



REGION-BASED SALIENCY DETECTION AND ITS APPLICATION IN OBJECT RECOGNITION

R.GUNASEKARAN^[1], K.BABU^[2],

^[1] P.G Scholar Prist University

^[2] AP Dept. of computer science

Assistant Professor

Dept. of Computer Science Prist University Kumbakonam – Campus Tanjavur

^[1] rgunacse@gmail.com

ABSTRACT

The saliency of each super pixel is measured by using its spatial compactness, which is calculated according to the results of Gaussian mixture model (GMM) clustering. To propagate saliency between similar clusters, we adopt a modified PageRank algorithm to refine the saliency map. Our method not only improves saliency detection through large salient detection and noise tolerance in messy background but also generates saliency maps with a well-defined object shape. To learn a more discriminative codebook and better encode the features corresponding to the patching of the objects, we propose a weighted sparse coding for feature coding. Moreover we also propose a saliency weighted max pooling to further emphasize the importance of those salient regions in feature pooling module. Experimental results on several datasets illustrate that our weighted ScSPM framework greatly outperforms ScSPM framework and achieves excellent performance for object recognition.

1. INTRODUCTION

Digital image processing deals with manipulation of digital images through a digital computer. It is a subfield of signals and systems but focus particularly on images. DIP focuses on developing a computer system that is able to perform processing on an image. The input of that system is a digital image and the system process that image using efficient algorithms, and gives an image as an output. The most common example is Adobe Photoshop. It is one of the widely used application for processing digital images. We have already defined a pixel in our tutorial of concept of pixel, in which we define a pixel as the smallest element of an image. We also defined that a pixel can store a value proportional to the light intensity at that particular location. Now since we have defined a pixel; we are going to define what resolution is. The resolution can be defined in many ways. Such as pixel resolution, spatial resolution, temporal resolution, spectral resolution. Out of which we are going to discuss pixel resolution.

You have probably seen that in your own computer settings, you have monitor resolution of 800 x 600, 640 x 480 etc. In pixel resolution, the term resolution refers to the total number of count of pixels in a digital image. For example. If an image has M rows and N columns, then its resolution can be defined as M X N. If we define resolution as the total number of pixels, then pixel resolution can be defined with set of two numbers. The first number the width of the picture, or the pixels across columns, and the second number is height of the picture,

or the pixels across its width. We can say that the higher is the pixel resolution, the higher is the quality of the image. We can define pixel resolution of an image as 4500 X 5500.

1.2 AVERAGE METHOD:

Average method is the simplest one. You just have to take the average of three colors. Since it's an RGB image, so it means that you have to add r with g with b and then divide it by 3 to get your desired grayscale image. It's done in this way. $\text{Grayscale} = (R + G + B / 3)$. For example: If you have a color image like the image shown above and you want to convert it into grayscale using average method. The following result would appear. There is one thing to be sure, that something happens to the original works. It means that our average method works. But the results were not as expected. We wanted to convert the image into a grayscale, but this turned out to be a rather black image. We are taking 33% of each that means, each of the portion has same contribution in the image. But in reality that not the case. The solution to this has been given by luminosity method.

1.3 WEIGHTED METHOD OR LUMINOSITY METHOD

You have seen the problem that occurs in the average method. Weighted method has a solution to that problem. Since red color has more wavelength of all the three colors, and green is the color that has not only less wavelength than red color but also green is the color that gives more soothing effect to the eyes. It means that we have to decrease the contribution of red color, and increase the contribution of the green color, and put blue color contribution in between these two. So the new equation that forms is: $\text{New grayscale image} = ((0.3 * R) + (0.59 * G) + (0.11 * B))$. According to this equation, Red has contributed 30%, Green has contributed 59% which is greater in all three colors and Blue has contributed 11%.

2. EXISTING SYSTEM

Super pixel representation and Page Rank algorithm, to improve saliency detection. Specifically, super pixels, the more perceptually meaningful units, are used to represent the input image, which could not detect large salient objects and tolerate the outliers in the messy background during saliency detection. It is worth noting that our saliency calculation is different from salient object extraction, in which an existing saliency method serves to guide object extraction. In other words, these works are applications of saliency detection. In contrast, our method aims to improve saliency calculation with the help of super pixel representation. The mean shift process is to segment the image into homogeneous regions.

2.1 DISADVANTAGES OF EXISTING SYSTEM:

In the Existing Work, the distance how much the target is being moved is identified. In the existing work, the location of the target is specified but target is not proposed existing studies also show that the background

also can help predict the content of the image to some extent, and they should also contribute to the image representation. In a word, all these works hint the potential application of saliency map for object recognition, but using saliency to boost the SPM (feature extraction + feature coding + feature pooling)-based object recognition is less explored.

