

Error Measurement & its Impact on Bilateral - Canny Edge Detector-A Hybrid Filter

Sangita Roy

ECE Department, Narula Institute of Technology, India

Sheli Sinha Chaudhuri

ETCE Department, Jadavpur University, India

Abstract—Image Processing, a subset of Computer Vision, is an important branch in modern technology. Edge detection is a subset of segmentation to detect object of interest. Different image edge detection filters and their evaluating parameters are introducing rapidly. But the performance of an edge detector is an open problem. In this paper different performance measures of edge detection have been discussed in details and their application on a hybrid filter using Bilateral and Canny is proposed. Its parametric performance has been evaluated and other well established or classical existing edge detecting filters have been compared with it to measure its efficiency.

Index Terms—Bilateral Filter, Canny Edge Detector, Pratt Figure of Merit, Ems.

I. INTRODUCTION

Automated Information System (AIS) is the buzz word in computer science. It is a collection of hardware, firmware, software or combination of all to perform a specific application like communication, data processing, storing etc. Objective as well as subjective evaluation is an integral part of any problem solving operation using Automated Information Processing. A comparative study of different measurement parameters of a given problem have been evaluated in this work. These parameters can be used as object functions in optimization. Through these assessments tuning and justifications are adjusted for different applications. Parameter tuning plays an important role in Machine learning. Machine learning is a subset of computer science which gradually developed from pattern recognition and computational learning theory of Artificial Intelligence. Object detection is an important branch of image processing, subset of computer vision. Application domains of object detection are face recognition, pedestrian detection, image retrieval, video surveillance, name a few. Therefore it is a challenging area. Edge detection in image processing is a subset of object detection. Optimum edge detection is an open problem and performance of an edge detector plays a significant role to determine how close the detector to the ideal one [45]. Objective measure is very important in case of edge detection [46]. This paper is organised as

follows: review of error measurements in edge detection and classical filters, definition of edge in an image with different concepts, different errors in edge detection with mathematical concepts, experiments of those error metrics on standard bilateral and state-of-the art canny edge detector, and then the same process applied on hybrid filter. After that step comparative analysis of those three filters are carried out. Finally Bilateral-Canny Edge detector has been found to be the better one in comparison with the other two counterparts from the point of view of their quantitative as well as qualitative analysis.

A. Literature Review in edge detection

Engineering education has evolved into the teaching of There are three categories of performance measurement in edge detection, i) quantitative, ii) qualitative, and iii) hybrid. Quantitative measurement is related with mathematical analysis, second one is associated with linguistics evaluation like human interaction, and it can't be measured. Repeated surveys are time consuming and impose extra burden on a process for repeated evaluation. Moreover repeated evaluation by different human being makes the survey diverse [1]. Hybrid evaluation makes the presence of human users providing numerical evaluation of results [2, 3]. But the said method is subjective, time consuming, and non-reproducible [4]. Qualitative and hybrid evaluation are not suitable because of human intervention that leads to inaccuracy. There are three basic difficulties in edge detection problems. i) How would edge image be formatted? ii) how would an perfect edge image be found? iii) How to compare two edge images? It is very difficult to define edge [5].

Edge detection is a demanding image analysis technique in image processing. In image analysis different intensity pixels are there and meaningful information have to be processed from the data set. Image segmentation separates meaningful data from the unnecessary data. Three different segmentation methods are broadly defined, namely a) Region growing and shrinking, b) clustering methods, and c) boundary methods. Region growing and shrinking method are operated on row and column of an image i.e., can be used in spatial domain. Boundary methods can be used in any domain. Edge detection can be said as a subset of boundary detection. Spatial Domain is of great

importance in image processing [6]. Performance evaluation of an edge detector is quite a puzzling problem. There are two types of parametric evaluation namely a) objective, and b) subjective. Finally human is the best judge for the quality of an image and it changes from person to person and area of use. Therefore perception of human vision and analytical performance both are important in evaluating quality of processed images. Besides the existing edge detectors newer hybrid detectors are appearing with improved performance. Here authors examined extensively one hybrid filters along with classical filters like canny edge detector and bilateral filter. This hybrid filter is a hybridization of bilateral filter with canny edge detector. In 1986 J Canny proposed an edge detection method where he first detected an edge and then localized the edge delimiting multiple responses by non-maxima suppression [22, 23]. In 1995 Aurich et al. proposed non-linear Gaussian diffusion smoothing image filter by using modified heat conduction equation which

is acquired by convolving initial data i.e., an image with Gaussian kernel. It is very simple as well as escapes iterative steps and convergence problems [24]. Smith et al. in 1997 suggested Edge, and corner detection with structure preserving and noise minimization. Local image region of similar intensity around a pixel are identified, minimised, and smoothed by using non-linear filter. This method is noise resistant, fast and accurate [25]. C Tomasi, R Manduchi first described the name Bilateral Filter in 1998 which smoothens while preserving edges in images by nonlinear combination of nearby pixel values. It can be operated on both grey as well as colour images [26]. In this paper authors have studied different EMs from literature. Then they synthesised and analysed the behaviour of those EMs on different benchmark and other simple images, specifically their quantification of errors on those given edge images using classical as well as one hybrid filter.

