Foundations of a rapid de-noising technique in real time image processing applications

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Abstract

A noise is an inherent entity of the imaging technologies that tend to deteriorate the quality of processed images at all levels. At the hardware level they appear as the dark current, shot noise etc. however at the imaging side they may involve artefacts arising from interference patterns, undesired shadows, flickering etc. Eliminating such signals are challenging. Though suggesting a hardware changes and improving the imaging technologies is one way, the problem still remains. An ideal de-noising technique should know apriori various estimates of the noisy data both spatially and temporally. In the context of devising an ideal de-noisy method, I chose to estimate the limits of the intensities levels for the raw data and the edges determined by abs-Laplacian, Robert, Sobel, Prewitt and Canny's method during day time, with incandescent lightning compared with darkness. Results show that the conventional wavelet based de-nosing can only deteriorate the edge profiles and are not useful in real time applications. abs-Laplacian still stands out as the better edge detection technique in comparison but with large bandgap. There is a negligible change in temporal distributions. A change of 12 units was observed during prolonged imaging of a static background that comprises about 4.7% of the maximum intensity. It appears that prolonged imaging has an effect of sharpening the edges or in other words a set of subsequent images would be useful in enhancing edge profiles. Keeping in view the timing constraints for real time applications, the only choice left in formulating rapid de-noising technique would be in learning the ways the noise manifest itself.

Keywords*:* *Abs-Laplacian*

I. Introduction

Image from conventional cameras are contaminated with various sources of noises, which not only degrade the quality but tend to reduce the SNR ratio to a greater extent in extreme situations. There are various sources of noise known; of them shot noise that can be considered as noise on the image itself and noises arising by thermal means predominates the rest. It should also be remembered that in absence of light, the electrons generated by thermal agitation can give rise to a signal in visual field. Or in other words thermally generated electrons give rise to dark currents and therefore reduce the level of sensitivity of the camera. With increase in temperature the dark current increase in a somewhat linear fashion. And therefore by cooling the CCD we can reduce the noise density. De-noising techniques would need additional computation which also means that they are going to delay the response times of our imaging systems. Rapid algorithms are not only useful but would need lower computational power and can be employed in real applications e.g. in traffic monitoring, automated navigation, automated surveillance for detecting suspicious activities in a zone, for human computer interaction etc [1]. Better algorithms mean better ways of dealing with the challenges involved. One occasionally encounters partially occluded objects, those that are interspersed with the shadows projected by neighbouring structures and of course the flexible objects and the reflections from mirrors cannot be neglected. Of these challenges the noise lies at the bottom. Noise and edges go hand in hand and to dissociate them one should learn the nature of noise distributions near the interfaces. If one were to see from the point of camera, the edges been captured would appear fluctuating in intensity levels about a base level. From edge point of view we are not interested in capturing those fluctuation rather we are interested in registering those base levels that are part of the edges. Streaming though these edges and monitoring those fluctuations would provide vital information for better detections. Robust technique would help in designing better robots which could perform real time edge detection and be able to interact with human gestures [2, 3] at lower computational loads.

In this paper, two parallels have been analyzed, one that attempts to compare the robustness of the edge detecting algorithms with the relatively newer method, abs-Laplacian [4] during day time, with incandescent lightning and darkness; and secondly attempt has been made to register the noise levels for various environments, also analysed with the conventional wavelet based de-noising to understand the noise margins of the edge detection techniques and find out specific signatures that are characteristics of the method.

II. Edge detection

Convolution is a commonly used mathematical operator in image processing to filter the images. To be precise they have been used to detect edges where in one convolves two functions, one being the image and the other is a kernel or mask or an operator to get another function. Convolution process can be considered as taking the mask or the kernel and moving it over the image right from the first pixel till the end. At a given pixel location for the kernel, we multiply the sub-image (I) with a kernel (K) and then sum up the matrix elements as shown in eq0.1 and eq0.2. Due to their filtering properties, they are used to smoothen, sharpen, intensity or enhance the image quality.

$$I_c = I \cdot K \tag{0.1}$$

$$I_c(i, j) = \sum_{k=1}^{m} \sum_{l=1}^{n} I(i + k - 1, + l - 1) \cdot K(k, l) \tag{0.2}$$

Some technique use 2 kernels for computing the convolution, one along the x-axis (G_x) and other along y-axis (G_y). In such cases where more than one kernel is employed, the final convoluted image is computed as the root of the sum of the squares of the convolution results of all axes. Some authors approximate the final convolution as a mere addition of the absolute of the convolution of along each direction rather than spending extra computation in finding the roots and squares [5-7]. Abs-Laplacian [4] is a relatively new kernel, that can be considered as near to Laplacian kernels but with minor differences. In this we take absolute of the Laplacian to get rid of the negative values. At shift of 1 the kernel appears like a normal Laplacian of order 3x3, but as the shift is increase the kernel size gets increased by 2. It should be remembered that the abs-Laplacian is equivalent of shift subtraction, wherein we take the shifted images, shifted along all axis and then subtract it from the non-shifted image and then take the absolute values and sum them up. In some environments it has been found that shift subtraction offers even higher speeds [4]. By, shift subtraction, we mean that the whole images are been dealt with in calculation of convolution, while in conventional methods we use kernel and compute convolution on a pixel by pixel basis. For the study, 5 different kernel have been considered (Table1) to assess the quality of edges obtained by convolution and find out key differences among them so we can possibly stream line our edge detecting algorithms that are reliable and allows speedy detection.

Table1. Kernels for various methods are listed here.

