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# A Pre-processing Step for Efficient Edge Extraction

**Naveen Kumar N, S. Rajkumar**

***Abstract***: ***In this paper, we propose a pre-processing step for an efficient edge extraction technique that takes input as an original image to generate an edge map. Generated edge maps could be inputted for state-of-art traditional edge detection algorithms like Canny, Sobel, Prewitt, and recent edge detection algorithms gb-UCM, CED Contours, Structured forest, Sparse Code Gradients and CNN based edge detection Deep Edge, N4 to get better performance. Further, the proposed algorithm has not required any training or learning to improve the edge detection method and is not depending on any parameters. Visual experiments and quantitative evaluation results show that our proposed algorithm greatly improves the modal quality of edge/edge maps. It preserves the original shape, structure of the objects and local features, which presents in an input image. The proposed method takes very less amount of time to execute and making it more suitable for real-time image processing and computer vision applications that depend on edge like classification, object localization, object recognition, image retrieval, segmentation, shape representation.***

***Keywords : Contour detection, Efficient edge extraction, Image retrieval. Local Binary Pattern(LBP), Structured forest.***

## I. INTRODUCTION

In image and computer vision, edge and contour detection of an image are fundamental pre-processing steps in applications like image segmentation [1], object recognition and shape matching [2], and scene understanding, etc. Edges are sets of pixels in the image regions with sharp intensity changes and correspond to visible contour features of objects in an image. Contours are boundaries that separate different objects from each other. Traditional edge detection techniques work either by finding the zero crossings of the second derivative operator LoG [3] or by finding the maximal pixels of the first derivative operator Canny [4] work by eliminating non-edge pixels as non-maximal suppression, hysteresis, edge thinning, morphological operators and recently Structured Forest [5] use same non-maximal suppression technique to obtain thinned edges for their edge maps and improve accuracy as well.

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* Correspondence Author
**Naveen Kumar N*,** Assistant Professor - Senior in SCOPE school, VIT University, Vellore 632014, India.
**S. Rajkumar**, Associative Professor in SCOPE School, VIT University, Vellore 632014, India



## II. RELATED WORK

Recently, a family of learning approaches called structured learning [6] has been applied to problems exhibiting similar characteristics. Structured Forest [5] Fast edge detection using structured forest [7] These two approaches allows us to take advantage of the inherent structure information and it is computationally efficient also shows promising results for edge detection and image segmentation as well. Spatially Coherent Random Forests [8] takes high computational time 240 seconds per image to construct a forest tree even by using GPU. CED Contours [9] using the three-channel color image in (R, G, B), each channel edge segments are identified in different scales and fuse them together, this approach has two main advantages, first to obtain fine-grained details in the image can be detected.Secondly, prominent boundaries of the large objects will be detected with smaller details getting wiped out by Gaussian smoothing. gp-UCM [1] consisting of two steps. First, Oriented Watershed Transform (OWT) used to construct a set of initial regions from an oriented contour signal. Secondly, the clustering procedure used to form regions into a hierarchy that can be represented by an Ultrametric Contour Map(UCM). Sparse Code Gradients (SCG) [10] measures local contrast and find contours using patch representations automatically learned through sparse coding, this technique retains local structure information along with contour map.Convolutional neural networks have great success, which is possible due to the large public image repositories, such as ImageNet [11], Microsoft COCO [12] with help of high-performance computing systems, such as GPUs or large-scale distributed clusters. Deep Contour [13], Deep Edge [14], N4-fields [15], boundary neural fields [16] are using Convolution neural networks to detect Edge, contour and image segmentation achieves the best result compared to existing techniques. The rest of the paper has been organized as follows. Section 2 presents the construction of the Nearest Neighbor Difference (NND). Dataset selection and experimental results are shown in section 3. Finally, Section 4 concludes the paper.

## III. PROPOSED METHODOLOGY

The well-known local binary pattern (LBP) [17] introduced by Timo Ojala et al, in the year 2002 is widely used for texture analysis by takes very less computational cost, because of simplicity and high accuracy rate, different variations of LBP and were used for many image and computer vision application, like texture classification [18], in medical image retrieval [19], very large scale image retrieval [20], face recognition [21].The proposed method called Nearest Neighbor Difference(NND) edge map detect an absolute difference of given 3x3 neighborhood operation with its centered pixel value, then every pixel's absolute difference is multiplied with constant value k. Summation of all these eight-pixel values stored in resulted edge map for the given coordinate g(x,y). Apply this entire operation on the whole image as overlapped manner to generate the complete edge map.