Table 1. Lists of Abbreviation Used

Sl. No.		EMs	Full Form
1.	Statistical EMs	Entropy	Amount of energy of an image
2.		Correlation	Relationship or similarity between two images
3.		PSNR	Peak Signal to noise ratio
4.		MSE	Mean Square Error
5.		MAXERR	Maximum absolute square deviation between two images
6.		L2RAT	Ratio of square norm of ground truth image to the candidate image
7.		PIXEL Count	Bright intensity pixels count i.e. edge pixels
8.		Egt	Ground Truth Image
9.		Ec	Candidate Image
10.		TP	True Positive(Hit)
11.		FP	False Negative(False alarm/ Type I error)
12.		FN	False Negative(Miss/ Type II error)
13.		TN	True Negative(Correct rejection)
14.		TPR	True Positive Rate
15.		BF	Ratio of FP to TP
16.		QP	Per cent ratio of TP to (TP+FP+FN)
17.		FPR	False Positive Rate
18.		ROC	Receiver Operating Characteristics
19.		Precision	Eq 11
20.		Recall	TPR
21.		FI	Eq12
22.		FI*	
23.		KI	Eq 13
24.		F	Eq 14
25.	Distance based EMs	Average Distance DK	Average point-to-set distance
26.		Haralick DK	DK proposed by Haralick
27.		SDK	Symmetric distance function/ another version of DK
28.		HD	Hausdorff distance
29.		BDM	Baddeley's Delta metric
30.		PFOM	Pratt Figure of Merit
31.		PFOM*	1-PFOM

B. What is an edge in an image?

Clear definition of an edge is absent due to its abstract nature. Haralick proposed a clear idea on an assumption that an image to be a continuous surface [7]. It suggested an edge is a set of pixels whose intensity values change abruptly from the surroundings. Moreover author expressed high first derivative of f , where f is the function representing the image. Van Vliet et al. elaborated in a general way an edge to be a contour, centre of the slope with a good amount of gray level difference between the

two regions [4]. Some wobbly definition are there, like localization intensity change, sharp changes in intensity [8]. Strict definition of an edge depends on its application [19]. Finally it is observed that human experience is more fruitful than mathematical evaluation [20]. Some author claims edge to be binary [21, 7]. Canny proposed widely recognised work [22, 23] by his optimal edge detector. Canny Edge Detector are characterised by i) Edge Detection, ii) Localization, iii) Non-maxima or multiple response Suppression iv) no spurious response. As the response is single the detected image is binary.

Low error rate (C1): edges that occur in the image should not be missed and there should be no spurious responses. Good localization (C2): the location of the edges should be as close as possible to their position in the image. Unicity(C3): each edge in the image should produce a single response.

C. Error in edge detection

It is now important to study error encountered in edge detection methods. There are commonly three kinds of errors. i) spurious responses (false positives, FPs), ii) missing edges (false negatives, FNs), and iii) displacements. For an edge detector it is not common for multiple responses for a single object boundary. FPs are associated with texture and noise. FNs are related with low contrast region. In case of image denoising excessive displacement of edges may occur from its true position. It has been found that displacement occurs with at least one FP and one FN, and it has been established that FP is quite closer to FN. In machine learning GT (Ground Truth) refers to a set of standard or benchmark or classical results, dataset or some standard object which is or is used as a reference. GT (Ground Truth) is widely used in image processing.

D. Edge detection Evaluation

Desirable properties of an EM q where E_{gt} is the ground truth image, E_c is the candidate image.

- i) Symmetry (E1): $q(E_c, E_{gt}) = q(E_{gt}, E_c)$
- ii) Single optimal solution (E2): $q(E_c, E_{gt}) = 0 \Leftrightarrow E_{gt} = E_c$
- iii) Sensitivity to degradation (E3): if $p \notin (E_{gt} \cup E_c)$, then $q(E_c, E_{gt}) < q(E_c \cup (p), E_{gt})$.
- iv) Sensitivity to improvement (E4): if $p \in E_{gt}$ and $p \notin E_c$, then $q(E_c, E_{gt}) > q(E_c \cup (p), E_{gt})$.

E. Quantitative Approach to Edge detection

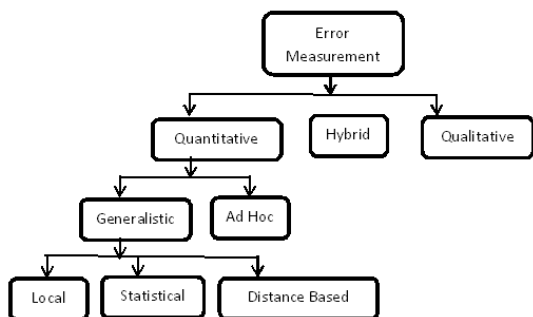


Fig.1. Error Measurement Hierarchy

There are three categories of performance measurement, i) quantitative, ii) qualitative, and iii) hybrid. Quantitative measurement is related with mathematical analysis, second one is associated with linguistics evaluation like human interaction, and it can't be measured. Repeated surveys are time consuming and impose extra burden on a process for repeated evaluation.

