Abs-Laplacian and Robert's cross operator offers high speed edge detection capabilities with comparable speed-quality tradeoffs

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Abstract—Abs-Laplacian is a newer technique for detecting edges. While the Sobel and Prewitt seems to be used predominantly in image processing due to better edge detection. However they need higher amount of complexity twice than that of abs-Laplacin. Moreover, qualities of images are no better than the newer kernel. While the new technique seems to perform better in speed and quality, there seems a bit of competition with the 1st order kernel i.e. Robert's cross operator. In terms of speed, Robert needs only 3 computational units against 7 for abs-Laplacian, but in terms of image quality analyzed by determining the intensity deviation of Robert's edge or abs-Laplacian edges with respect to the Sobel's edges shows that Robert's kernel show major deviation indicating a low quality image while the new technique showed negligible deviation. Intensity profiles of edges detected for various kinds of images shows similar behavior for each kernel which also suggests that the inherent nature of kernels tend to remain the same for whatever complex images we deal with. In conclusion, the results show that there exists a speed-quality tradeoff between the abs-Laplacian and the Roberts operators.

Keywords – abs-Laplacian

I. INTRODUCTION

Edge detection [1, 2] relies on how efficiently a process could detect intensity changes at the proximity of edges. Also the proximal intensity at edges vary greatly and highly dependent on the prevailing situations e.g. lightning conditions, noise levels and others and therefore it has been a challenging to devise new methodologies that are immune to such environmental factors [3]. With developments in newer kernels it seems that there is good possibility that we would be able to develop a one such kernel immune to the above factors. Abs-Laplacian is one such kernel, first reported on Mar 2013 [4]. There could be occasions where one there is wrong predictions due to shadow or arte-facts in images. To justify whether the new technique can smartly handle such wrong prediction one would to analyze their inherent features which is the subject of interest in the current study. Also high speed image processing demands that one does a reliable prediction in real time without major delays.

In this paper, a comparative analysis of abs-Laplacian was carried out against 9 commonly used kernels. Previous reports have showed that the abs-Laplacian performs better than Sobel and Prewitt and therefore we employed similar analysis here by considering a crystal and a clear image. Intensity variations over local regions were analyzed and the edge intensities over local and global scale were also carried out for detailed profiling of edges obtained by various kernels. Finally the algorithm complexity was measured and compared with the image quality of edges for speed-quality tradeoff analysis.

II. THEORY

The convolutions of an image with appropriate kernels are carried out as follows. They are more like a mathematical operator used in image processing for smooth or filter the images and sometime to modify the image to increase sharpness. By convolution of two functions, one being the image and the other is a kernel or mask or an operator, we mean that to get another function. In this process, one considers taking the mask or the kernel and moving it over the image right from the first pixel till the end. For e.g. given a pixel location for the kernel, we multiply the sub-image (I) with a kernel (K) and perform a summation over the matrix elements as per the formulation shown in eq1 and eq2.

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

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

Lists of 10 kernels are shown in table1 of which most of them are commonly employed in imaging processing algorithms. While some kernels are small in dimension other may be big as 7x7 not shown here. Sometimes it's been a trend to use simply the convolution calculations where there needs to perform a square root operation where more than 1 kernels are employed as in case of Sobel, Prewitt and others denoting convolution along the x-axis (G_x), y-axis (G_y) and along arbitrary axis. In such cases, the roots of the sum of the squares are approximated as absolute sum of all these components [5-7].

