	2 4 5 4 2	
	-1 0 1	-1 -2 -1
	-2 0 2	0 0 0
	-1 0 1	1 2 1
Robert's cross operator	1 0	0 1
	0 -1	-1 0

Laplacian kernels has its origin from the Laplace operator containing 2 order derivative of X and Y directions and hence we see the kernels having 1's along the respective axis while the weight at the centre is -4. Absolute of the Laplacian is just a small modification version of the way Laplacian operators are used for edge detection. With the same kernel containing 1's in the four orthogonal directions and a -4 at its base or centre point, the convolution is carried out with the input image to obtain a value at the corresponding $(i, j)^{th}$ location. and then followed by taking absolute value to eliminate the negative values. The rationale for choosing such a modification came along while I was performing Laplacian operation over the image where the filtered data was blurry. The operator is highly sensitive to noise; and the edge quality appears blurred in comparison to the sobel and prewitt techniques. While following the values of the blurry data, it struck me that the occurrence of such a image may be because of the negative value and that's how the new technique came about. Abs-Laplacian edges are extremely clear and would be a promising tool in real time image processing.

A list of variations that are possible in abs-Laplacian kernels are shown in Table2. The parameter shift represents an offset from the centre pixel or gives an indication of farthest pixel we are going to use. A shift of one means that we will do a subtraction of centre pixel will it's adjacent ones along X and Y directions. While for a shift of 2 we would take neighbours that are location 2 pixels from the centre. Though only few variations are listed down, there might be many others. The best feature of the technique is that they only involve one kernel and that too with fewer non-zero elements. Also, it is important to remember that larger the number of non-zero elements large will the algorithm complexity.

Table2. Variations in abs-Laplacian kernels

Shift = 1	Shift = 2	Shift = 3
0 1 0	0 0 1 0 0	0 0 0 1 0 0 0
1 -4 1	0 0 0 0 0	0 0 0 0 0 0 0
0 1 0	1 0 -4 0 1	0 0 0 0 0 0 0
	0 0 0 0 0	1 0 0 -4 0 0 1
	0 0 1 0 0	0 0 0 0 0 0 0
		0 0 0 0 0 0 0
		0 0 0 1 0 0 0

III. Results and Discussions

In one of the previous reports the real time imaging experiments were conducted to assess the performance of the new kernel and see if the time series edges do not arise any flaws. With a complexity of 7 additions [4] the tool seems to a promising one for real time imaging application e.g. robotic vision where the edge detection is routinely performed or during surveillance etc. During the real time processing the tool seems to work better and without any delay in Matlab. Though Matlab platform won't provide a real time data at higher frame rates including the computation, it should be remembered that the complexity of 7 times the image size is what we are dealing with and response times for each frame analyzed would be dependent on the clock speeds. Figure1 depicts the effects of variations in shifting sub-images with respect to the kernel. Contour maps clearly depicts the larger shifts broadens the edges and vice versa. Shifting the image to a large distance becomes very important when we want to capture the objects with thick edges so that post-analysis and object position can be detected at ease. Arte-facts and faint edges that are actually not a part of the desirable edge can significantly decrease the efficiency.

How can one say for sure that the abs-Laplacian works better than the other methods? I ponder around this question trying to figure out the nature of experiments that would be sufficient enough to convince that the technique can performs better. For this, I carried out detailed edge profiling and did comparative analysis of the edges obtained by the new technique with rest of kernel. (Fig2) An image that does contain faint edges detectable by human eye and a sharp image were chosen for the analysis and edge detection was carried out. Following the panel (b) we find that the edge determined by abs-Laplacian are much comparable to sobel, prewitt, kirch and robinson while the canny shown up with light color with blurred thick line. Simple laplacian operation doesn't highlight the lines due to the grey background which consume the contrast making those edges vague. Check out the intensity map at the pixel row equal to 100 in panel (c). The plot clearly shows the fluctuations that are present in the brownish regions.