Moreover repeated evaluation by different human being makes the survey diverse [1]. Hybrid evaluation makes the presence of human users providing numerical evaluation of results [2, 3]. But the said method is subjective, time consuming, and non-reproducible [4]. Qualitative and hybrid evaluation are not suitable because of human intervention that leads to uncertainty. Ad Hoc EM is problem specific whereas generalistic EM assesses globally [10, 11]. Therefore AdHoc EMs can't be useful for general purpose edge evaluation. Therefore generalistic EMs is the point of interest here. This can be subdivided into three i) local, ii) statistical, and iii) distance based. Local EMs checks properties of every edge pixel neighbouring for its regularity and continuity. This is a cumulative process and generates local information which leads to quality evaluation of edge image. One interesting and important criteria of Local EM with respect to any other EMs is that it does not require any ground truth. But it has one drawback that it can't locate the exact location of edge [13]. Local EMs depict the good looks of an edge image, but unable to detect the accuracy of the edge image. But the above study does not mean that Local EMs are not useful. It is used for local features, like regularity, continuity which is worthy where true images are missing. Cost Function is a plot of cost vs. production in economics. It is widely used in edge detection minimization. An edge detection criterion consists of accurate localization, thinning, continuity and length. By using cost function between ground truth image and edge image minimization of edge have been found out. Edge detection is interpreted as a problem of cost minimization by using simulated annealing for optimization of five different EMs in the work of Tan et al. [9]. Local EMs cannot localize the exact edge location, due to this drawback it is not worthy for edge EMs [14, 8, 15-19].

F. Statistical edge measurement

Edge detection is a classification problem. In case of binary output it is a binary classification. The candidate edge image can be divided into four categories with respect to ground truth image, i) True Positive (TP), ii) True Negative (TN), iii) False Positive (FP), iv) False Negative (FN). It is evident that a very small portion of an image are edge pixels. Therefore an imbalance binary classification problem arises [27] where negative class dominates. Binary Classification problem is also known as binomial classification where class of data is divided into two groups. Example: medical test of a patient's cancerous cell, pass or fail in the quality control in factory [c]. When the data sets in binary classification problem become extremely unequal, then it is called unbalanced binary classification problem. Classification problem is the task of assigning a specific object to a class out of several predefined classes [28]. Spam or non-spam depends on the header and content of an email messages. Malignant or not also classify according the cell MRI scan. Classification of galaxies also depends on their shapes [28]. Confusion Matrix is a branch of machine learning. It is also known as contingency table

or error matrix. It reflects the algorithm performance by means of a table. In supervised learning it is known as confusion matrix whereas in unsupervised learning it is known as matching matrix. In a classification system it has been given to train and discriminate between cats, dogs, and rabbits. The confusion Table 2. will enumerate a visualization of the algorithm. In the algorithm there are 27 animals, out of these 8 cats, 6 dogs and 13 rabbits [29].

Table 2. Confusion Table

Actual Class	Predicted Class		
	Cat	Dog	Rabbit
Cat	5	3	0
Dog	2	3	1
Rabbit	0	2	11

Table 3. Basic Architecture of a Confusion Matrix

TP(True Positive)	FP(False Positive)
FN(False Negative)	TN(True Negative)

Table 4. Confusion Matrix of Table 2.

5 True positives(actual cats that were correctly classified as cats)	2 false positives(dogs that were incorrectly labeled as cats)
3 false negatives(cats that were incorrectly marked as dogs)	17 true negatives(all the remaining animals , correctly classified as non-cats)

In edge detection edge pixels are very small in amount in comparison with the whole image. Therefore edge detection is imbalanced classification problem. A simple edge detection problem using confusion matrix is as shown below.

$$TP = \frac{|E_c \cap E_{gt}|}{|P|} \tag{1}$$

$$FP = \frac{|E_c \cap \neg E_{gt}|}{|P|} \tag{2}$$

$$TN = \frac{|\neg E_c \cap \neg E_{gt}|}{|P|} \tag{3}$$

$$FN = \frac{|\neg E_c \cap E_{gt}|}{|P|} \tag{4}$$

All the operators have been used above as normal mathematical meaning.

$$S_1(E_{gt}, E_c) = \frac{|E_c \ominus E_{gt}|}{|P|} \tag{5}$$

$$S_2(E_{gt}, E_c) = \frac{|E_{gt} \setminus E_c|}{|E_{gt}|} \tag{6}$$

$$S_3(E_{gt}, E_c) = \frac{|\neg E_{gt} \cap E_c|}{|\neg E_{gt}|} \tag{7}$$

$$NSR(E_{gt}, E_c) = \frac{|E_c \ominus E_{gt}|}{|E_c \cap E_{gt}|} \tag{8}$$

S1 is the ratio of misclassified pixels. (S2, S3) is the ratio of edge/ non-edge pixels missed, and NSR is the ratio of the noise to signal. Statistical EMs have some shortcomings of spatial concerns i.e., FP closeness to actual edge pixels and regularity of the edges. P1 is the ratio between the number of points detected in the edges and those due to both the intensity transition and the noise. P2 is the percentage of rows covered by, at least, one edge point. These two measure hold good for specific images, rarely be used to other images [1]. Statistical EMs doesn't compete fully with the canny constraints C1, C2, C3. Shortcomings of C1 tend to increment of FPs and FNs. Not satisfying C2 does not generate any change in FPs or FNs unless localization is perfect. Failing to the criteria C3 only increments FPs. To overcome these problems of statistical EMs, two statistical EMs are combined by receiver operating characteristic (ROC) plot [30, 31, 32, and 33]. True Positive Rate and False Positive Rate are the two measures which are displayed in the ROC plot as the quality of an edge image.

$$TPR = Recall = \frac{TP}{TP+FN} \tag{9}$$

$$FPR = \frac{FP}{FP+TN} \tag{10}$$

Alternative ROC plot can be evaluated by the Precision-Recall (PR) plots [34]. In this process TPR is denoted as recall and FPs are different, known as PREC where precision concept deploys.

$$P_{REC} = \frac{TP}{TP+FP} \tag{11}$$

$$BF = FP/TP$$

$$QP = 100 * TP / (TP + FP + FN)$$

Therefore PR plots employ eq (9) and (11) which are free from TN. This signifies that alternative PR plot is unaffected by true negative which in turn makes the evaluation more stable. This should be mention here that TN is much pronounced than its counterpart TP, FP, and FN. At the time of enlarging an image positive pixels increases linearly whereas negative pixels increases quadratically. The ROC and PR plot can be converted into their scalar and compatible version [33].

$$\emptyset(E_{gt}, E_c) = \frac{TP}{TP+FN} \cdot \frac{TN}{TN+FP} = \frac{TP \cdot TN}{TN+FP} \tag{12}$$

It is a coefficient of evaluation of edge image using different thresholding procedures [35, 36].