Kernel	Gx	Gy
abs-Laplacian (shift=1)	$\begin{matrix}0 & 1 & 0\\ 1 & -4 & 1\\ 0 & 1 & 0\end{matrix}$	
Robert's cross operator	$\begin{matrix}1 & 0\\ 0 & -1\end{matrix}$	$\begin{matrix}0 & 1\\ -1 & 0\end{matrix}$
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	$\begin{matrix}-1 & 0 & 1\\ -1 & 0 & 1\\ -1 & 0 & 1\end{matrix}$	$\begin{matrix}1 & 1 & 1\\ 0 & 0 & 0\\ -1 & -1 & -1\end{matrix}$
Canny's method apply Gaussian filter and then use sobel/prewitt or other kernels	$\begin{matrix}2 & 4 & 5 & 4 & 2\\ 4 & 9 & 12 & 9 & 4\\ 5 & 12 & 15 & 12 & 5\\ 4 & 9 & 12 & 9 & 4\\ 2 & 4 & 5 & 4 & 2\end{matrix}$	
	$\begin{matrix}-1 & 0 & 1\\ -2 & 0 & 2\\ -1 & 0 & 1\end{matrix}$	$\begin{matrix}-1 & -2 & -1\\ 0 & 0 & 0\\ 1 & 2 & 1\end{matrix}$

III. Results and discussion

In the current study we explore the edges qualities determined by various kernels in real time at different occasions: during day time, under incandescent lightning and during darkness. In the previous publication it has been shown that the abs-Laplacian out performs the rest of kernels in terms of time or complexity and the edge profiles [4]. The same are now investigated in detail. Edges determined by abs-Laplacian, Robert, Sobel and Prewitt kernels udirng day time are shown in panel (a) of figure1. The actual image consists of hangers, hand and the head of a subject. The background is a white colour wall. Pixel intensities of the abs-Laplcian images are very sharp and allow perfect delineation of the edges of arm and head from its background with crystal clarity. Robert's kernel in the other hand is 1^{st} order accurate and considers 2 neighbours for derivative calculations. But however the image quality appears to be somewhat clear but not like the one obtained by abs-Laplacian. Few traces that should be appearing are chopped off due to unknown reasons. There are some similarities that can be drawn here is that the intensity level are comparable and the roughness in the background. Sobel and Prewitt share nearly similar features though the edges calculated by Prewitt are better, even then they are of low quality. With incandescent lightning (panel b), the edge profiles of the abs-Laplacian grew better in comparison to the day light. The same can also be noticed for the rest.

The study was also conducted over de-noised images that were carried out using special wavelet schemes. It is well known that wavelet based de-noising provide better quality images and hence we considered to implement the technique to check whether there is a possibility that using the same can the edge profiles be enhanced? Edges determined with incandescent lightning (see figure 2) hasn't showed any improvement, but rather they were destructive. It was a bit surprising to notice, the lightning that was focussed on the wall comes out very clear in Sobel and Prewitt predictions.

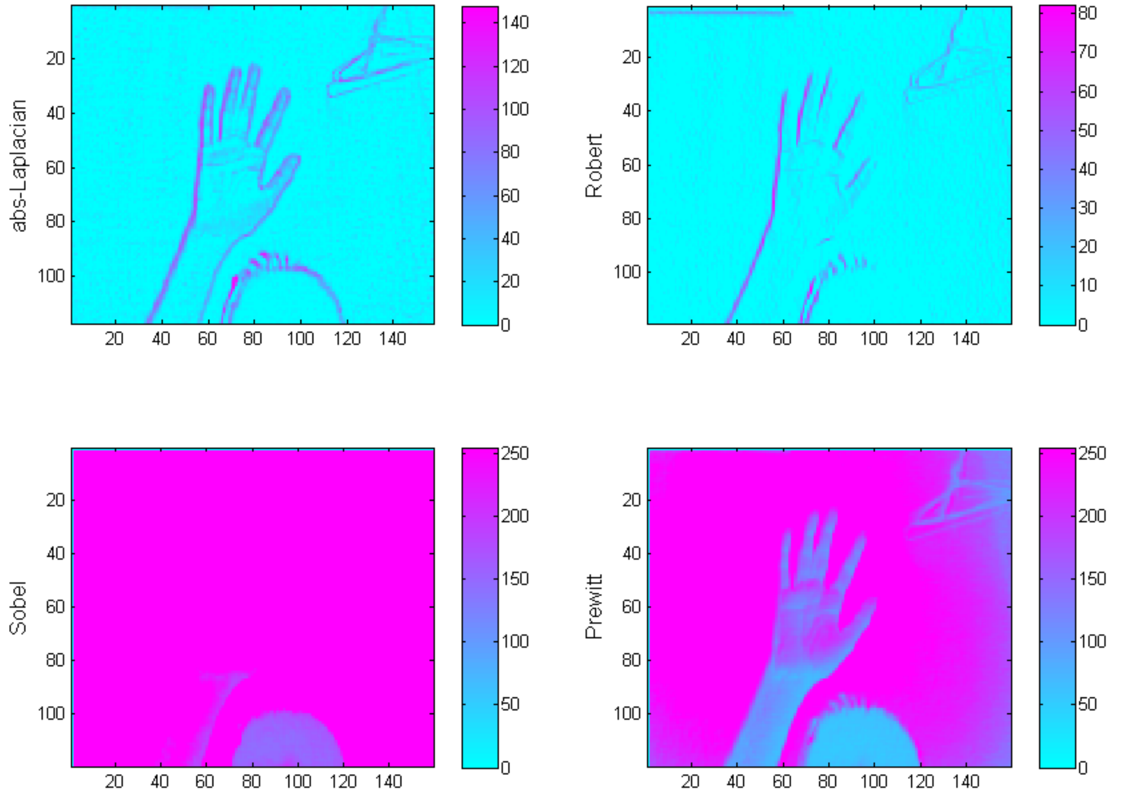
Choice of shift parameter is crucial for abs-Laplacian for obtaining sharp edges. A shift of '1' is like taking adjacent neighbours for calculating edges, while a shift of '2' would involved considering the neighbours that are at a distance of 2 unit cells. The parameter can have a profound impact on the edge profiles obtained by shift subtraction. For sharper images where the pixels vary to a larger extent at the interfaces we may prefer choosing a lower shift value. However when the interface thickness is larger or the variations in pixels are small then large shift values come in handy. In the current scenario we find that shifts of 1 and 3 are equally preferable (figure3). The problem with the shift of 1 is the some portion of the edges fade away. The situation arises when we have the neighbours with nearly equal values.