Figure1. Effects of varying shift parameter in abs-Laplacian method are illustrated here. A shift of 1 shown as abs-Laplacian 1 denotes that one considers only adjacent pixel for calculating convolution while for shift of 2 it would the neighbours that are 2 pixels further. Notice the changes in the edge thickness for the same image taken simultaneously during real time. Line thickness become broader with increasing shift parameters but also blurs the edges to an extent so an optimal e.g. shift of 3 should be chosen for best results. Note: Figure is adapted from authors previous publication [5].

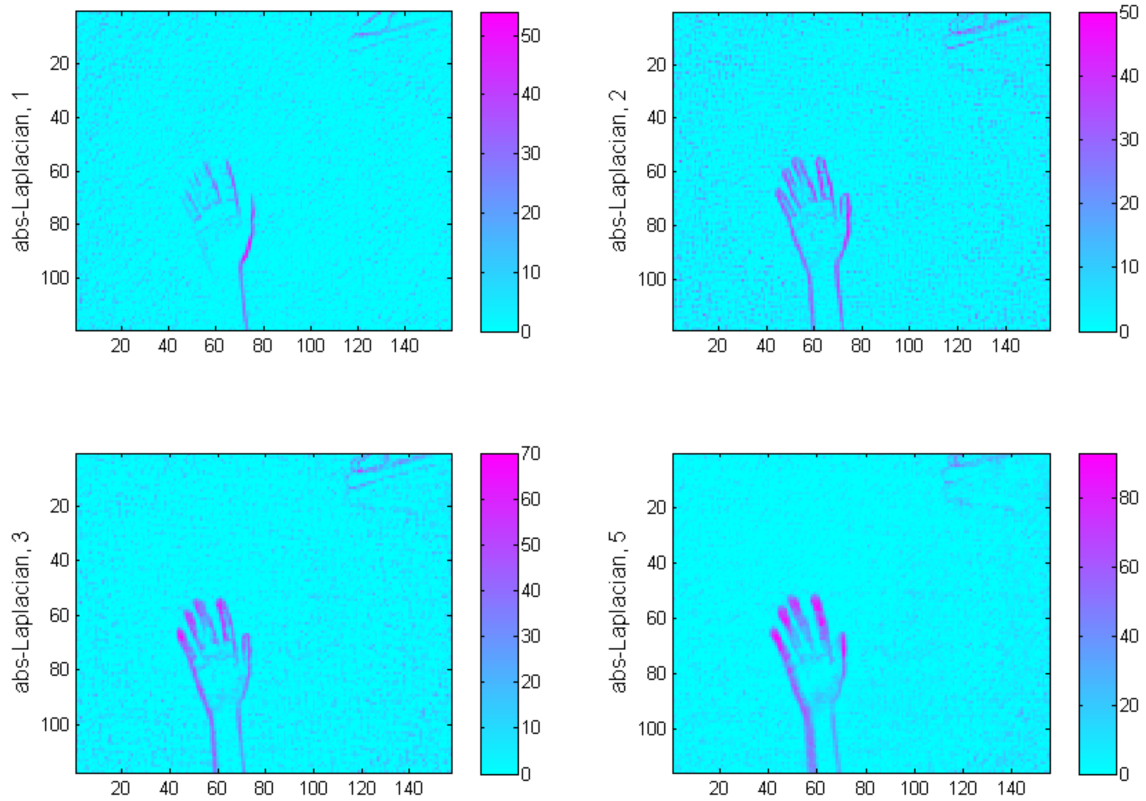
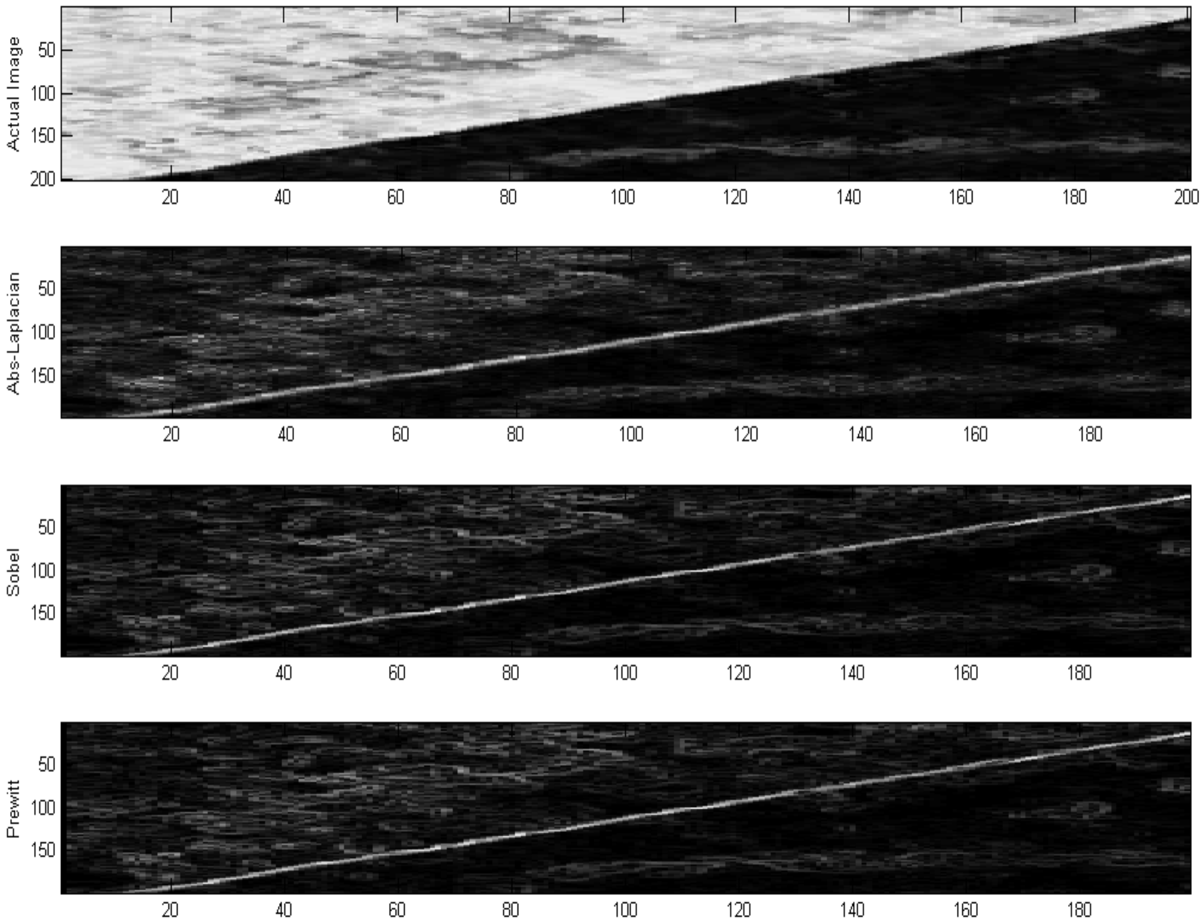
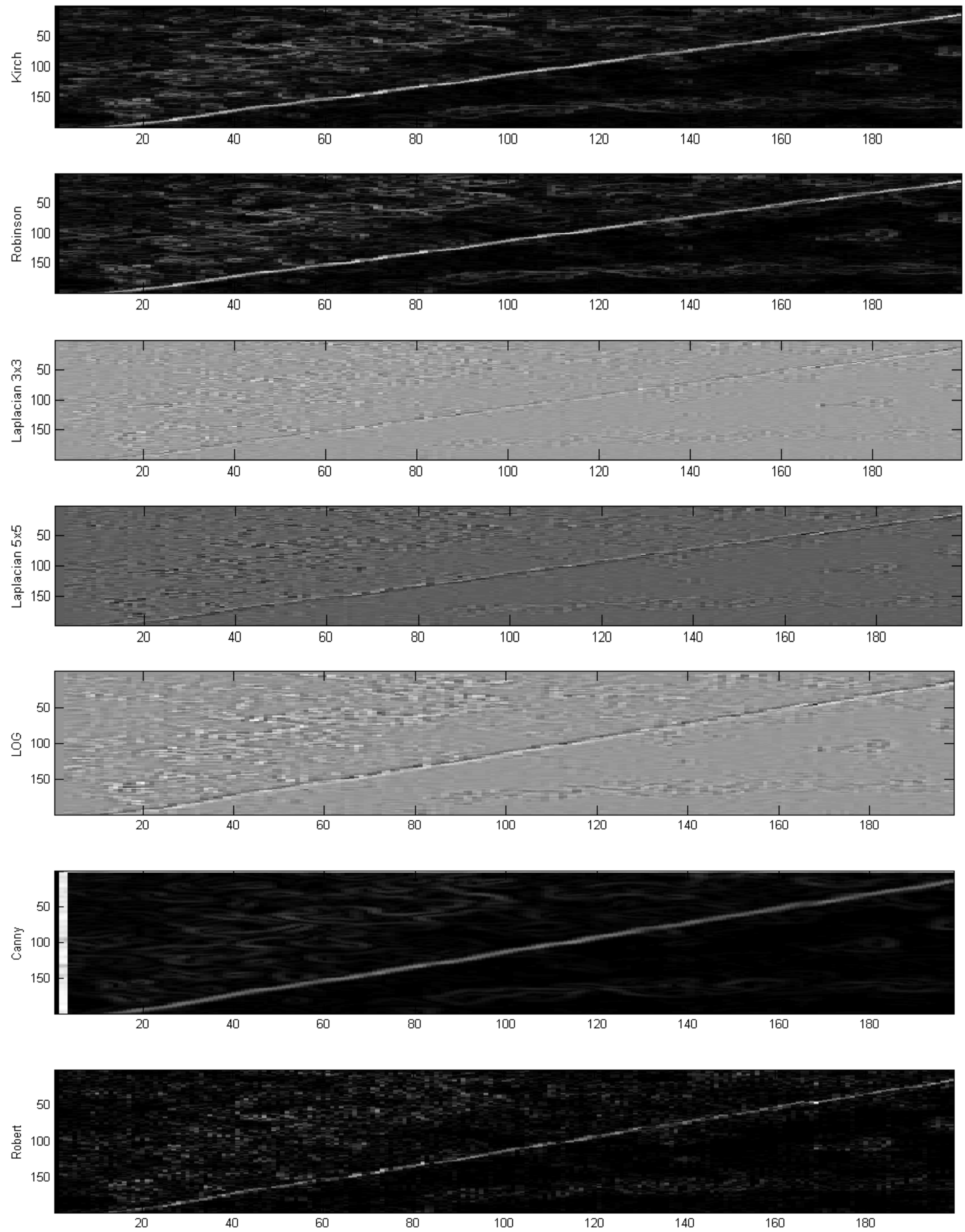