Another evaluation coefficient is famous χ^2 [37, 38].

$$\chi^2(E_{gt}, E_c) = \frac{TPR-Q}{1-Q} \cdot \frac{(1-FPR)-(1-Q)}{Q} \tag{13}$$

where Q=TP+FP.

Another measuring parameter is F measure [39].

$$F_{\alpha}(E_{gt}, E_c) = \frac{P_{REC} \cdot TPR}{\alpha TPR + (1-\alpha) P_{REC}} \quad (14)$$

where $\alpha \in [0,1]$ a weighing parameter according to precision-recall evaluations. Now some interesting properties will be explored. As it has already been established that error measurement is the most important goal not its quality. Therefore compliment of equations (12), (13), and (14) are as follows:

$$\Phi^*(E_{gt}, E_c) = 1 - \Phi(E_{gt}, E_c) \quad (15)$$

$$\chi^{2*}(E_{gt}, E_c) = 1 - \chi^2(E_{gt}, E_c) \quad (16)$$

$$F_{\alpha}^*(E_{gt}, E_c) = 1 - F_{\alpha}(E_{gt}, E_c) \quad (17)$$

$\Phi^*, \chi^{2*}, F_{\alpha}^*$ Satisfy the basic properties E2, E3, E4. But E1 only embraces true for χ^{2*} . E_{gt} is a ground truth image. E_{c1} and E_{c2} are two candidate images for this EMs evaluation [reference fig 4]. In E_{c1} one false negative is added whereas in E_{c2} ten false positives are added. EMs q are quantified in the table 5.

Table 5

Measurement	Φ^*	χ^{2*}	$F_{0.25}^*$	$F_{0.5}^*$	$F_{0.75}^*$
$q(E_{gt}, E_{c1})$	0.143	0.158	0.111	0.078	0.040
$q(E_{gt}, E_{c2})$	0.140	0.599	0.222	0.364	0.416

There are ten false positive points in E_{c2} . But Φ^* is unresponsive to E_{c1} and E_{c2} . Whereas other two parameters suffer from drastic changes. Statistical EMs depend on spatial tolerance i.e., the exact edge pixel located t or $t+1$ pixel away. A quality measure is precise if small changes in the detector output are reflected by small changes in its value [33]. This statement shows the light on distance based EMs.

G. Distance based Error Measurement

The distance-based EMs are established on the deviance of the edges from their true position [4], and studies the spatial location during evaluation. Its main objective is to fine an edge point consistently according to its distance from its actual point. Hence evaluation of an edge image is carried out as a mapping of distance to the ideal solution.

$p_1, p_2 \in p$, be the position of an image, $d(p_1, p_2)$

denoted as Euclidean distance between them. $d(p, E)$, where $p \in P$ and $E \in \mathbb{E}$ is an edge image, the distance from p to the nearest point $p' \in E$, i.e., $d(p, E) = \min\{d(p, p') | p' \in E\}$. Euclidian distance is the most widespread option, still few authors prefer to practice other benchmark distance functions like Chebyshev[40]. Few EMs use average point-to-set distances[46, 7]. An average distance form edge pixel of the candidate image with respect to ground truth image

$$D_k(E_{gt}, E_c) = \frac{1}{|E_{c1}|} \sqrt{\sum_{p \in E_c} d^k(p, E_{gt})} \quad (18)$$

with $k \in \mathbb{R}^+$

$$H(E_{gt}, E_c) = \frac{1}{|E_c \cup \neg E_{gt}|} \sum_{p \in E_c \cap \neg E_{gt}} d(p, E_{gt}) \quad (19)$$

$$SD_k(E_{gt}, E_c) = \frac{(\sum_{p \in E_c} d^k(p, E_{gt}) + \sum_{p \in E_{gt}} d^k(p, E_c))^{\frac{1}{k}}}{(|E_c \cup E_{gt}|)^{\frac{1}{k}}} \quad (20)$$

$$PFoM(E_{gt}, E_c) = \frac{1}{\max(|E_{gt}|, |E_c|)} \sum_{p \in E_c} \frac{1}{1+k \cdot d^2(p, E_{gt})} \quad (21)$$

$$HD(E_{gt}, E_c) = \max\left(\max_{p \in E_c} d(p, E_{gt}), \max_{p \in E_{gt}} d(p, E_c)\right) \quad (22)$$

$$\Delta_w^k(E_{gt}, E_c) = \left[\frac{1}{|p|} \sum_{p \in P} \left| w(d(p, E_{gt})) - w(d(p, E_c)) \right|^k \right]^{\frac{1}{k}} \quad (23)$$

II. EXPERIMENT OF BILATERAL-CANNY HYBRID EDGE DETECTOR USING EMS Q (ERROR MEASUREMENTS)

A. Canny Edge Detector

Performance of Canny Edge Detection is optimum under step edges. The Canny Edge Algorithm:

- Step 1. Smoothing – blurring of the image to remove noise by Gaussian Kernel.
- Step 2. Finding the Gradients of edges and assigned where the gradient of the pixels are largest in magnitudes
- Step 3. Non Maxima Suppression-local maxima intensity pixels are found to be edges.
- Step 4. Double Thresholding – Eligible edges are determined by double thresholding
- Step 5. Edge Tracking by Hysteresis-Finally edges are marked by strong continuous line.