Table1. List of kernels

Kernel	Gx	Gy
abs-Laplacian, with shift=1	$\begin{matrix} 0 & 1 & 0 \\ 1 & -4 & 1 \\ 0 & 1 & 0 \end{matrix}$	
Sobel	$\begin{matrix} -1 & 0 & 1 \\ -2 & 0 & 2 \\ -1 & 0 & 1 \end{matrix}$	$\begin{matrix} -1 & -2 & -1 \\ 0 & 0 & 0 \\ 1 & 2 & 1 \end{matrix}$
Prewitt	$\begin{matrix} -1 & 0 & 1 \\ -1 & 0 & 1 \\ -1 & 0 & 1 \end{matrix}$	$\begin{matrix} 1 & 1 & 1 \\ 0 & 0 & 0 \\ -1 & -1 & -1 \end{matrix}$
Kirch	$\begin{matrix} -3 & -3 & 5 \\ -3 & 0 & 5 \\ -3 & -3 & 5 \end{matrix}$	$\begin{matrix} -3 & 5 & 5 \\ -3 & 0 & 5 \\ -3 & -3 & -3 \end{matrix}$
	$\begin{matrix} 5 & 5 & 5 \\ -3 & 0 & -3 \\ -3 & -3 & -3 \end{matrix}$	$\begin{matrix} 5 & 5 & -3 \\ 5 & 0 & -3 \\ -3 & -3 & -3 \end{matrix}$
	$\begin{matrix} 5 & -3 & -3 \\ 5 & 0 & -3 \\ 5 & -3 & -3 \end{matrix}$	$\begin{matrix} -3 & -3 & -3 \\ 5 & 0 & -3 \\ 5 & 5 & -3 \end{matrix}$
	$\begin{matrix} -3 & -3 & -3 \\ -3 & 0 & -3 \\ 5 & 5 & 5 \end{matrix}$	$\begin{matrix} -3 & -3 & -3 \\ -3 & 0 & 5 \\ -3 & 5 & 5 \end{matrix}$
Robinson	$\begin{matrix} -1 & 0 & 1 \\ -2 & 0 & 2 \\ -1 & 0 & 1 \end{matrix}$	$\begin{matrix} 0 & 1 & 2 \\ -1 & 0 & 1 \\ -2 & -1 & 0 \end{matrix}$
	$\begin{matrix} 1 & 2 & 1 \\ 0 & 0 & 0 \\ -1 & -2 & -1 \end{matrix}$	$\begin{matrix} 2 & 1 & 0 \\ 1 & 0 & -1 \\ 0 & -1 & -2 \end{matrix}$
	$\begin{matrix} 1 & 0 & -1 \\ 2 & 0 & -2 \\ 1 & 0 & -1 \end{matrix}$	$\begin{matrix} 0 & -1 & -2 \\ 1 & 0 & -1 \\ 2 & 1 & 0 \end{matrix}$
	$\begin{matrix} -1 & -2 & -1 \\ 0 & 0 & 0 \\ 1 & 2 & 1 \end{matrix}$	$\begin{matrix} -2 & -1 & 0 \\ -1 & 0 & 1 \\ 0 & 1 & 2 \end{matrix}$
Laplacian, 3x3	$\begin{matrix} 0 & 1 & 0 \\ 1 & -4 & 1 \\ 0 & 1 & 0 \end{matrix}$	
Laplacian, 5x5	$\begin{matrix} 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & -4 & 0 & 0 \end{matrix}$	

<table>
<tr><td></td><td colspan="2">0 0 0 0 0
0 0 0 0 0</td></tr>
<tr><td>Laplacian of Gaussian</td><td colspan="2">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</td></tr>
<tr><td rowspan="2">Canny’s method apply Gaussian filter and then use sobel/prewitt or other kernels</td><td colspan="2">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</td></tr>
<tr><td>-1 0 1
-2 0 2
-1 0 1</td><td>-1 -2 -1
0 0 0
1 2 1</td></tr>
<tr><td>Robert’s cross operator</td><td>1 0
0 -1</td><td>0 1
-1 0</td></tr>
</table>

III. RESULTS AND DISCUSSIONS

Abs-Laplacian [4, 8, 9], which involves taking absolute of the Laplacian that not only provide good quality edges but are 2nd order accurate. High speed detection is necessary, especially to execute real time tasks e.g. tracking an object in real time, monitoring systems for failures based on visual interpretation, navigation at remote places etc. For such applications, the detection algorithms may vary to great extents in terms of quality of edges captured, response times, computation load went into de-blurring an images or filtering the image in real time etc. The kind of images being dealt can significantly affect the results. For noisy images like those obtained by an ultrasound one would prefer considering de-noising before applying any edge detection techniques whereas on the other hand a crystal clear images won’t even need such pre-processing rather one would directly carry out edge detection. The principle in better detection lies on how well the technique delineates signals around the edges. Clear and distinct edges will show sharp signals on either sides or in other words, as we traverse the checkerboard one would see that signals are darker in black boxes while we just begin to enter the white box we would encounter a sudden change in pixel values to full bright color.

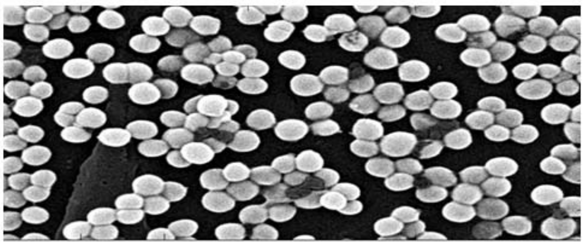
The author has showed that abs-Laplacian is best suitable for real time image processing application and performs better than Sobel and the Prewitt kernels [4, 8]. In the current context, the study has been extended to various kernels including Canny’s algorithm to understand the relative performance of abs-Laplacian kernel.