Figure2. Edge profiling was carried out for comparative analysis to figure out differences that occur and also in terms of edge quality. 10 kernel edges of a sample image in panel (a) is shown in panel (b). Panel (c) depicts intensity plot corresponding to pixel intensity at row equal to 100 and followed by edge intensity plot where the red line indicated abs-Laplacian edge, green line for the Sobel and black for Prewitt respectively. Notice the peak in edge intensity plot refers to an edge in the real image. Minor peaks represent local edges that are not part of the edge of an object under consideration.

a)

b)




Kirch
Robinson
Laplacian 3x3
Laplacian 5x5
LOG
Canny
Robert
50 100 150
20 40 60 80 100 120 140 160 180

c)

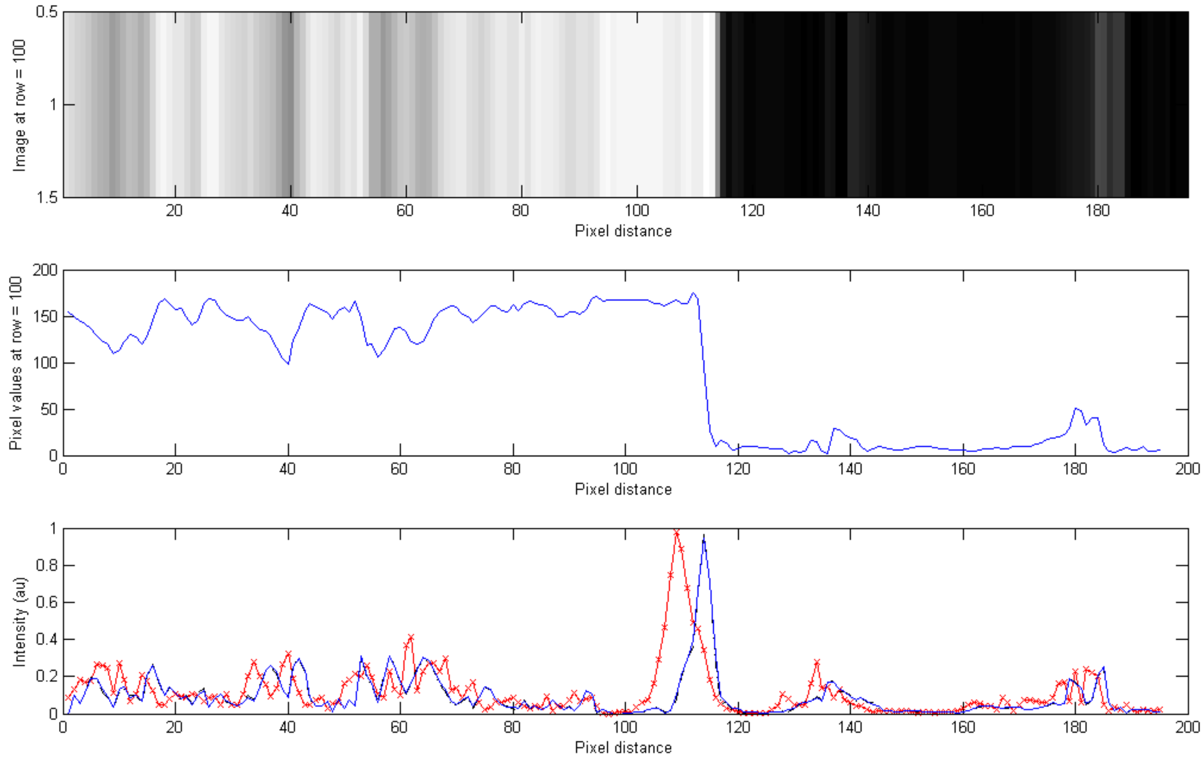
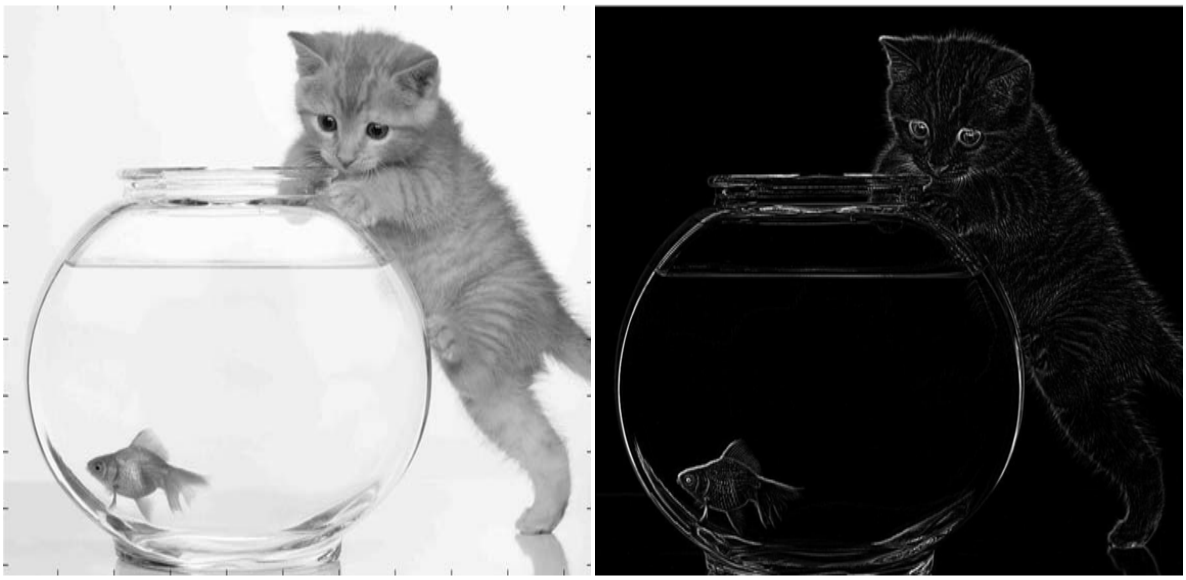