Canny detector uses Gaussian filters in four directions- horizontal, vertical, and diagonal directions. The edge magnitude and direction can be determined by G and θ

$$G = \sqrt{(G_x)^2 + (G_y)^2} \quad (24)$$

$$G = |G_x + G_y| \quad (25)$$

G_x and G_y are the gradients in x-direction and y-direction respectively. The direction of edge can be determined by

$$\theta = \tan^{-1} \frac{|G_x|}{|G_y|} \quad (26)$$

After step one nonmaxima suppression is carried out where edge thinning is obtained. This results blurring of edges. Out of those blurred edges the brightest edge pixels are detected and the other pixels are reset to zero. After nonmaxima suppression there may be some spurious responses which may be due to noise and colour variation. These can be removed by keeping the highest

gradient values while rejecting weak ones. After this stage there is double thresholding. Two threshold values are determined. If some edge pixels are above the threshold value, then they are definitely real edges. Those who are below the lower threshold are rejected. A lot of debate is on about whether the in between values are weak edges. Generally these weak edges are generated out of true edge extraction or noise or colour variation. Edge extracted pixels are recognized as edge and noise or colour variations pixels are rejected. Edge extracted pixels are connected to strong edge pixels by using BLOB (Binary Large Object) Detection. BLOB gives complementary information about a region where edge detector fails. This step is known as hysteresis.

B. Bilateral Filter

Bilateral filter image can be defined as spatial domain, nonlinear, edge conserving and noise decreasing smoothing image filter. In this filter intensity value of each pixel is replaced by weighted average of its surrounding pixel values which is determined using Gaussian distribution not only by Euclidean distance of pixels but also by depth difference, colour intensity difference, and range difference. That is why sharp edges are preserved by symmetric looping of each pixel and correcting adjacent pixels accordingly.

$$I^{filtered}(x) = \frac{1}{W_p} \sum_{x_i \in \Omega} I(x_i) f_r(\|I(x_i) - I(x)\|) g_s(\|x_i - x\|) \quad (27)$$

Where the normalization term

$$W_p = \sum_{x_i} f_r(\|I(x_i) - I(x)\|) g_s(\|x_i - x\|) \quad (28)$$

$I^{filtered}(x)$ is the filtered image. I is the original image. W_p is the normalised term. f_r is the range kernel for smoothing differences in intensities (may be Gaussian Function). G_s is the spatial kernel for smoothing differences in coordinates (may be Gaussian Function). X is the coordinate of the current pixel to be filtered. Ω as given in eq(4) is the window centred to $x(i, j)$ is the pixel of interest to be denoised in the image. (K, l) is the one of the neighbourhood pixels. The weight assigned to the pixel (k, l) to denoise the pixel (i, j) is given as

$$w(i, j, k, l) = e^{-\frac{(i-k)^2 + (j-l)^2}{2\sigma_d^2} - \frac{\|I(i, j) - I(k, l)\|^2}{2\sigma_r^2}} \quad (29)$$

σ_d and σ_r are smoothing parameters and $I(i, j)$ and $I(k, l)$ are the intensity of pixels (i, j) and (k, l) respectively. After calculating the weights, they are normalized.

$$I_D(i, j) = \frac{\sum_{k, l} I(k, l) w(i, j, k, l)}{\sum_{k, l} w(i, j, k, l)} \quad (30)$$

$I_D(i, j)$ is the denoised intensity of pixel (i, j) . σ_r is the intensity or range control parameter and σ_d is the spatial control parameter for the filter kernels. By increasing these parameters, intensities and spatial domain features are smoothed respectively. Stair case effect like

cartoon effect and gradient reversal i.e., false edge detection are the shortcoming of Bilateral filter.

III. PROPOSED METHODOLOGY

In edge detection hybrid or improved edge detector often gives little better results than that of the original filters. Here authors have developed a new hybrid edge detector where bilateral filter is acted upon canny edge detector.

Algorithm:

- Step-I. Get Benchmark Input Image
- Step-II. Bilateral Filter operated on the Image
- Step-III. Canny Edge Detector operated on Step-II
- Step-IV. Get Output Image from Step-III.

Flow Chart:

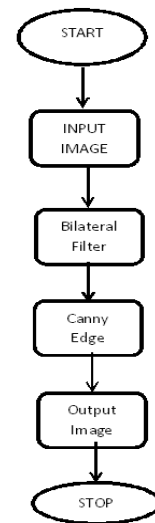


Fig.2. Flow Chart of New Methodology

A. Performance Evaluation

As it has already been stated that a new hybrid filter has been developed in this work. Here output of a bilateral filter has been passed through an Optimal Canny Edge Detector. To validate the new filter authors have evaluated its Parametric Performance. Some standard parametric performance has been tabulated using three standard benchmark images as well as four other images.

1). Input Standard Benchmark Images with their Entropy

In this work some standard benchmark images along with a few other images have been used. The resultant images for Canny Edge Detector, Bilateral Filter and proposed hybrid filter are shown in table 6 below.