Now that we have did general comparison of the abs-Laplacian, can we say they the method is superior? Well, the Canny's algorithm which is widely used, offers a pretty good quality edges. Here, Gaussian prefiltered images, convoluted with some specific kernel were done to obtain Canny's edges as shown in figure4. On comparison with abs-Laplacian edges we observe that the peak intensities of the edges do not come clear as in case of the abs-Laplacian and also the edges appear to be faded away. Further, it is necessary to understand that the core details of the image are not modified due to abs-Laplacian operation and that the hangers too are mildly visible.

Formulating a technique that can allow rapid de-noising means that we should be well aware of the limits of the noise intensities and their spatial and temporal distributions. In the current context we considered taking a time derivative with time difference equated to one. In other words we are interested to find the changes in the subsequent intensity at a particular pixel location. Imaging was carried out continuously over a non-changing background for about 1000 time steps and samples were logged for 10 random pixel locations. For the analysis the first 100 and the last 100 samples were eliminated to remove any artefacts in the imaging and those arised by the camera adjustments during start up. Changes in the intensity level in edges calculated by abs-Laplacian, Robert, Sobel, Prewitt and Canny were also plotted. The first band in the figure5 corresponds to the time derivative of the red component of the image shown as a function of time. If we carrying out a survey of the distributions we find that the samples follow a same trend in the temporal direction keeping the similar distribution at all time points. Suggesting that the temporal profiles of 1^{st} derivatives at a pixel location remains unchangeable. Information worth noting is the band gap which sets the limits of the resolutions. Larger the band gap, the larger would be the uncertainty in our predictions. As we move from day light to darkness we notice a reduction in the gap. Though in darkness we see few populations at higher intensity levels, majority of them lie at the central line indicating no change in intensity. Distributions for de-noised images also follow similar trend. Though abs-Laplacian may show sharp edges they suffer from poor sensitivity. In comparison to the rest, they show higher noise margins. Sobel on the other hand surprisingly shows nearly zero noise margins. In ideal case, we would presume that when there is no change in image or that the back ground image is static we should see no change in intensities across the methods.

Figure1. A snap shot of the convoluted images taken during the progression of an experiment is shown. Objects identifiable are the hangers on the top right, hand and the head of a subject. Images in panel are taken during a) Daytime and b) Incandescent lightning. The intensity levels of the convolved images are shown as colorbars.

a)



b)

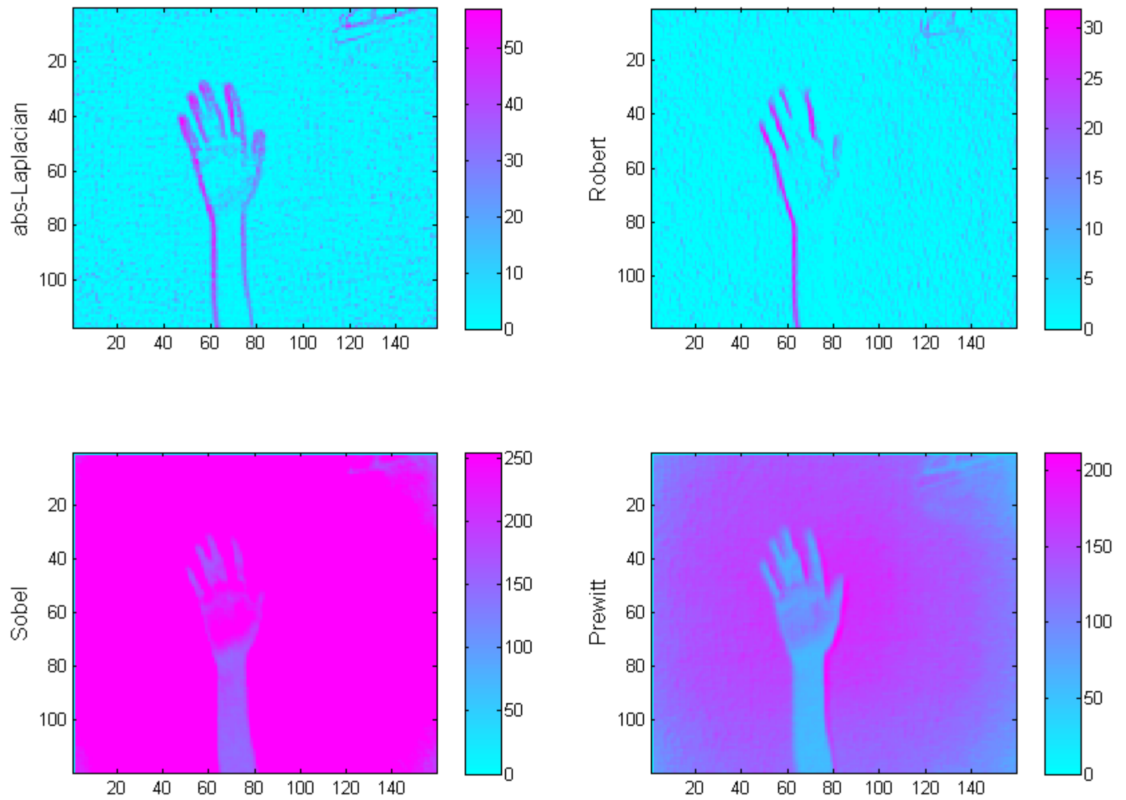


Figure2. A snap shot of the convolved images (de-noised using a special wavelet scheme) is shown. Objects identifiable are the hangers on the top right, hand and the head of a subject. The intensity levels of the convolved images are shown as colorbars.