Figure3. Galley of abs-Laplacian determined edges for complex gray scale images are shown here. It was observed that a shift of 3 seemed appropriate and wherever necessary the shift parameter was increased to 5 as in panel (b) to highlight the edges of birds. Choice of shift depends on what we are resolving, if we were to predict a bird with shift of 1 it would highlight as thin line with sharp edge but in such case the location of that bird becomes difficult.

a)

b)

c)



d)

IV. CONCLUSION

Edge detection form the most preliminary step and of course one of the most crucial one. Any approximation at this level means that we are introducing lots of arte-facts which at the later post-processing stage become difficult. Denoising is one of the best examples to explain. We would though suppose that the noise levels can be eliminated but in conjunction we also degrade the image quality. As shown in previous report, wavelet based denoising showed no improvement in the edge profile of abs-Laplacian and also for other [5]. In addition abs-Lapalacian of denoised images degraded the edge quality to great extent. But it doesn't mean that we can't apply denoising. Unless we aren't sure of the noise trends or the noise behaviors ideal denoising would be challenging. In conclusion, I would like to say that the experiences with using abs-Laplacian has been so far excellent and this tool can be preferred readily over Sobel, Prewitt, Canny and the rest for real time imaging. Before ending, I have also added a gallery of the abs-Laplacian edges of high resolution images in gray scale to highlight the features that the new kernel can provide us and all of this in real time (fig3).

V. ACKNOWLEDGMENTS

None

VI. REFERENCES

[1] D. Marr and E. Hildreth, "Theory of edge detection," Proc R Soc Lond B Biol Sci, vol. 207, pp. 187-217, Feb 29 1980.
[2] R. Maini and H. Aggarwal, "Study and Comparison of Various Image Edge Detection Techniques," International Journal of Image Processing (IJIP), vol. 3.
[3] G. T. Shrivakshan and C. Chandrasekar, "A Comparison of various Edge Detection Techniques used in Image Processing," International Journal of Computer Science Issues, vol. 9, 2012.
[4] A. Ravi Kant, "A novel high-speed image processing technique for detecting edges using abs-Laplacian kernel," International Journal of Computer Science and Engineering Technology, vol. 4, 2013.
[5] A. Ravi Kant, "Foundations of a rapid de-noising technique in real time image processing applications," International Journal of Computer Science & Engineering Technology, vol. 4, 2013.