2). Filtered Output

Subjective analyses have been given in the above tables. Its objective counterpart is being validated below. Table 11 shows perception of visual effects of original images and their Bilateral, Canny, and Hybrid output. These images are different in nature, e.g., human figure,

human face, landscape, small lane as well as lane with mist, human in rain which gives a variety of contrast images. Whereas in table 7-10 analytical outlook of those same images have been shown. In almost every case it is evident that pixel count of hybrid filtered images decreases whereas PFOM increases or are same in comparison with Canny which signifies that real edges are more pronounced in case of Bilateral Canny with lesser number of false edge detection. Image 5 and 6 are either foggy or dimmed. In these figures PFOMs are not improved by hybrid filter whereas false edges are removed as far as possible. PFOM increases in case of figure 7 which is a rainy image. At the same time according to the perception of vision object of interest are clearer in case of hybrid filtered images which is established by taking several human opinions. In table 8

it has been shown by graphical representation. Therefore in all the above seven figures fewer edges are detected without losing the meaning of edge detection and object of interest. Therefore in all kind of images this proposed hybrid filter works well.

Table 6. Standard Benchmark Images with Their Entropy

Sl. No.	Benchmark Image	Entropy
1.	Peppers	7.3785
2.	Lena	7.525
3.	Cameraman	7.0097
4.	Aerial1	7.1779
5.	Car in a Lane	7.3723
6.	Car in a Lane with mist	7.5190
7.	Woman in Rain	7.4983

3). Statistical EMs

Table 7. Statistical Ems

Image: Pepper					Image: Cameraman				
Sl. No.	EMs	Canny	Bilateral	Bilateral Canny	Sl. No.	EMs	Canny	Bilateral	Bilateral Canny
1.	Entropy	0.3581	6.9487	0.3127	1.	Entropy	0.4713	6.8866	0.3684
2.	Correlation	0.1146	0.9971	0.1036	2.	Correlation	0.0474	0.9950	0.0543
3.	PSNR	8.6743	8.7016	8.6731	3.	PSNR	5.5878	5.6164	5.5861
4.	MSE	8.8237e+03	8.7683e+03	8.8261e+03	4.	MSE	1.7960e+04	1.7842e+04	1.7967e+04
5.	MAXERR	255	254.0318	255	5.	MAXERR	253	252.0554	253
6.	L2RAT	7.6857e-06	1.5363e-05	6.3746e-06	6.	L2RAT	5.6022e-06	1.5302e-05	3.9297e-06
7.	Pixel Count	13354	54838	11222	7.	Pixel count	6602	48374	4631
8.	Time (s)	0.458482	14.943126	15.740298	8.	Time (s)	0.182248	3.656065	4.009621
9.	TPR	31.7733	71.5463	32.6930	9.	TPR	73.1785	99.1733	65.1279
10.	BF	6.6612	1.8524e-04	7.7087	10.	BF	7.0775	0.0025	9.8120
11.	QP	9.1396	71.5344	8.0717	11.	QP	9.7229	98.9279	5.9643
12.	FPR	6.6612	1.3927e-04	7.9251	12.	FPR	7.0775	0.0019	9.7227
13.	Precision	0.1091	0.9998	0.0949	13.	Precision	0.0996	0.9980	0.0620
14.	Recall	0.3177	0.7035	0.3345	14.	Recall	0.7318	0.9909	0.6532
15.	FI	0.3177	0.7173	0.3221	15.	FI	0.7318	0.9909	0.6602
16.	FI*	0.6823	0.2827	0.6779	16.	FI*	0.2682	0.0091	0.3398
17.	KI	0.3177	0.7163	0.3244	17.	KI	0.7318	0.9910	0.6560
18.	KI*	0.6823	0.2837	0.6756	18.	KI*	0.2682	0.0090	0.344
19.	F(0.25)	0.4318	3.8387	0.3794	19.	F(0.25)	0.3966	3.8744	0.2466
20.	F(0.5)	0.2174	1.9719	0.1847	20.	F(0.5)	0.1988	1.9763	0.1226
21.	F(0.75)	0.1452	1.3268	0.1232	21.	F(0.75)	0.1327	1.3261	0.0807
Image: Lena					Image: Aerial1				
Sl. No.	EMs	Canny	Bilateral	Bilateral Canny	Sl. No.	EMs	Canny	Bilateral	Bilateral Canny
1.	Entropy	0.4857	7.0902	0.4204	1.	Entropy	0.5680	6.7678	0.4704
2.	Correlation	7.4574e-04	0.9889	0.0041	2.	Correlation	0.1160	0.9821	0.0860
3.	PSNR	7.7316	7.7575	7.8175	3.	PSNR	7.8205	7.8427	7.8176
4.	MSE	1.0963e+04	1.0898e+04	1.0967e+04	4.	MSE	1.0741e+04	1.0686e+04	1.0748e+04
5.	MAXERR	237	237.1804	237	5.	MAXERR	255	254.0792	255
6.	L2RAT	9.5909e-06	1.5246e-05	7.7627e-06	6.	L2RAT	1.2432e-05	1.5179e-05	9.3262e-06
7.	Pixel Count	5309	29030	4297	7.	Pixel count	30787	172950	23439
8.	Time (s)	0.156482	4.115834	4.303424	8.	Time (s)	0.520656	16.267749	16.776854
9.	TPR	29.6691	60.7175	28.9106	9.	TPR	77.4981	89.2524	74.8551
10.	BF	6.6409	7.7493e-05	7.9667	10.	BF	4.8365	7.5091e-04	6.4148
11.	QP	8.2587	60.7110	6.5176	11.	QP	14.9700	89.1916	10.9890
12.	FPR	6.6409	6.0834e-05	7.6765	12.	FPR	4.8365	4.8919e-04	6.5183
13.	Precision	0.0931	0.9998	0.0683	13.	Precision	0.1554	0.9992	0.1141
14.	Recall	0.2967	0.6089	0.2844	14.	Recall	0.7750	0.8922	0.7482
15.	FI	0.2967	0.6089	0.2982	15.	FI	0.7750	0.8883	0.7494
16.	FI*	0.7033	0.3911	0.7018	16.	FI*	0.2250	0.1117	0.2506
17.	KI	0.2967	0.6074	0.2971	17.	KI	0.7750	0.8927	0.7495
18.	KI*	0.7033	0.3926	0.7029	18.	KI*	0.2250	0.1073	0.2505
19.	F(0.25)	0.3690	3.8108	0.2747	19.	F(0.25)	0.6180	3.8669	0.4484
20.	F(0.5)	0.1856	1.9675	0.1358	20.	F(0.5)	0.3102	1.9762	0.2238
21.	F(0.75)	0.1240	1.3260	0.0925	21.	F(0.75)	0.2071	1.3274	0.1504