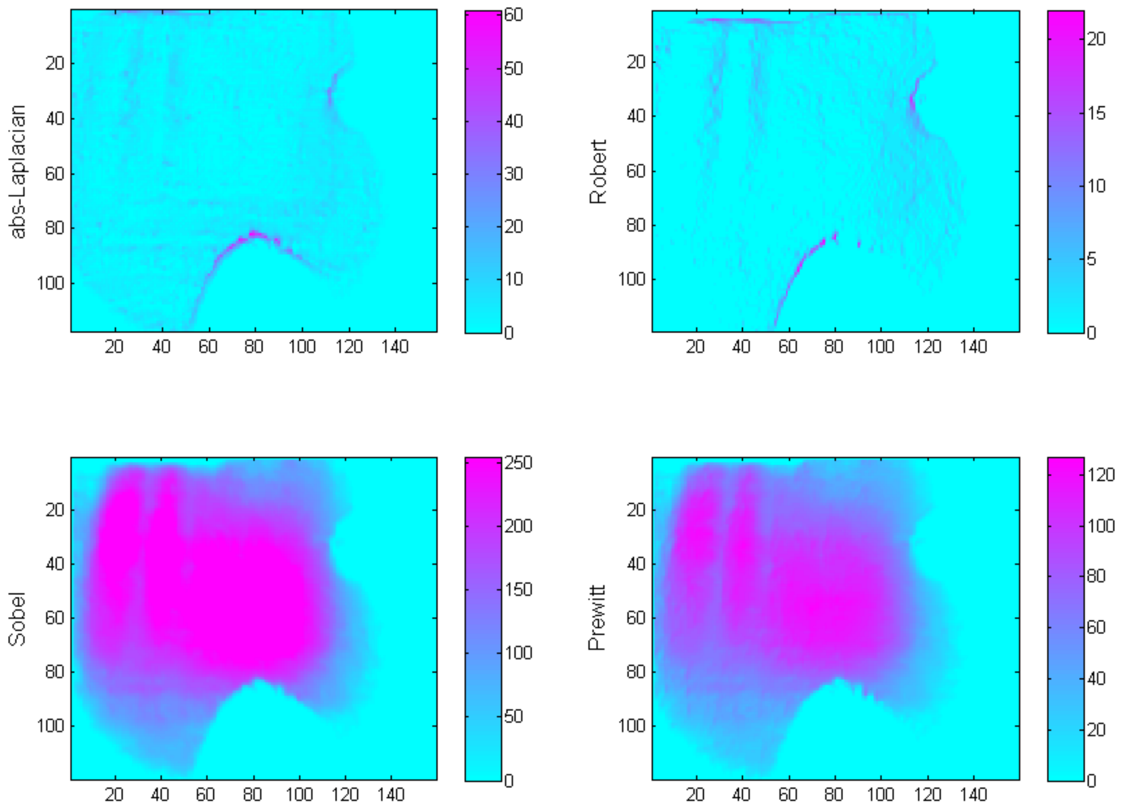


Figure3. Effects of varying shift parameter of the abs-Laplacian are shown. Notice the thickness of the edges determined and at various regions of the object.

