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NEURAL NETWORK BASED IMAGE SEGMENTATION FORNATURAL IMAGES

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ABSTRACT

This paper presents a new Neural Network based region image segmentation using grow cut. This method is developed to obtain improved performance in seed based region growing method. The results shown in normal seeded region growing method are unsatisfactory so we propose a new method to increase the performance of the result by adding a neural network to the system. By training the neural network it will easily put the seeds for growing and merging. The performance of the proposed system is better compared with the seed region growing and the values inferred from result evaluation gives good result.

KEYWORDS: Image segmentation, neural networking, seed-based region growing, watershed algorithm,

INTRODUCTION

Image segmentation means separating the desired objects from the background based on certain measurements. The main aim of image segmentation is to simplify the representation of an image and make it in an understandable way [2]. Some of the practical applications of image segmentation are Content-based image retrieval, machine vision, medical imaging, Recognition tasks, traffic control systems, video surveillance.

Region based segmentation is one of the main existing segmentation method. Region based segmentation includes seeded and un seeded region growing algorithms [6]. First region growing method was the seeded region growing method. This method takes a set of seeds as input along with the image. The seed marks of each of the objects to be segmented. The regions are iteratively grown by comparing all unallocated neighbouring pixels to the regions. The difference between a pixel intensity value and the region’s mean, is used as a measure of similarity. The pixel with the smallest difference is measured and this way is allocated to respective region. This process continuous until all the pixels are allocated to the region. Seeded growing requires seeds as the additional input. The segmentation results are dependent on the choice as seeds. Noise in the image can cause seeds to be poorly placed. Unseeded region growing is a versatile and fully automatic segmentation technique suitable for multispectral and 3D images. This approach integrates region-based segmentation with image processing techniques based on adaptive anisotropic diffusion filters. The segmentation method is fast, reliable and free of tuning parameters. It is indeed a general purpose segmentation method and has been successfully applied in a range of image analysis tasks.

The remnants of the paper are organized as follows. The next section describes the about the related works. Section III explains about the proposed method. Section IV reports the implementation and result analysis. Section V presents concluding remarks.

RELATED WORK:

PREWITTE OPERATOR:

The Prewitt operator is used in image processing, particularly within edge detection algorithms. Technically, it is a discrete differentiation operator, computing an approximation of the gradient of the image intensity function. At each point in the

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image, the result of the Prewitt operator is either the corresponding gradient vector or the norm of this vector. The Prewitt operator is based on convolving the image with a small, separable, and integer valued filter in horizontal and vertical directions and is therefore relatively inexpensive in terms of computations. On the other hand, the gradient approximation which it produces is relatively crude, in particular for high frequency variations in the image. The Prewitt operator was developed by Judith M. S. Prewitt.

(a) (b)

ROBERTS OPERATOR:

The Roberts cross operator is used in image processing and computer vision for edge detection. It was one of the first edge detectors and was initially proposed by Lawrence Roberts. As a differential operator, the idea behind the Roberts cross operator is to approximate the gradient of an image through discrete differentiation which is achieved by computing the sum of the squares of the differences between diagonally adjacent pixels.

(a) (b)

PROPOSED METHOD:

In order to increase the performance of segmented images we introduced a Neural network technique . By applying this technique we have to select the seeds and find the seed pixel from each block. Then, apply seed based region growing algorithm is applied and we got segmented images. And we have to evaluate the performance.

Method used for Neural Network is feed forward method.

PROPOSED METHADOLOGY

1. Creation of over segmented image using one of the many segmentation methods such as watershed based and edge counter based method.
2. Scanning the original image block-by-block and takes the overlapped blocks
3. Using Neural Network find the seeds used and seed pixels of seeds selected.
4. Seed based region growing is used to produce segmented image.
5. Performance are evaluated.