For analyzing edge profiles a clear image containing multiple white colored solid spheres over solid black background was selected as the standard (Fig1a). Though there can be many choices for the images, the main objective was to quantify the performance levels of the new technique against currently available ones using clear images. Since there are multiple spheres, we therefore have multiple edges and therefore many replicates to visualize the edge qualities. Fig1b shows the edges computed by abs-Laplacian with a shift of 2. The classical 3x3 laplacian operator considers one neighbor. By introducing a shift we mean that laplacian kernel of size three is expanded by a unit length. Remember that, a shift of one considers into account only one adjacent neighbor, while a shift of two would take two neighbors [4]. By introducing large gaps, we are purposefully trying to increase the kernel size or in other words the range of sampling and hence broaden the edge lines. Previous report has shown that that such operation is equivalent to shift subtraction. Notice that the edge profiles obtained are thick and very bright and show similar intensity for all other spheres.

Edge profiles of various kernels are shown in fig2 along with the abs-Laplacian edges. For the experimental consistency the Sobel and Prewitt were presumed to be the controls as they are widely used. Therefore, when comparing the edge profile or in other words the nature of the edges that are detected should be compared with those obtained by Sobel/Prewitt. The controls (see panel ‘b’ and ‘c’ in fig2). Panel ‘a’ shows edges determined by abs-Laplacian are higher in intensity in comparison to controls. Kirch edges are lower in intensity and Robinson edges are comparable to controls. Edges determined are blurry and lower in contrast as the background seems to fade the whole image. Canny’s edges are similar to those of controls while Robert’s edges are a bit lesser in intensity. To have better understanding of the intensity profile of the edges, pixels at 100th row were compared and plotted as shown in fig3. Intensity variations along an arbitrary axis provide changes in pixels values or in layman's words we can detect objects and their edges by following such changes. Fig3 panel 'b' shows the corresponding pixel intensity of the real image. Depending on whether the image is smooth or complex we expect a corresponding plot. Abs-Laplacian edge profile is shown in fig3 panel 'c' as red line, while Sobel in green and Prewitt as blue line. Peaks in edge intensity represent sharp changes on the image. So, if there were many such sharp intensity changes there will be a so many spikes and hence we are sure to expect an edge at that location. Abs-Laplacian edges seems to show a left shift of multiple pixels with those of Sobel/Prewitt which are almost coinciding. But the patterns are more or less similar. Kirch and Robinson edge intensity plots coincide with each other and match nearly with the controls. Laplacian edges of kernel 3x3 and 5x5 and the LOG do not seems to show a trend, they plots show no resemblance of the edges and therefore computer prediction are more difficult. Canny's plots in panel 'f' give perfects details of the edges while the Robert's edges though shows a trend of edge occurrences but fails to predict with confidence as their intensity level are very less.

To learn more about the inherent features of various kernels, edges intensity profiling was carried out for various types of images; grasslands, wall, wood, nature and other denoted as unclassified (fig4). Images were specifically chosen that covers wide range of images given a particular theme and that they are HD images at least 1000 pixels in a dimension. Cumulative intensity of the all the edges determined from each image are plotted as a data point. The plots obtained surprised me a lot, as I wasn't expecting the plots to be very stubborn. What I found out was that, whatever be the kind of image one deals with, the inherent kernel properties would predict them with cumulative edge intensity within certain intensity levels. For image having same theme and also those that are different in themes tend to follow a trend. Abs-Laplacian, Sobel and Prewitt tend to align themselves at about 14 intensity units regardless of the image type. Robert's cumulative intensity levels are little less, but it should not be confused with the edge profiles we observe in fig2 and fig3 where they image quality is low compared to controls. Laplacian based kernel (excluding abs-Laplacian) shows low level intensity which also corroborates with edge profiles shown in fig2 and fig3 suggesting that these kernels cannot be used directly for edge detection alone. Krich and Robinson cumulative edge intensity level tops the list, in the said order.

Fig. 1 Intensity plots of a) Actual image and the edges detected by b) abs-Laplacian are shown at same length scales. An edge detected by the novel technique "abs-Laplacian" clearly demarcates the solid microsphere from the background. While the edges are true representative of the spheres, the noises can also be seen that are not part of the edges. Of course not all the aberrations in the edges can be regarded as noise but since the intensity variations within the spheres are not important at this image resolution, hence it may be considered as undesirable in the current context.