Image: Car in a Lane					Image: Car I a Lane with mist				
Sl. No.	EMs	Canny	Bilateral	Bilateral Canny	Sl. No.	EMs	Canny	Bilateral	Bilateral Canny
1.	Entropy	0.3546	7.6566	0.2578	1.	Entropy	0.3568	7.4205	0.2696
2.	Correlation	0.0576	0.9993	0.0368	2.	Correlation	0.0611	0.9991	0.0412
3.	PSNR	3.9101	3.9415	3.9092	3.	PSNR	4.3380	4.3691	4.3371
4.	MSE	2.6428e+04	2.6238e+04	2.6434e+04	4.	MSE	2.3948e+04	2.3778e+04	2.3954e+04
5.	MAXERR	255	254.0280	255	5.	MAXERR	234	233.1000	234
6.	L2RAT	2.5338e-06	1.5316e-05	1.6426e-06	6.	L2RAT	2.8195e-06	1.5377e-05	1.9239e-06
7.	Pixel Count	15438	117880	10008	7.	Pixel Count	15568	118240	10623
9.	Time (s)	0.369753	16.012605	16.382358	9.	Time (s)	0.334783	14.688716	15.23499
10.	TPR	43.8537	99.6880	45.6370	10.	TPR	43.6213	99.6957	45.9964
11.	BF	11.2238	0.0076	15.1957	11.	BF	11.2357	0.0100	15.6300
12.	QP	5.4461	98.9212	3.8537	12.	QP	5.3880	98.6777	3.7832
13.	FPR	11.2238	0.0079	15.2860	13.	FPR	11.2357	0.0096	14.9373
14.	Precision	0.0575	0.9920	0.399	14.	Precision	0.0397	0.9903	0.0569
15.	Recall	0.4385	0.9969	0.4751	15.	Recall	0.4549	0.9969	0.4362
16.	FI	0.4385	0.9968	0.4737	16.	FI	0.4362	0.9967	0.4522
17.	KI	0.4385	0.9968	0.4657	17.	KI	0.4362	0.9973	0.4611
18.	KI*	0.5615	0.0032	0.5343	18.	KI*	0.5638	0.0027	0.5389
19.	F(0.25)	0.2290	3.8638	0.1600	19.	F(0.25)	0.2266	3.8464	0.1630
20.	F(0.5)	0.1148	1.9651	0.0785	20.	F(0.5)	0.0758	1.3160	0.0786
21.	F(0.75)	0.0766	1.3181	0.0536	21.	F(0.75)	0.0569	0.9901	0.0540

Image: Woman in Rain				
Sl. No.	EMs	Canny	Bilateral	Bilateral Canny
11.	QP	10.2862	94.1000	7.2919
12.	FPR	5.8427	0.0136	7.4542
13.	Precision	0.1062	0.9862	0.0738
14.	Recall	0.5767	0.9542	0.5412
15.	FI	0.5767	0.9544	0.5413
16.	KI	0.5767	0.9539	0.5419
17.	KI*	0.4233	0.0461	0.4581
18.	F(0.25)	0.4225	3.8256	0.2988
19.	F(0.5)	0.2120	1.9516	0.1523
20.	F(0.75)	0.1415	1.3109	0.0968

Table 8. Plot of Statistical Ems q

Sl. No.	EMs	Plot	Sl. No.	EMs	Plot
1.	Entropy		8.	BF	
2.	Correlation		9.	QP	
3.	PSNR		10.	FPR	
4.	L2RAT		11.	Precision	

5.	Pixel Count		12.	Recall	
6.	TPR		13.	FI	
7.	F(0.25)		14.	F(0.5)	

4). Distance Based EMs















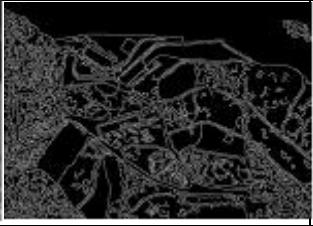
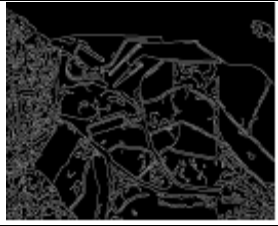