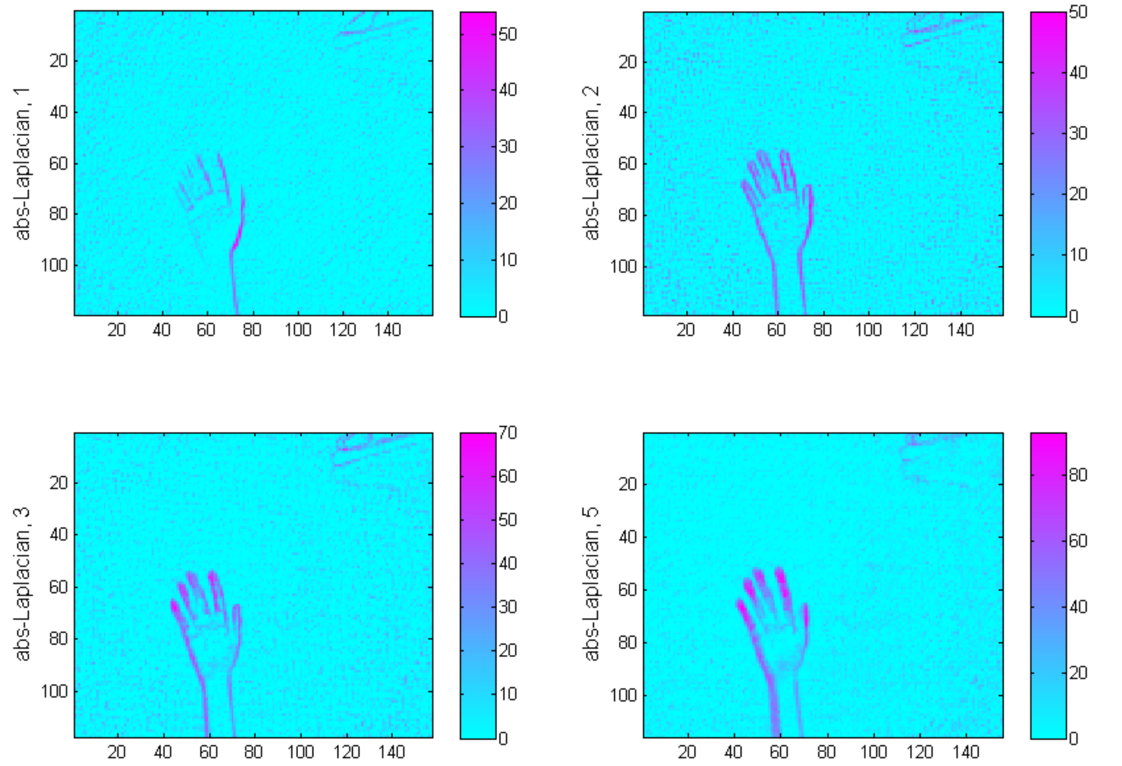


Figure4. Edges determined by abs-Laplacian 3 and Canny's methods are shown for comparison. Notice the differences in the edge quality, the fading of the pixels at the core region and the blurring that is an inherent feature of Canny's algorithm.