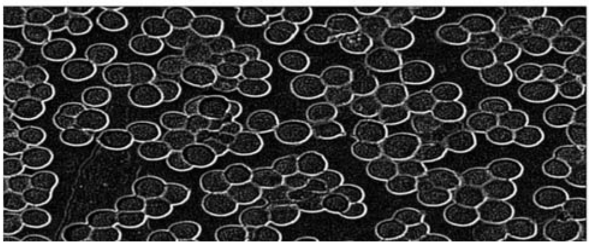


Fig. 2 Intensity plots of the edges computed by various kernels: a) abs-Laplacian (1st panel on left side), b) Sobel, c) Prewitt, d) Kirch, e) Robinson, f) Laplacian 3x3 (1st panel on right side), g) Laplacian 5x5, h) Laplacian of Gaussian or LOG 5x5, i) Canny's algorithm and, j) Roberts cross operator are shown.

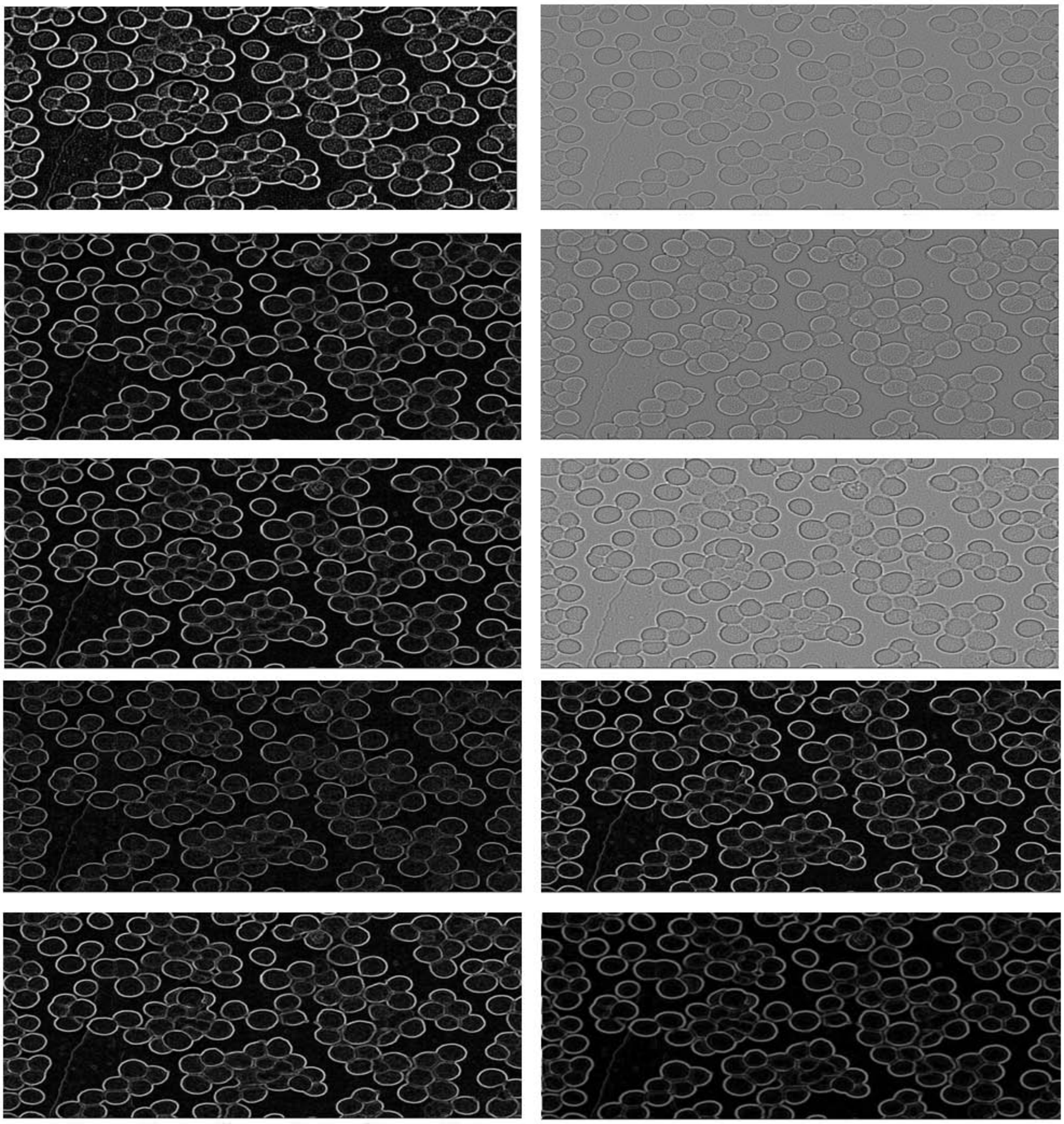


Fig. 3 Contour map of an image at 100th row is shown in panel (a) and variations in pixel values along the horizontal direction are plotted in (b). Notice the sharp and gradual changes near the intensity peaks; about 5 major peaks can be clearly distinguished. Edges determined from the image convolution with various kernels are shown in subsequent panels; the kernels abs-Laplacian (red line), Sobel (green line) and Prewitt (blue line) are showed collectively in panel c), Kirch and Robinson that uses 8 matrices are shown in d), Laplacian 3x3, 5x5 and the LOG in e) and Canny's and Roberts are shown in panel f). Red line in panel (c) is abs-Laplacian edge while the green and blue (hidden behind blue line) indicate Prewitt and Sobel respectively.