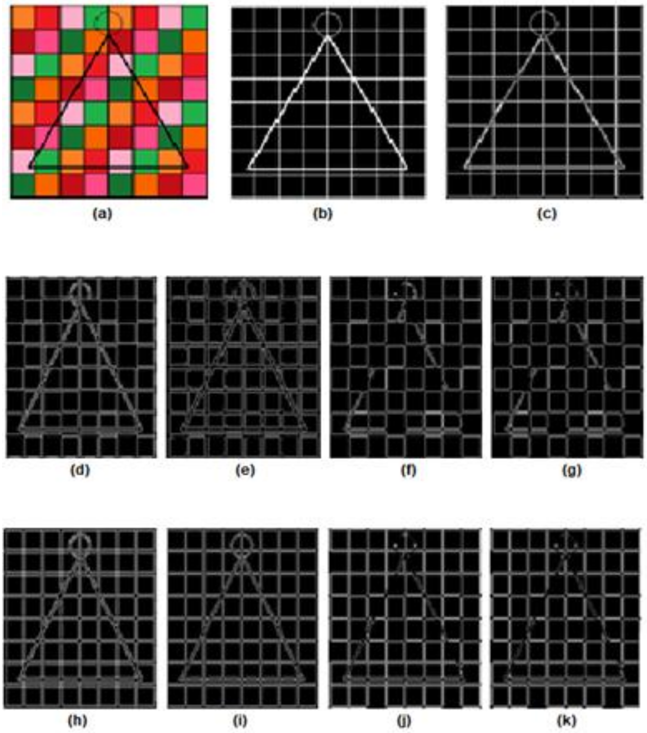


**Fig. 1. Importance of proposed method Edge map. (a) Input image, (b) Ground truth edge, (c) Edge map generated by proposed method, (d) Canny, (e) LoG, (f) Sobel, (g) Prewitt, (h) PM+Canny, (i) PM+LoG, (j) PM+Sobel and (k) PM+Prewitt edge detection.**

$$\mathrm{NND}(p)=\sum_{P=0}^{P-1} | g_p - g_c | K \qquad \text{---(1)}$$

Equation (1) explains our NND edge map method for the grayscale image, where p is a neighbor pixel size which is fixed as 8, k is the constant value should be greater than 1 and gp is the center pixel and gp neighbor pixel. In this paper, we considered the constant k value as 1, when the k value is increased more detailed information will be highlighted. Fig.1 shows the toy example, the importance of NND edge map method compared to traditional state-of-art edge detection techniques which are widely used in the last two decades for many image and computer vision applications. But this simple pattern of 8x8 check board with triangle and circle shape image, all traditional methods not properly detected the edges. To improve these techniques proposed NND edge map combined with traditional methods shows a better result than the original methods also retains the structure, edge strength. This added advantage reveals more edges on input images. We mainly focus on Canny method for two main reasons, the first reason is Canny method uses non-maximum suppression method to thin the edges SF [5], FEDSF [7] also use the same technique for non-maximum suppression to gain more accuracy and second reason is familiarity, simplicity and widely used in computer vision applications.

## IV. RESULT AND DISCUSSION

We select the most popular and challenging BSDS500 dataset [1] widely used for edge, contour and image segmentation to evaluating our edge map result. This dataset contains 500 natural images. For each image, peoples were asked to draw a contour map separating different objects presents in an image. All 500 images are divided into 3 subsets, with 200 for training, 100 for validation and 200 for testing.

## V. RESULT AND DISCUSSION: OBJECTIVE EVALUATION

Full reference image quality assessment metrics are used to show our NND edge map preserve structure information, edge strength and low-level features, because these metrics are mimic and close to the Human Vision System (HSV), even though the HVS itself is not well understood until now. Along with these metrics, the proposed edge map method detects /highlights objects or parts of objects clearly also localization of object very well compared to any of the techniques discussed in the introduction section, an example shown in Fig.1. Signal to Noise Ratio(SRN) and Peak Signal Noise Ratio(PSNR) are most widely used but these metrics do not consider the properties of the human visual system (HVS) and show poor consistency with structure, edge strength, low and high-level features.To analysis the structure quality we use SSIM [22], GMSD [23], SRSIM [24] HaarPIS [25], SSIM is assumed that the HVS is highly adapted for extracting structural information from an image. GMSD image gradients are very sensitive to image distortions, while different local structures in a distorted image suffer different degrees of degradations, a standard deviation of the gradient magnitude similarity (GMS) between the reference and distorted images can predict accurately perceptual image quality. SRSIM the spectral residual visual saliency (SRVS) is taken into account changes in the local horizontal and vertical gradient magnitudes, additionally, it incorporates changes in a spectral residual-based visual saliency estimate. HaarPIS utilizes coefficients obtained from Haar wavelet decomposition to assess local similarities between two images, the magnitude responses on the two scales of the wavelet transform associated with the highest frequencies are used to compute local similarities. Edge quality and strength analysis we use ESSIM [26], it assumes semantic information of an image fully represented by edge strength. For feature analysis we use FSIM [27] it assumes that the HVS perceives images according to low-level features as edge information. SCIGSS [28] extracts the gradient direction based on the local information of the image gradient magnitude, which not only preserves gradient direction consistency in local regions but also demonstrates sensitivities to the distortions introduced to the screen content image (SCI). The main reason why we choose SCIGSS because the minimum of 20 percentages of BSD500 dataset images are actually captured from photographs, we assume that these 20 percentage images are captured from high-end display devices.