Table 9. Distance Based Ems

Image: Peppers				Image: Cameraman					
Sl. No.	EMs	Canny	Bilateral	Bilateral Canny	Sl. No.	EMs	Canny	Bilateral	Bilateral Canny
1.	PFoM	0.8563	0.7267	0.8424	1.	PFoM	0.8757	0.7678	0.8788
2.	PFoM*	0.1437	0.2733	0.1576	2.	PFoM*	0.1243	0.2322	0.1212
3.	HD	15.0333	11.7047	14.9332	3.	BDM	26.4701	0.1928	26.5544
4.	BDM	19.3050	8.8822	14.1190	4.	HD	12.4900	5.3852	13.6748
Image: Lena				Image: Aerial					
Sl. No.	EMs	Canny	Bilateral	Bilateral Canny	Sl. No.	EMs	Canny	Bilateral	Bilateral Canny
1.	PFoM	0.8581	0.7363	0.8647	1.	PFoM	0.8840	0.6654	0.8009
2.	PFoM*	0.1419	0.2637	0.1353	2.	PFoM*	0.1159	0.3346	0.1991
3.	BDM	5.4565	3.6568	6.5517	3.	BDM	4.3942	0.4270	6.1752
4.	HD	12	10.0995	11.9583	4.	HD	20.4450	10.3923	20.7846
Image: Car in a Lane				Image: Car in a Lane with mist					
Sl. No.	EMs	Canny	Bilateral	Bilateral Canny	Sl. No.	EMs	Canny	Bilateral	Bilateral Canny
1.	PFoM	0.8486	0.4960	0.7371	1.	PFoM	0.8534	0.5307	0.7463
2.	PFoM*	0.1514	0.504	0.2629	2.	PFoM*	0.1466	0.4693	0.2537
3.	BDM	47.4500	5.3654	45.8977	3.	BDM	47.2729	7.4160	45.6978
4.	HD	22.5167	6.7082	23.1948	4.	HD	22.8254	6.8557	23.7697
Image: Woman in Rain									
Sl. No.	EMs	Canny	Bilateral	Bilateral Canny	Sl. No.	EMs	Canny	Bilateral	Bilateral Canny
1.	PFoM	0.8558	0.7063	0.8626	3.	BDM	6.9423	1.4940	9.9340
2.	PFoM*	0.1442	0.2937	0.1374	4.	HD	19.3907	9.0554	19.5704

Table 10. Plot of Distance Based Ems q

Sl. No.	EMs	Plot	Sl. No.	EMs	Plot
1.	PFoM		2.	PFoM*	
3.	BDM		4.	HD	

Table 11. Visual Output of Different Original and Their Filtered Images

Sl.	Original Image	Bilateral Image	Canny Image	Bilateral Canny Image
1				
2				
3				
4				
5				
6				
7				

IV. CONCLUSION & FUTURE SCOPE

Authors have studied different EMs both statistical as well as distance based in edge detection, then bilateral filter and Canny Edge Detector in detail using different types of jpeg, png images. Quantitative analysis of the

statistical as well as distance based EMs study gives a detail idea of EMs q which have been utilised in the performance measure of classical as well as hybrid filter. The new proposed method is a hybridization of both the mentioned filters. The parametric performance of the proposed method shows better edge detection with the

object of interest. From the tables it is evident that time required for the proposed filter is quite high than that of Canny Edge Detector, but almost same in comparison to Bilateral filter. In real time application this may not be suitable, but in case of off line processing it gives good result. Though proper graphics hardware can make bilateral filter to be used on real time [41], [42] which shows the proposed hybrid filter is also efficient in real time application. All the above tables and graphs show that the hybrid filter plays a significant role in edge detection in comparison with Canny from the point of view of pixel count, PFOM [43], Precision-Recall, ROC, HD, BDM, TPR, FPR, FI, KI, F measure etc. Qualitative measure also proved to be better in case of hybrid filtering by using human experience. In future efficient hybridization may be developed using these experiences. This is to be acknowledged that it is not optimal filter. Optimal filter is that filter that eliminates all false edges. The above operation can be repeated by using Linux and FPGA platform with high speed and efficiency.

ACKNOWLEDGMENT

In this paper authors have used Matlab Version R2014a and Microsoft excel for the experimental result. It is working under windows8 environment.

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Authors' Profiles



Sangita Roy is an Assistant Professor at ECE Department of Narula Institute of Technology under WBUT. She has a teaching experience of more than eighteen years. She was in Bells Controls Limited (instrumentation industry) for two years and West Bengal State Centre, IET (Kolkata) in administration for two years. She completed her Diploma (ETCE), A.M.I.E (ECE) and M-Tech (Comm. Egg.). Currently pursuing her PhD under Dr. Sheli Sinha Chaudhuri at ETCE Department of Jaduvpur University since 2012. She is the member of IET, IETE, FOSET, ISOC, and IEEE ComSoc. She has published Journals as well as conference papers.



Dr. Sheli Sinha Chaudhuri is an Associate Professor at ETCE Department of Jaduvpur University. She completed her B-Tech, M-Tech, and PhD at Jaduvpur University. She has a vast teaching experience of fourteen years. She has large number of papers in International and national level journals as well as conferences. Currently research scholars are pursuing PhD under her guidance. She is the member of IEEE and IET.

How to cite this paper: Sangita Roy, Sheli Sinha Chaudhuri, "Error Measurement & its Impact on Bilateral -Canny Edge Detector-A Hybrid Filter", *International Journal of Modern Education and Computer Science(IJMECS)*, Vol.8, No.2, pp.30-41, 2016.DOI: 10.5815/ijmeecs.2016.02.04