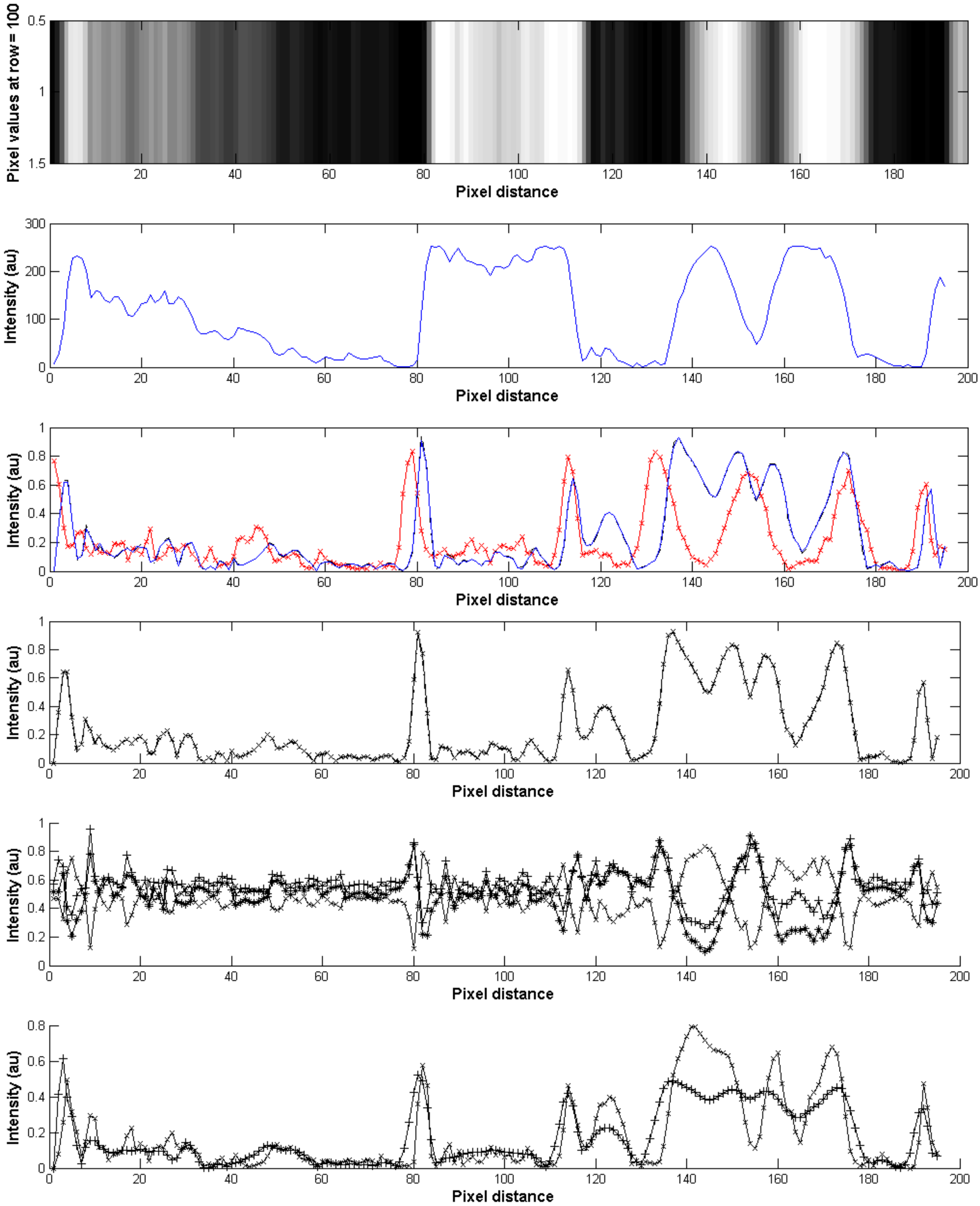
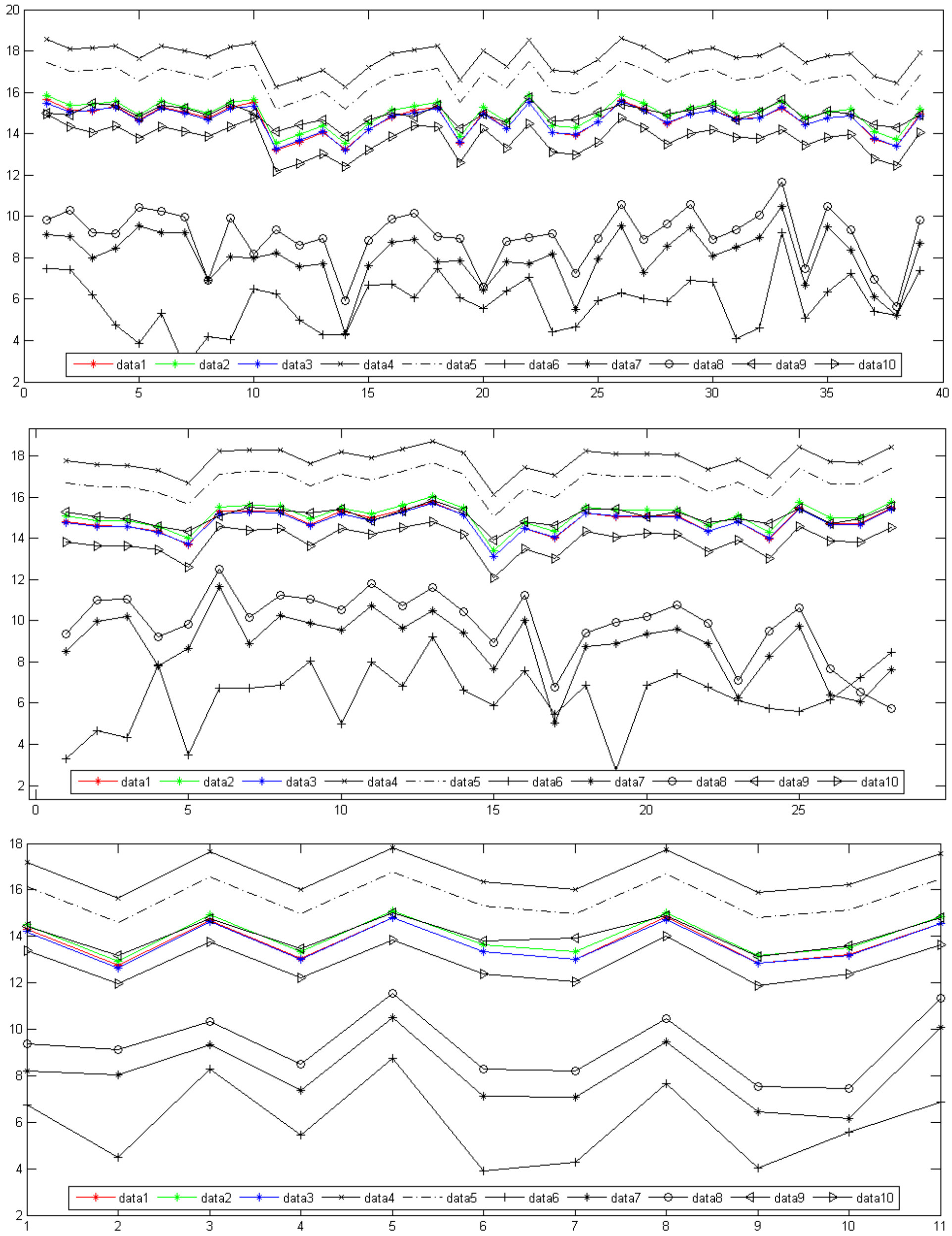