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**Table-I (a) Comparison results of Canny and proposed edge map methods on BSDS500 Dataset**

| *Method* | *PSNR* | *SSIM* | *ESSIM* |
|---|---|---|---|
| Canny[4] | **6.3773** | 0.0127 | **0.9885** |
| PM+Canny[4] | 6.2982 | **0.0189** | 0.9868 |

**Table-I (b) Comparison results of recent edge map methods on BSDS500 dataset**

| Method | PSNR | FSIM | SRSIM | HaarPSI | GMSD |
|---|---|---|---|---|---|
| Proposed Edge map | **7.62** | **0.65** | **0.8** | **0.33** | **0.21** |
| CEDCompass | 6.56 | 0.47 | 0.63 | 0.08 | 0.32 |
| CEDDiZenzo | 6.62 | 0.48 | 0.64 | 0.09 | 0.3 |
| gb-UCM | 6.88 | 0.58 | 0.7 | 0.12 | 0.29 |
| SCG | 6.85 | 0.56 | 0.69 | 0.1 | 0.29 |

**Table-I (c) Comparison results of GUP/CNN based edge map methods on BSDS500 test dataset**

| Method | PSNR | FSIM | SRSIM | HaarPSI | GMSD |
|---|---|---|---|---|---|
| Proposed Edge map | 7.57 | **0.65** | **0.8** | **0.33** | **0.22** |
| SF | 7.55 | 0.59 | 0.7 | 0.18 | 0.27 |
| FEDSF | 6.86 | 0.59 | 0.72 | 0.14 | 0.28 |
| DeepEdge | 7.5 | 0.54 | 0.69 | 0.18 | 0.26 |
| N4 | **7.84** | 0.63 | 0.72 | 0.22 | 0.26 |

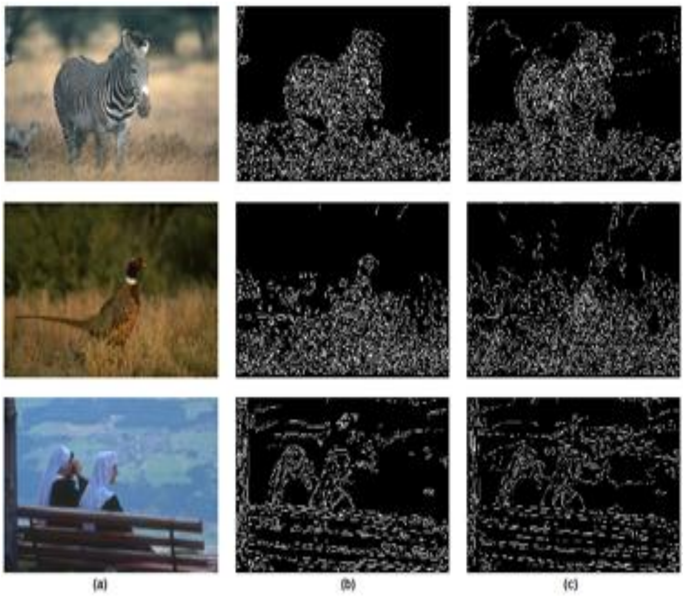

**Fig. 2. Proposed Method compared with Canny edge detection (a) original dataset images (b) Proposed edge map + Canny (c) Original Canny method**