3. PROPOSED SYSTEM

A common hypothesis for bottom-up saliency is that the salient stimulus is distinct from its surrounding stimuli. This hypothesis is also known as center-surround mechanism, which consists with the performance of human vision system in the early phase. Therefore, researchers usually focus on identifying those regions with high center-surround contrast in bottom-up methods. Itti *et al.* proposed to determine the contrast by the difference of Gaussians (DoG). Instead of directly calculating similarity of two pixels, Seo *et al.* measured the likeness of a pixel (voxel) to its surroundings by the local regression kernels. Although these local contrast based methods perform well on most of natural images, they will fail on images with scattered background.

Therefore, some methods-based on global contrast are proposed. Achanta *et al.* measured the saliency of each pixel by the difference between the feature of each pixel and the mean feature of the whole image in *Lab* color space. Zhai and Shah measured the global contrast of a pixel by comparing it with all the other pixels in the image. Goferman *et al.* model both local and global contrast by taking the positional distance into account when computing similarity between two patches. In this paper, we advocate super pixels as the basic units in saliency detection. We first use the adaptive mean shift algorithm to extract super pixels from the input image, then apply Gaussian mixture model (GMM) to cluster super pixels based on their color similarity, and, finally, calculate the saliency value for each cluster using spatial compactness metric together with modified PageRank propagation. Shows the overview of the proposed framework for salient region detection

3.1 ADVANTAGES OF PROPOSED SYSTEM:

1. Easily to find which place are be there.
2. Object recognition. We can easily identify the humans by recognising the face

4. SYSTEM ARCHITECTURE

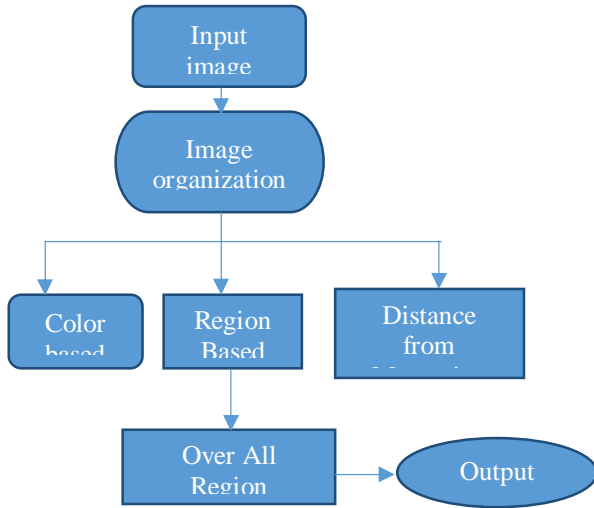


Fig 4.1 architecture for region based saliency detection

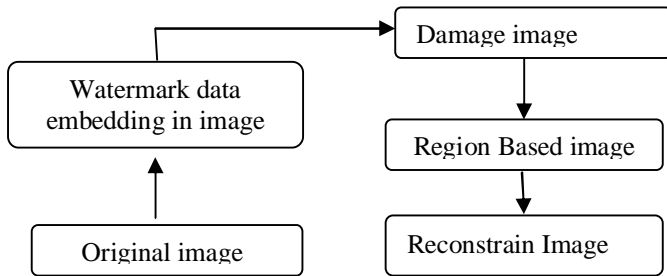


Fig 4.2 data flow diagram for damaged image

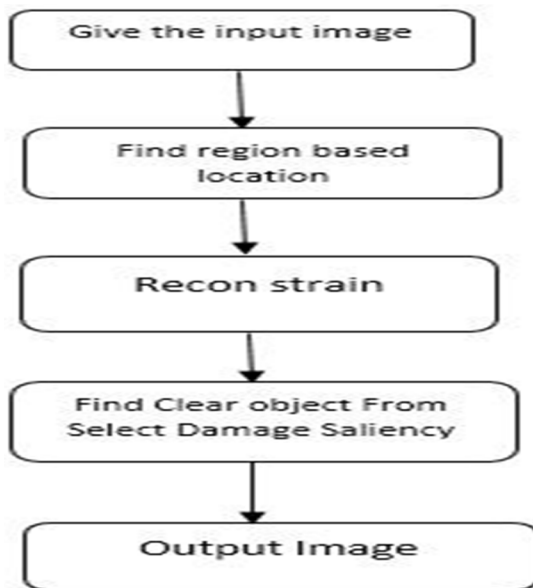


Fig 4.3 data flow diagram for clear image

5. MODULE DESCRIPTION

5.1 FACE RECOGNIZATION

The objects are usually more salient than the background. Therefore, the features located on the object should play more important roles for the recognition of the object in the images. Class-specific regions. The saliency of each super pixel is measured by using its spatial compactness, which is calculated according to the results. This Module only think find Object recognition. For object recognition, the objects are usually more salient than the background.