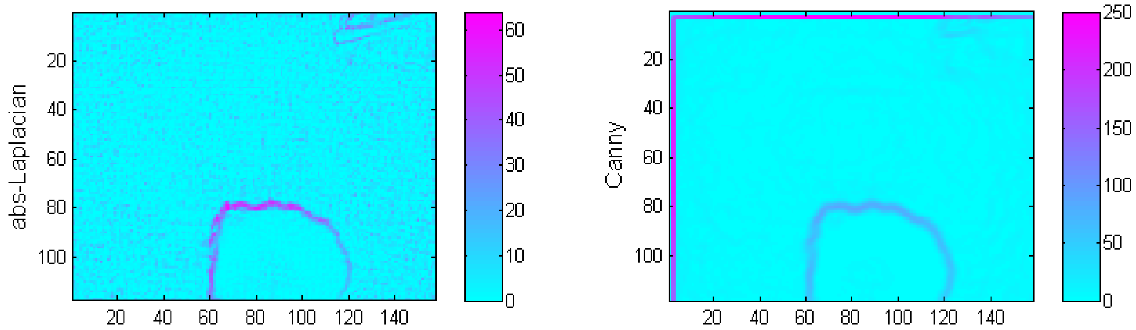
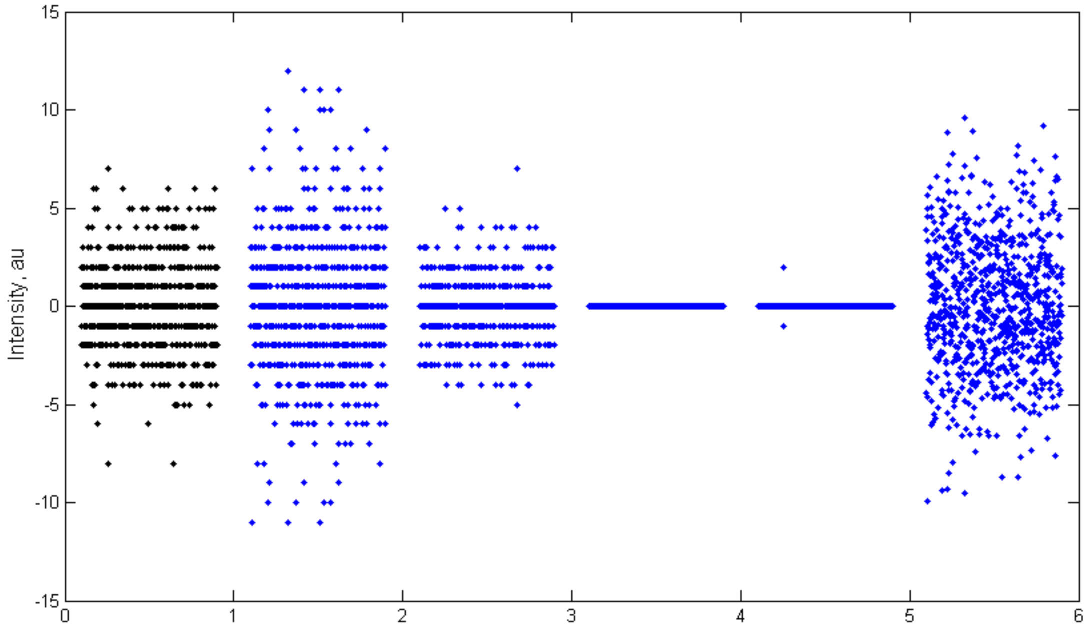
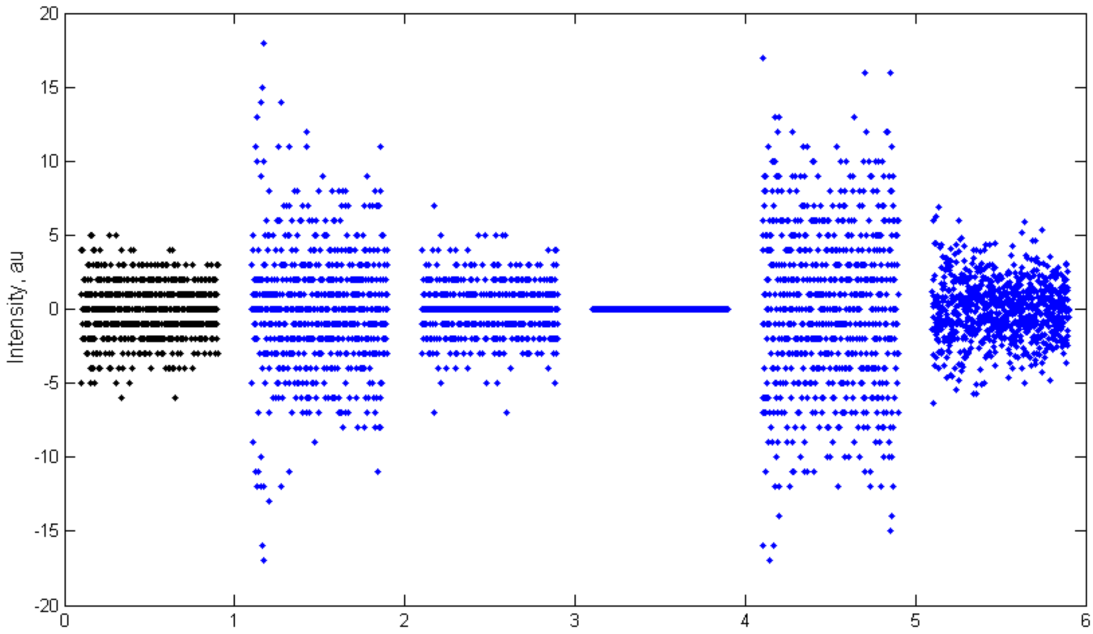
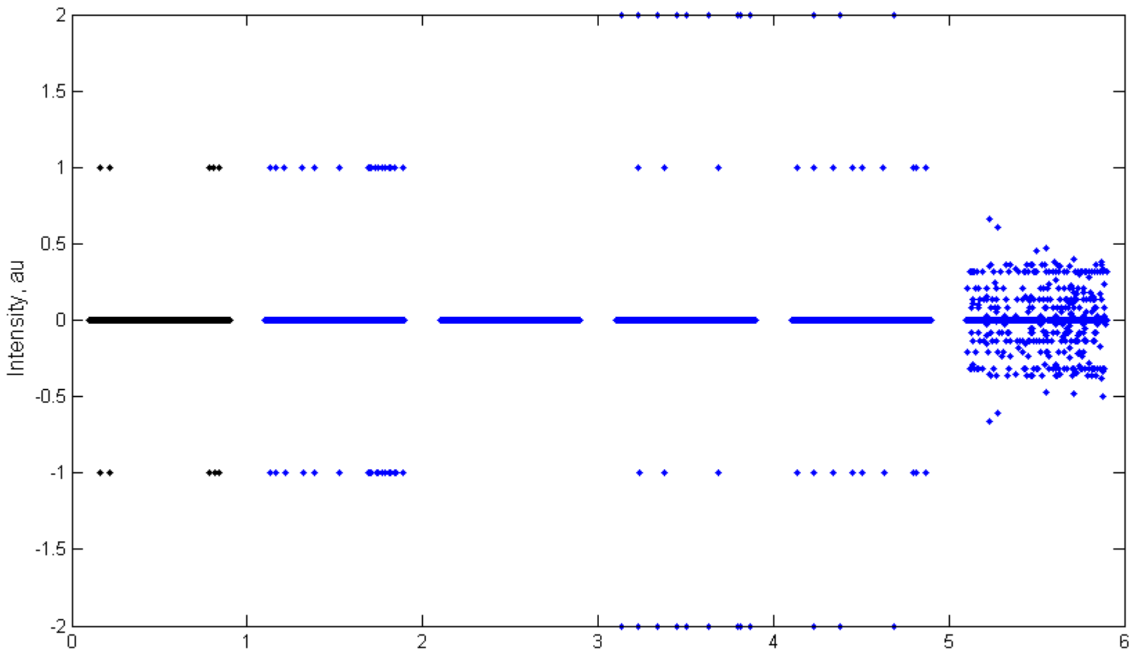
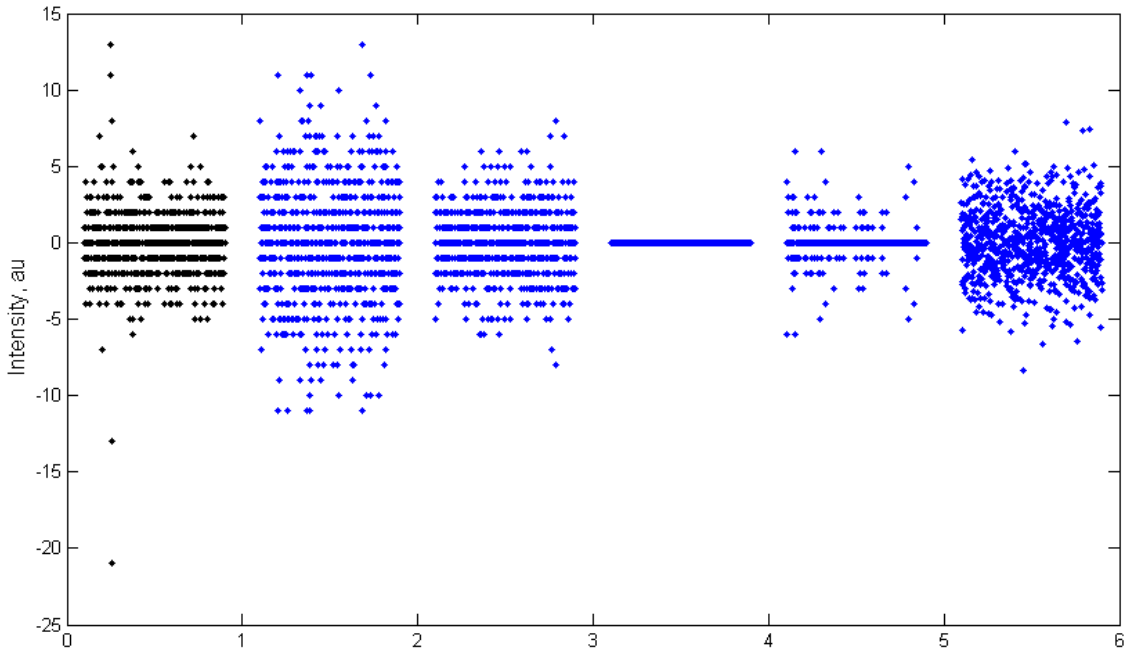