The proposed edge map combined with Canny, original Canny results were compared with PSNR, SSIM, ESSIM in Table-I (a) the proposed method gain more structural information when combined with Canny method, but ESSIM is little bit low compared with Canny method but it's close to Canny method on complete BDS500 dataset, Fig.2 is revealing more detailed edges with less/unwanted background details of an images, all three images are located object more clear, also easy to recognize object in complex background. In Table-I (b) the proposed edge map compared with SCG, gb-UCM, CEDContorus_Compass and CEDContorus_DiZenzo method edge maps, it shows proposed NND edge map achieved best in all quality metrics result is highlighted in bold text additionally Fig.3 shows NND edge map highlighted detailed foreground details compared to SCG, gp-UCM and CEDContour edge maps and fewer backgrounds.In Table-I (c) proposed NND edge map compares based on structure learning methods using GPU and Convolution Neural Network methods. The proposed NND edge map retains more edge strength and low-level features when compared with other techniques in the table. If structure information is blurred in a grayscale image, the structure similarity index always gives very high values; even blurred structure is not retained original structure. Due to this reason, SSIM is not considering edge map images.

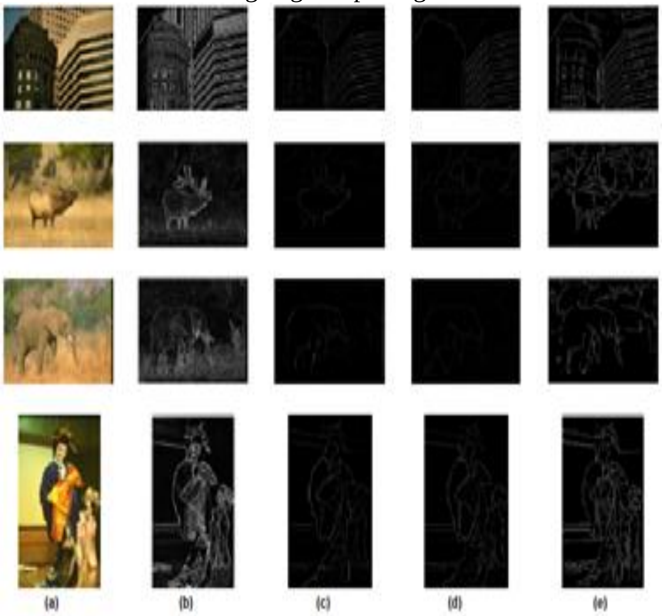

**Fig. 3. Proposed method compared with feature learning methods (a) original dataset images, (b) proposed edge map, (c) SCG edge map (d) gb-UCM edge map and (e) CED Contours-Compass edge map results.**

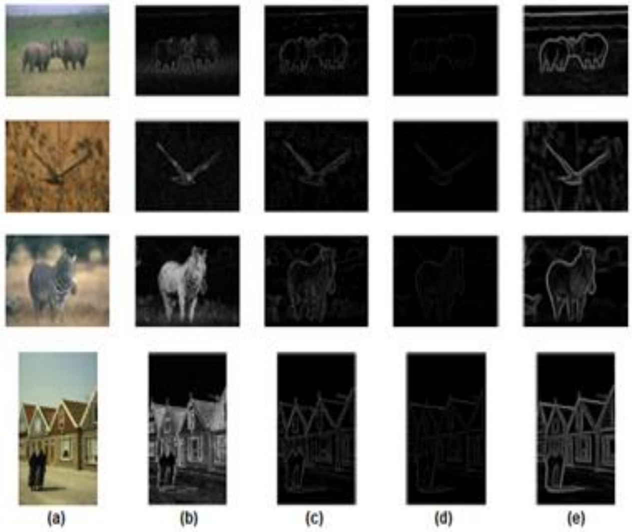

**Fig. 4: Proposed method compared with CNN methods (a) original dataset images, (b) proposed edge map, (c) Deep Edge's edge map (d) FEDSF edge map (e) N4 edge map results.**

## RESULT AND DISCUSSION: SUBJECTIVE EVALUATION

The fundamental pre-processing step of many image processing and computer vision application is edge detection, so we compare all edge maps results in the following application to analysis performance as subjective evaluation.

**a) Human Detection:** Human Detection: From the BSD500 test dataset we selected 35 images to detect humans on the basis of visible human pose, out of 35 images, totally 77 humans are present. We use normalized aggregate channel features(ACF) [29] method to detect people, all edge maps with original color images then try to detect the humans from images. Based on the edge map result the proposed NND, N4[15] and SF[5] detected 51, 47 and 38 humans respectively and NND edge stands in the top rank, Fig. 5 shows the F1 score performance measures of all edge map methods. Interestingly, the proposed NND edge map method detected the humans form the dataset image name “64061.jpg”, “230098.jpg”, “259060.jpg” that was not detected by any other edge map methods, even original color image also fails to detect the human from those images. Likewise, N4 [15] method detects a human from the dataset image name “217013.jpg” that was not detected by any other edge map methods.