PROPOSED ARCHITECTURE

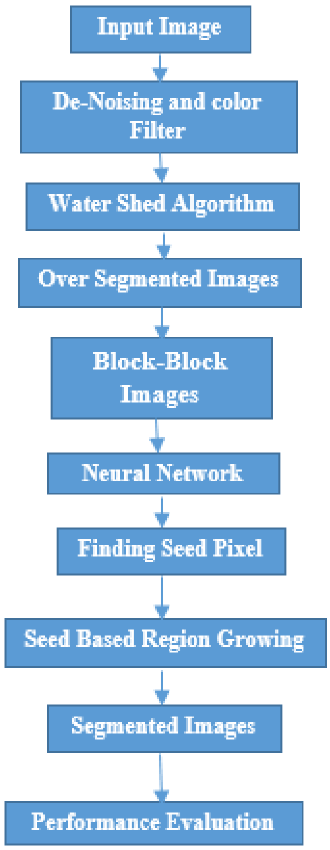


Figure 3.1

ALGORITHM

Step 1: Input the image

Step 2: Perform the de-noising operation

Step 3: Create the over segmented images using watershed algorithm.

S.Amith, S.John Livingston, et al., Inter. J. Int. Adv. & Res. In Engg. Comp., Vol.–03 (04) 2015 [419-426]

Step 4: Create block-by-block images using matrix.

Step 5: Select the seeds to be taken using neural networks.

Step 6: Finding the seed pixel of the selected seeds

Step 7: Use seed based region growing algorithm for segmented images

Step 8: Performance of the segmented images is evaluated using the parameters.

IMPLEMENTATION DETAILS:

Experiments are implemented on a computer with Intel(R) Core(TM) i5 2640 M @2.80 GHz , 4 GB RAM, Windows 8 Home Basic, Mat lab R2010a, Mat lab.

For implementation, entire project is divided into three modules. They are Creating over segmented images, Neural Network phase, Seeded Region Merging.

In creating over segmented images here by, using watershed algorithm to get over segmented images. First the input image is passed through a filter for remove noises. The filter used for de-noising is Edge Preserving and smoothening filter. The working of the filter is explained below

- The ESPF is applied independently to every image pixel using different coefficients.
- Calculate the coefficients of convolution mask of every pixel.
- Manhathan color distance di=1,2,…8 are calculated between central pixel and neighboring pixels

di = |Rac – Rai| + |Gac – Gai| + |Bac – Bai| / 3*255 (4.1)

After filtering the image we go for watershed algorithm. There we convert the image into greyscale. Apply sable edge detector of horizontal edges, to emphasize vertical edge the s, transpose the filter H: H'. Using infielder filtering of multidimensional images over segmentation takes place.

In Neural Network Phase, there we have three sections in neural networks. They are

- Data base buildup.
- Train Neural Networks.
- Test Neural Network

In data base build up we create the database of the images for the training of neural networks. Here the inputted images is divided into patches or blocks, the size of each patch is given as w called window size and there is a gap between each patches and is given as g called gap. Then we descript the image to HOG features. HOG determines mainly on shapes variance, means and co-variance are calculated and taken as feature. HOG is more accurate and speed compared to other techniques. The user gives the x, y data to separate object from the background. HOG algorithm is

1. Compute gradients for each pixel of an image.
2. Perform binning of gradients orientation (from 0 to 180 degrees, opposite directions count as the same).
3. Collect the histogram within a cell of pixels.
4. Weight the histogram by blocks and cells for local normalization of the contrasts.
5. Normalize the histogram.
6. Train a linear support vector machines (SVM) to detect an object. The output from the trained linear SVM is a set of coefficients for each element in a feature vector.

In Training set we train the neural network with user specified data images. Feed forward method is used to train neural networks. Feed-forward nets are the most well-known and widely-used class of neural network. The popularity of feed-forward networks derives from the fact that they have been applied successfully to a wide range of information processing tasks in such diverse fields as speech recognition, financial prediction, image compression, medical diagnosis and protein structure prediction; new applications are being discovered all the time.