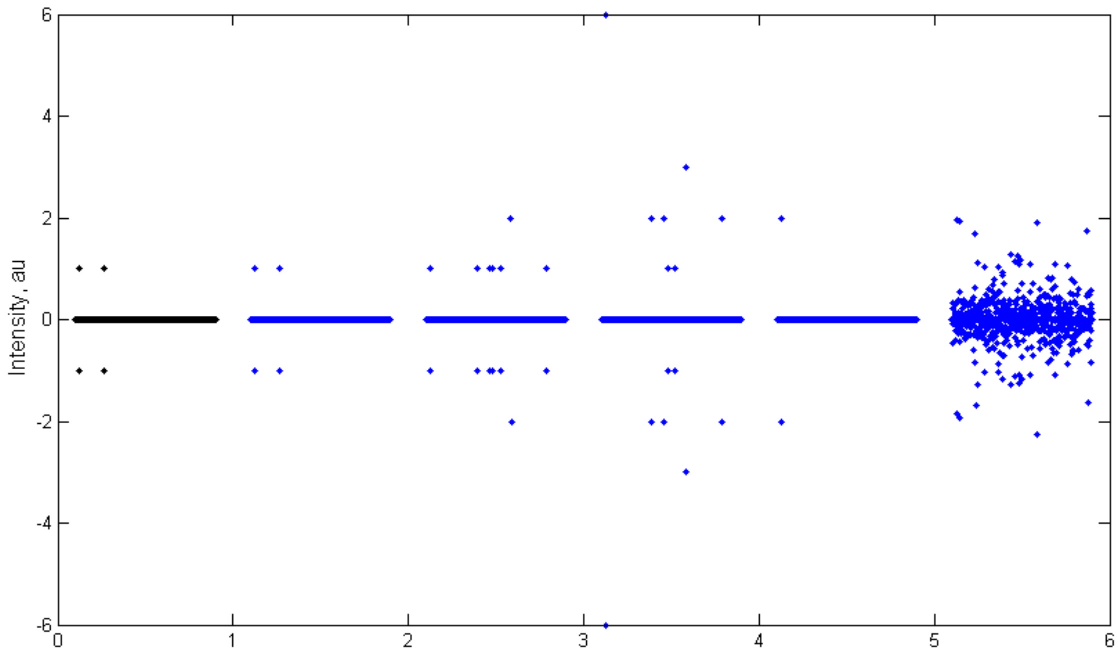
Figure5. Changes in the intensity levels at a particular pixel location under various environments are shown. The six distinctive columns correspond to the 1st time derivatives of red component of the image 'Vr', 1st time derivative of the edges determined by the kernels: abs-Laplacian, Robert, Sobel, Prewitt and Canny respectively. The samples were collected during a) Daytime, b) Under Incandescent light and c) Near darkness. Effects of de-noising and its influence on edge quality were also studied. De-noised samples, were analyzed during d) Daytime, e) Under Incandescent light, and f) Near darkness. The six distinctive columns correspond to the 1st time derivatives of red component of the de-noised image 'Vr', 1st time derivative of the edges determined from de-noised images by the kernels: abs-Laplacian, Robert, Sobel, Prewitt and Canny respectively.