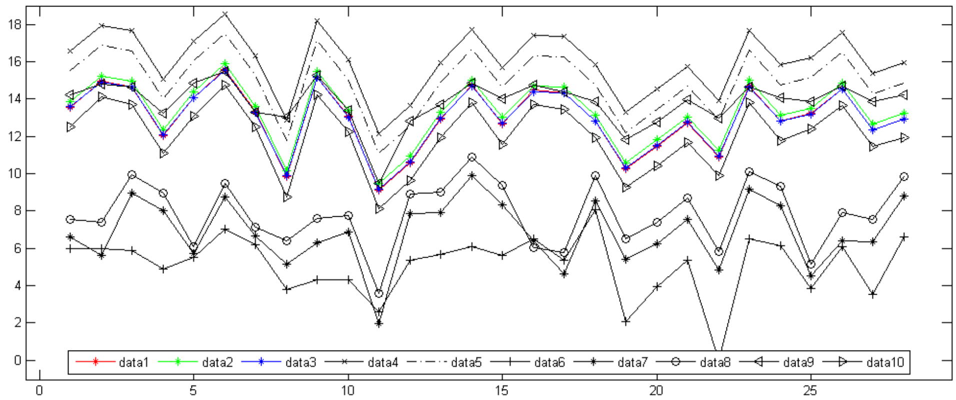
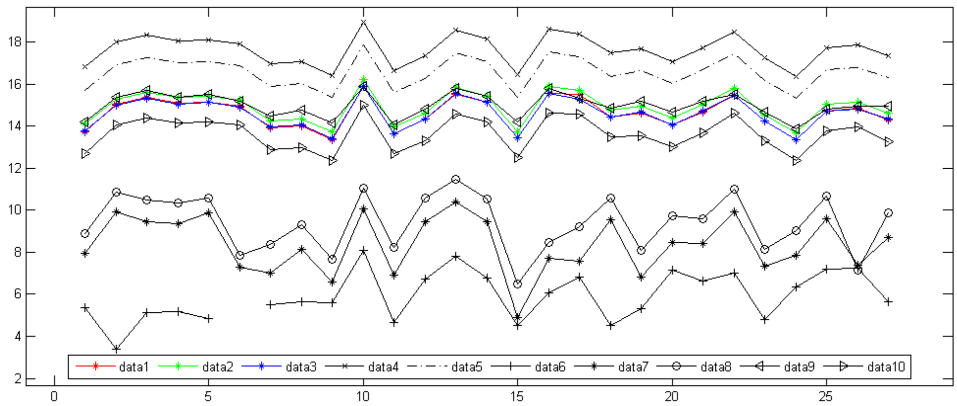