S.Amith, S.John Livingston, et al., Inter. J. Int. Adv. & Res. In Engg. Comp., Vol.-03 (04) 2015 [419-426]

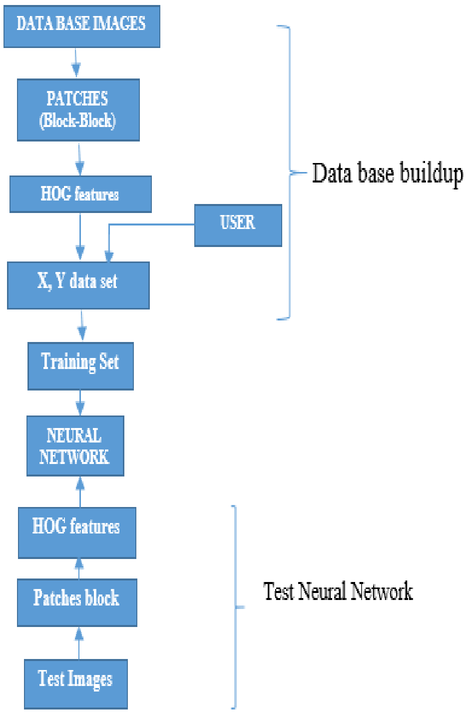


Figure 4.2

In Testing part we test the neural network with another inputted image which is similar to the trained image. Hog features of the two images are same and neural network performs well.

- By training the Neural Network it can put the seeds in the appropriate positions where the object is located.
- By training it puts seeds in the images that is similar to the trained images

In seeded based region growing, one of many different approaches to segment an image is seeded region growing. The user identifies different regions in an image. These identification tags are called a seed mark. While the region expands, the algorithm has to decide which pixels are incorporated into the given seed mark region and which not. This decision is based on a similarity measure.

EXPERIMENTAL RESULT ANALYSIS:

PSNR (Peak Signal to Noise Ratio):

PSNR represents region homogeneity of the final partitioning. Higher the value of PSNR better is the segmentation. PSNR in decibels is computed using,

$$PSNR=10\log_{10}(255^2/MAE) \qquad (5.1)$$

MAE in the mean absolute error of the segmented image computed as follows

$$MAE=1/MN\sum\sum|F(i,j)-f(i,j)| \qquad (5.2)$$

F (i,j)-segmented image, f(i,j)-source image that contains M by N pixels

RI (Rand Index):

The Rand index between test and ground truth segmentations S and G is given by the sum of number of pairs of pixels that have the same label in S and G and those that have different labels in both segmentations, divided by the total number of pairs of pixels.

$$RI=a+b/(a+b+c+d) =[(n/2)[0.5\{\sum_i(\sum_j n_{ij})^2 + \sum_j(\sum_i n_{ij})\}^2 -\sum\sum n^2_{ij}]]/(n/2) \qquad (5.3)$$

Where a. the number of pairs in S that are in the same set U and in the same set in V; b, the number of pairs of elements in S those are in different sets in U and in different sets in V; c, the number of pairs of elements in S that are in the same set in U and different sets in V; d, the number of pairs of elements in S that are in the different set in U and same sets in V. $n_{ij}$is the number of objects in the i^{th} cluster in U and j^{th} cluster in V, and (n/2) is the binomial coefficient, which gives the number of distinct pairs found in a set of n objects.

GCE (Global Consistency Error):

The global consistency error measures the extent to which one segmentation can be viewed as a refinement of the other. Segmentations which are related are considered to be consistent, since they could represent the same image segmented at different scales. The formula for GCE is as follows

$$GCE=1/n \min \{\sum_i E (S1, S2, pi),\{\sum_i E (S1, S2, pi)\} \qquad (5.4)$$

Where, segmentation error measure takes two segmentations S1 and s2 as input, and produces a real valued output in the range [0::1] where zero signifies no error. For a given pixel pi consider the segments in S1 and S2 that contain that pixel

VOI (Variation of Information):

The variation of information metric defines the distance between two segmentations as

S.Amith, S.John Livingston, et al., Inter. J. Int. Adv. & Res. In Engg. Comp., Vol.–03 (04) 2015 [419-426]

the average conditional entropy of a segmentation given the other and thus roughly measures the amount of randomness in a segmentation which cannot be explained by other. Lower the value of VOI better is the result.

VI(c,c')=H(c)+H(c')-2I(c,c') (5.5)

Where H(c) &H(c') are entropies associated with cluster c and c'; I(c,c') is the mutual information between the associated random variables.