Intensity, au
20
15
10
5
0
-5
-10
-15
-20
0
1
2
3
4
5
6


Intensity, au
2
1.5
1
0.5
0
-0.5
-1
-1.5
-2
0
1
2
3
4
5
6


15
10
5
0
-5
-10
-15
-20
-25
Intensity, au
0
1
2
3
4
5
6


6
4
2
0
-2
-4
-6
Intensity, au
0
1
2
3
4
5
6

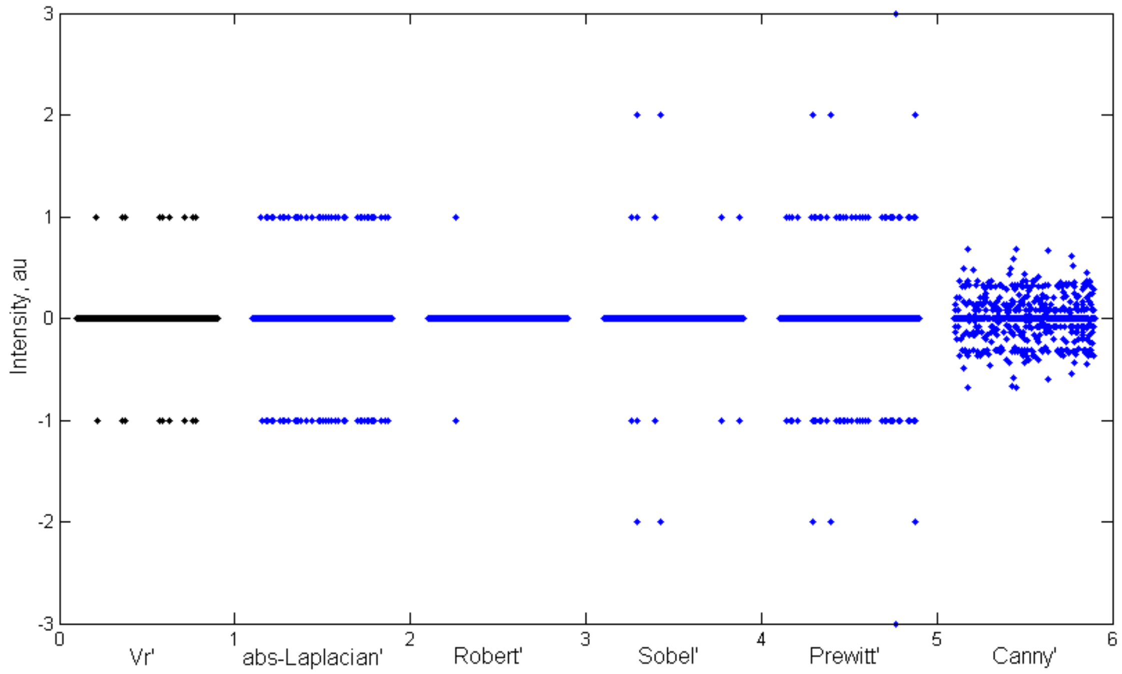
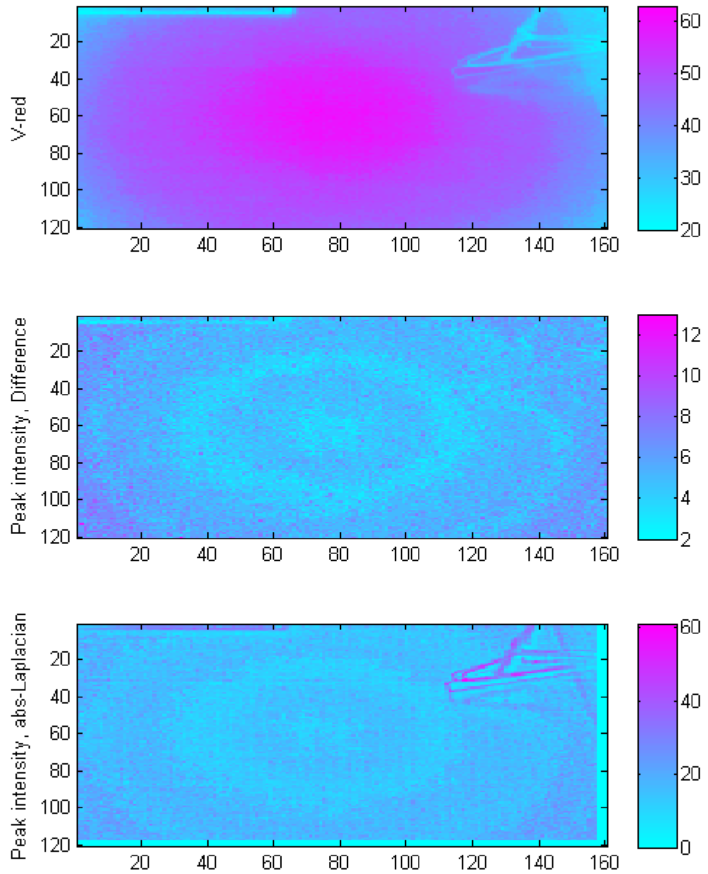


Figure6. Peak intensity levels of the 1st time derivative are shown for Vr, difference in Vr and abs-Laplacian images.



Prolonged imaging of the static background offers interesting results. With prolonged imaging one would expect that the images would become stronger in intensity and would increase the contrast of the objects from its background. Probably this may be the reason for the hangers coming out to clear to an extent (panel a, figure6). In ideal case the 1st time derivatives should vanish but it doesn't seems to follow the general notion. We observe that the peak intensities differing as much as 12 units in static background. Hangers are out of question as they do not appear in panel b. The abs-Laplacian edges are sharpened by prolonged imaging can be noticed with pink colour at the hangers. The question we are dealing here is that, can we employ prolonged imaging to enhance edge detection?

IV. Conclusion

Reliable edge detection is always desirable in applications where it is necessary to analyse objects in real time. However in most of the cases the noise would fade the signals to a level that the edge profiles may not become visible due to the inherent nature of the algorithms used. abs-Laplacian is one such example, whereby being the best technique in edge detection fails to settle the noise levels to a minimum.

In the study we have analyzed the nature of edges for various methods and also during various occasions e.g. day time, incandescent lightning and during darkness. It is to be remembered that the noise levels at the hardware level aren't tunable but the edge detection methods does allow. 1^{st} time derivative of the peak intensities suggests that the noise levels tend to remains similar over time at a random pixel location. Previous report does suggest that the abs-Laplacian has the lowest complexity in comparison to Sobel and Prewitt and therefore seems like the most preferable choice in real time processing. De-noising would be a bad choice for applications where time is the big constraint. Given that abs-Laplacian can compute best edges with 7N complexity with N being the size of image, addition of any further algorithms would only delay the speed. It is clear that addition of methods is a not a good choice, rather intelligence ways are preferable whereby the noise levels can be judged and used in the favour of kernels to improve the edge profiles. I think that best estimations of the noise would be the best choice. Estimations that would allow us to make corrections around the edge but having lesser complexity are intended. Formulations of rapid de-noising technique would require that one learns the principles of noise generation at the level of imaging from software side and come up with better estimates.

V. References

[1] Yilmaz, O. Javed, and M. Shah, "Object Tracking: A Survey," ACM Computing Surveys, vol. 38, 2006.

[2] Ravi Kant, "Ascertaining cognition abilities of 1st generation cognition robot using Bayesian models," Indian Journal of Automation and Artificial Intelligence, vol. 1, 2013.

[3] L. Aryananda and J. Weber, "Mertz: A Quest for a Ro-bust and Scalable Active Vision Humanoid Head Robot.," IEEE-RAS/RSJ International Conference on Humanoid Robots, 2004.

[4] 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] 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.

[6] S.-C. Tai and S.-M. Yang, "A fast method for image noise estimation using Laplacian operator and adaptive edge detection," in 3rd International Symposium on Communications, Control and Signal Processing, ISCCSP, 2008.

[7] R. Maini and H. Aggarwal, "Study and Comparison of Various Image Edge Detection Techniques," International Journal of Image Processing (IJIP), vol. 3.