Fig. 4 Cumulative edge intensities (au) (Y-axis) were calculated for various kernels and for various kind of image observable in nature e.g. a) Grasslands (39 samples), b) Wall (28), c) Wood (11), d) Nature (17) and, e) Unclassified ones that are collection of arbitrary images. X-axis represents the samples. The plots indicated by data1 to data10 denote kenels in the following order; a) abs-Laplacian, b) Sobel, c) Prewitt, d) Kirch, e) Robinson, f) Laplacian 3x3, g) Laplacian 5x5, h) Laplacian of Gaussian or LOG 5x5, i) Canny's algorithm and, j) Roberts cross operator repectively.







IV. DISCUSSION

The edge qualities of Abs-Laplacian are comparable to the most popular ones e.g. Sobel, Prewitt and the Canny's method. So, far we developed some idea that the newer technique has lots of potential in real time image processing and may be better than the controls. Experiments suggest that kernels tend to retain their inherent characteristics regardless of the kind of image we provide. Some kernel are best and show sharp edges while on the other hand the Laplacin 3x3, 5x5 and the LOG shows up a faint image. To further our understanding, deviation of cumulative edge intensity was done with respect to Sobel's edge (fig6). The Laplacian class of kernel show linear variation, while the abs-Laplacin, controls and the Roberts and the kirch and Robinson go parallel with X-axis suggesting that these kernel share same features to that of Sobel's. Abs-Laplacian indicated by red scatter plot shows nearly zero deviation suggesting that they image quality are more like that of Sobel's prediction.

Real time imaging requires that the technique detects the edge at high speed while good quality edges come next. Complexities of 10 kernels were determined as shown in table2. Reduced complexity calculation as previously described in the article was used here to maintain consistency across the kernels [4]. In terms of speed, Roberts seems be take only 3 additions, whereas abs-Laplacian and Laplacian 3x3 takes second place in the list with 7 additions. Sobel and Prewitt tend to take more amount of computation. Canny's method which is a popular technique goes at the bottom of the list and is not a preferred choice for rapid imaging.

Fig. 6 Deviation of cumulative edge intensities detected by various kernels with respect to Sobel was analyzed. Y-axis shows the kernel's cumulative intensity deviation from Sobel while the X-axis represents the cumulative intensity level of the kernel.