Test image	**PSNR**	**RI**	**GCE**	**VOI**
Apple	62.2049	0.5850	0.0136	0.9308
Turtle	76.4769	0.5363	0.0298	0.5363
Panther	66.5440	0.5561	0.8370	0.1025
deer	63.5633	0.5273	0.0255	1.0372

Table 5.1 PSNR, RI, GCE and VOI are calculated for neural network based images

Test images	PSNR	RI	GCE	VOI
Apple	60.4767	0.5642	0.0560	1.0659
Turtle	72.5139	0.5336	0.9880	1.2542
Panther	56.1529	0.5534	0.9420	1.2132
deer	60.4229	0.5078	0.1017	1.2434

Table 5.2 PSNR, RI, GCE and VOI are calculated using privet method

Test iamges	PSNR	RI	GCE	VOI
Apple	61.0827	0.5858	0.0168	0.9172
Turtile	60.8483	0.5159	0.4140	1.0555
Panther	56.4791	0.5113	0.1025	0.1114
deer	59.2111	0.5010	0.1090	1.1571

Table 5.3 PSNR, RI, GCE and VOI are calculated using Roberts method

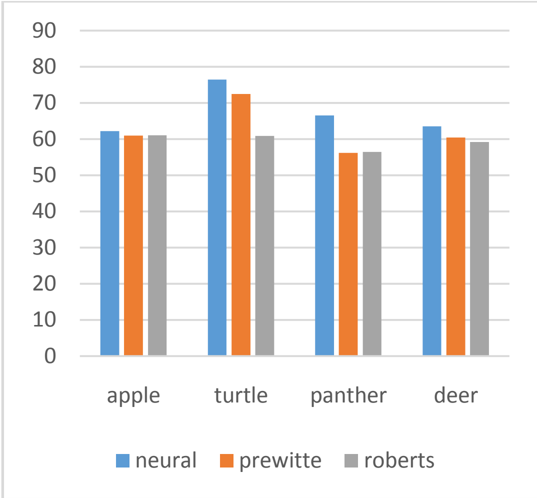


Figure 5.1 illustration of PSNR for three methods

The figure 5.1 shows that the proposed method gives Higher values for PSNR. The other two methods will give the same results. The proposed method for segmentation is better results when compared with the others when evaluating the PSNR values.

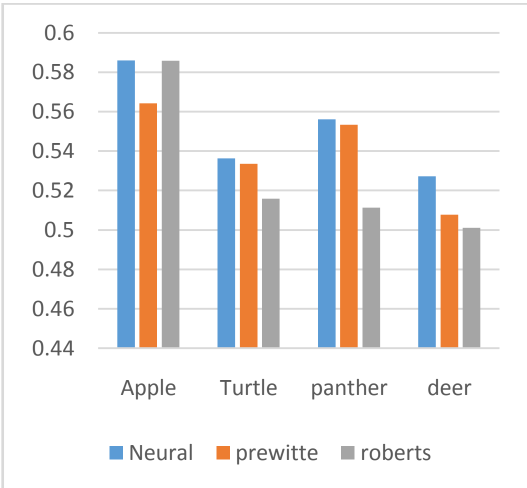


Figure 5.2 illustration of RI for three methods

For good segmentation results the RI value should be higher .The range for the RI value will be 0 to 1. For measuring the RI value the segmented image is compared with the ground truth image. According to the Fig 5.2 the proposed method gives better results when compared with the other two methods.

S.Amith, S.John Livingston, et al., Inter. J. Int. Adv. & Res. In Engg. Comp., Vol.–03 (04) 2015 [419-426]