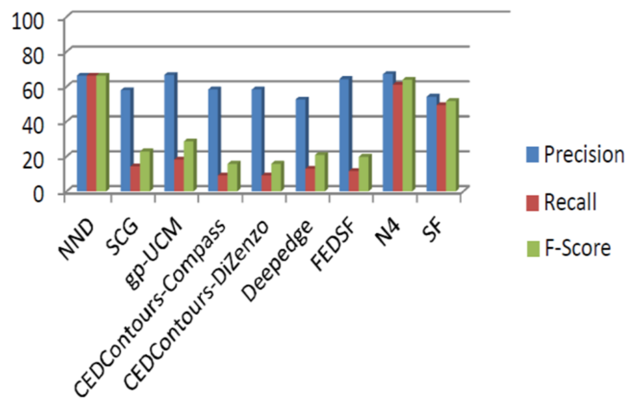


**Fig. 5. Human detection F1 Score**

**b) Image Retrieval:** According to [30] BSD500 dataset looks very similar to the original BSD300 dataset, by considering this we train bag of visual words on BSD300 dataset to perform image retrieval task, totally 20,000 visual word frequencies were generated by using normalized large vocabularies object retrieval method [31] to retrieve relevant images from collections of trained bag of visual words.

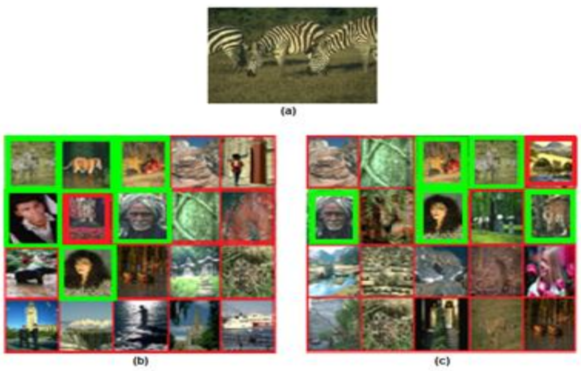


**Fig. 6. Image retrieval (a) Database query image, (b) retrieval using proposed method, (c) retrieval using structured forest.**

## VI. CONCLUSION

We present a pre-processing step for efficient edge extraction called Nearest Neighbor Difference (NND) for grayscale images, which generate the edge map that could be inputted for state-of-art traditional edge detection algorithms. The objective evaluation shows that the proposed NND edge map gain more structure similarity, edge strength and low-level features in Table-I (a) when we combine our edge map with Canny edge detection method it gains 33% more similarity structure than the original Canny method this shows the importance of NND edge map. For recent edge map methods CEDC-Compass, CEDCDiZenzo, gb-UCM on BSD500 dataset the proposed NND edge map stands top in all seven image quality metrics shows in Table-I (b). Convolutional Neural Networks and GPU based edge map methods on BSD500 test dataset the proposed NND edge map stands top in ESSIM, FSIM, GMSD, SRSIM, HarrPSI and SCIGSS except for PSNR.On another side, the subjective evaluation shows that the proposed NND edge map in human detection application, it detects more human from the input image even that can’t be detected by the original color images, result shown in Fig.5. Image retrieval task we used bag of visual words methods to extract features, there were 20,000 visual features are extracted. The Proposed NND edge map retrieved five images that exactly same pattern as well as the same visual frequency out of top ten images, whereas structured forest detects five images but the best match for the query image was detected at the fourth best match, result shown in Fig.6. Other edge map results are not considered, because for the top ten images of image retrieval task NND and Structured forest edge maps alone retrieved five images that are mostly similar to the given query. We conclude that NND edge map produces one of the best results in the literature on objective, subjective evaluation. Running time to generate NND edge map for a single image, it just takes less than 0.5 seconds which is very less time, based on time complexity, objective and subjective evaluations prove that the proposed NND edge map could be combined with state-of-art techniques to improve the results.

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## AUTHORS PROFILE

**Naveen Kumar N,** working as an Assistant Professor-Senior in Vellore Institute of Technology (VIT) University, Vellore, Tamil Nadu, India. His research interest include Image Processing, Computer Vision, and Web Technology.

**S. Rajkumar,** working as an Associate Professor in Vellore Institute of Technology (VIT) University, Vellore, Tamil Nadu, India. His research interest include Digital Image Processing, Medical Image Analysis, Computer Vision, Image Feature Description, Biometrics