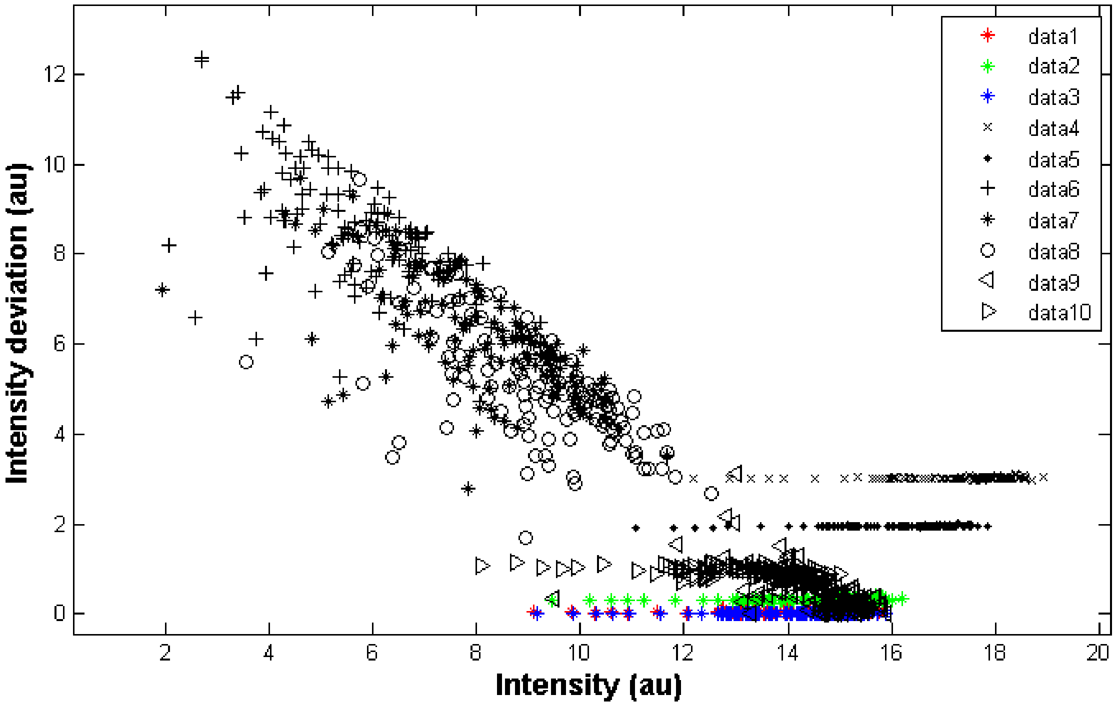


Table. 2 Averages times taken by various techniques are compared. Measurements were carried out in Matlab (R2011a) environment for all the samples considered and an average value was calculated as shown. Algorithm complexity is also tabulated.

No.	Method	Time, sec	Complexity, (+, x)
1	abs-Laplacian	*0.5928 **0.0468	7, 0
2	Sobel	2.4804	11, 15
3	Prewitt	2.5116	11, 15
4	Kirch	#6.4428	63, 64
5	Robinson	#6.4584	47, 48
6	Laplacian 3x3	0.5928	7, 0
7	Laplacian 5x5	1.7940	12, 13
8	LOG 5x5	1.7940	24, 1
9	Canny	4.2744	35, 39
10	Robert	+0.0418	3, 0

Note: For techniques with # prefix, the matrix multiplication was carried out without taking advantage of the multiple zero containing elements as they may not make a significant difference in comparison to abs-Laplacian. The abs-Laplacian kernel was tested in 2 ways, firstly by accessing individual elements from a single copy of the image (*) and secondly by making 4 copies that are shifted by 1 pixels (**) relative to the actual image. Of course, the second approach can also be used for the Laplacian operator but since they involved same kind of operations with the exception of absolute operation it won't make any difference. One with + prefix had to be analyzed using customized C-program, as the technique does not allow us to take advantage of shift based subtraction as in abs-Laplacian case find lowest possible run time.

V. CONCLUSION

Abs-Laplacian, a newer kernel in image processing offers immense potential in rapid imaging while Roberts cross operator emerges as the most powerful technique in terms of speed they do not provide good quality edges as that of abs-Laplacian. Upon detailed profiling of heterogeneous images analyzed it seems clear that the edge quality of Roberts is below desired levels. There seems a clear indication that the kernels tend to maintain their characteristics across wide spectrum of images with similar range of cumulative edge intensity. Though the current study suggest abs-Laplacian kernel as the best for rapid imaging but Robert's kernel can't be neglected since they need a little less than half the calculations required by abs-Laplacian. It is yet questionable, whether the Robert's edge detection is sufficient enough for predicting edges so that technique can still be preferred in place of abs-Laplacian.

VI. ACKNOWLEDGMENTS

None

VII. REFERENCES

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