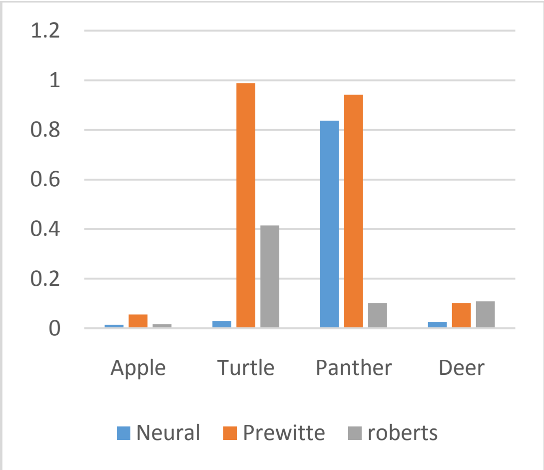


Figure 5.3 illustration of GCE for three methods

To evaluate the GCE value the one segmentation result is compared with the other segmentation results using the Fig 5.3. For a segmentation is said to be good the value of GCE should be lower. By using the proposed method, getting lower values for GCE. Thus the proposed method give better results when compared with the other two methods

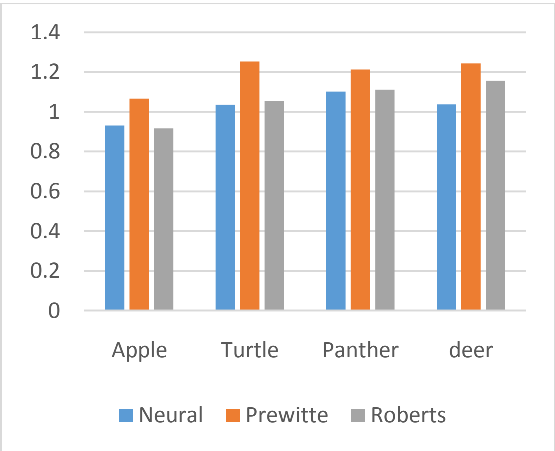
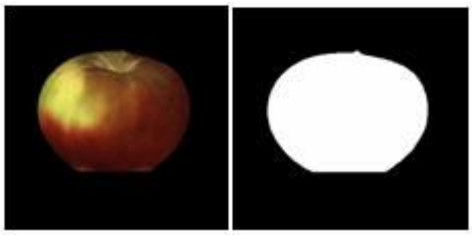


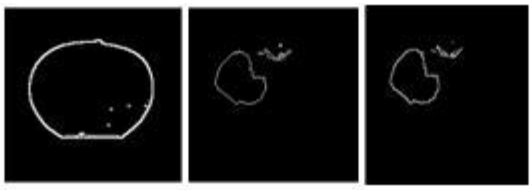
Figure 5.4 illustration of VOI for three methods

To evaluate the VOI value the one segmentation result is compared with the other segmentation results using the Fig 5.4. For segmentation is said to be good the value of VOI should be lower. By using the proposed method, getting lower values for VOI. Thus the proposed method give better results when compared with the other two methods.

Figure 5.4 Apple Images



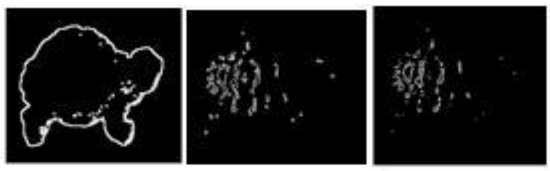
(a)Input Image (b) Ground Truth Image



(c)Segmented output after neural network (d) segmented output after prewritten method (e) Segmented output after Roberts method

Figure 5.5 Turtle Images

(a)Input Image (b) Ground Truth Image



(c)Segmented output after neural network (d) segmented output after prewritten method (e) Segmented output after Roberts method

Figure 5.6 Panther Images

(a)Input Image (b) Ground Truth Image

S.Amith, S.John Livingston, et al., Inter. J. Int. Adv. & Res. In Engg. Comp., Vol.–03 (04) 2015 [419-426]

(c)Segmented output after neural network (d) segmented output after prewritten method (e) Segmented output after Roberts method

Figure 5.7 Deer Images

(a)Input Image (b) Ground Truth Image

(c)Segmented output after neural network (d) segmented output after prewritten method (e) Segmented output after Roberts method

CONCLUSION:

Neural Networks combined with seed based region growing is implemented. Performance metrics of the proposed system is increased compared to the existing systems. The performance matrix is calculated based on Peak Signal to Noise Ratio(PSNR), Rand Index(RI), Global Consistency Error(GCE), Variation of Information(VOI).By analysing the values obtained in our results we came to the conclusion that our proposed method is better than the existing methods.

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