5.2. OBJECT MATCHING:

For object recognition, the objects are usually more salient than the background. Therefore, the features located on the object should play more important roles for the recognition of the object in the images. It's matching each pixel by pixel. And compare. We first use the adaptive mean shift algorithm to extract super pixels from the input image, then apply Gaussian mixture model (GMM) to cluster super pixels based on their color similarity Super pixels, the more perceptually meaningful units, are used to represent the input image, which could detect large salient objects and tolerate the outliers in the messy background during saliency detection. The Page Rank algorithm is then applied to propagate saliency among similar clusters and refine our region-base

5.3 .RECONSTRAIN:

Saliency detection methods can be divided into two categories. One is top-down method, which is task-dependent and based on prior knowledge about the scenes, objects, face, and their interrelations. Due to the prior in format. A common hypothesis for bottom-up saliency is that the salient stimulus is distinct from its surrounding stimuli. This hypothesis is also known as center-surround mechanism, which consists with the performance of human vision system in the early phase. Therefore, researchers usually focus on identifying those regions with high center-surround contrast in bottom-up methods. Itti *et al.* [38] proposed to determine the contrast by the difference of Gaussians (DoG). Instead of directly calculating similarity of two pixels.

5.4. ALBEDO METHOD:

Advocate super pixels as the basic units in saliency detection. We first use the adaptive mean shift algorithm to extract super pixels from the input image, then apply Gaussian mixture model (GMM) to cluster super pixels based on their color similarity, and, finally, calculate the saliency value for each cluster using spatial compactness metric together with modified PageRank propagation.

6. SCREENSHOTS

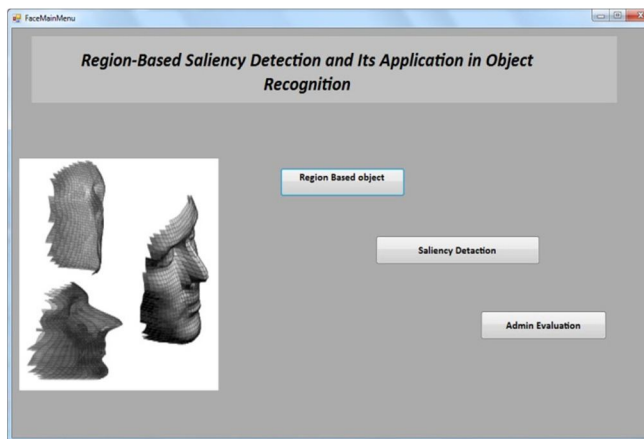


Fig6.1 Menu form

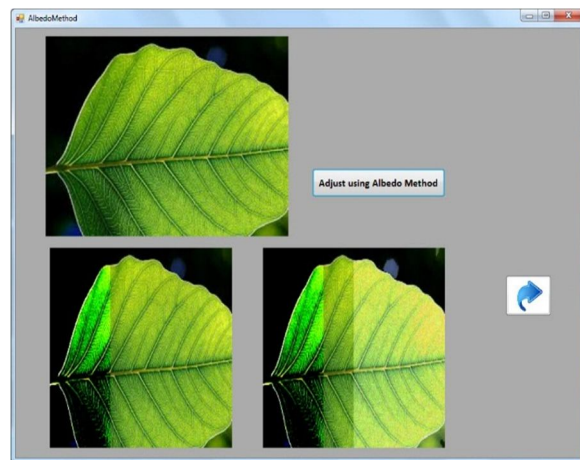


Fig6.4 Albedo method

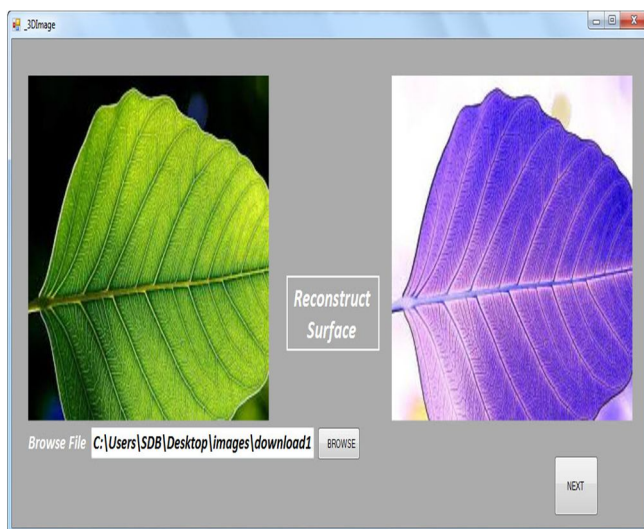


Fig6.2 Saliency detection

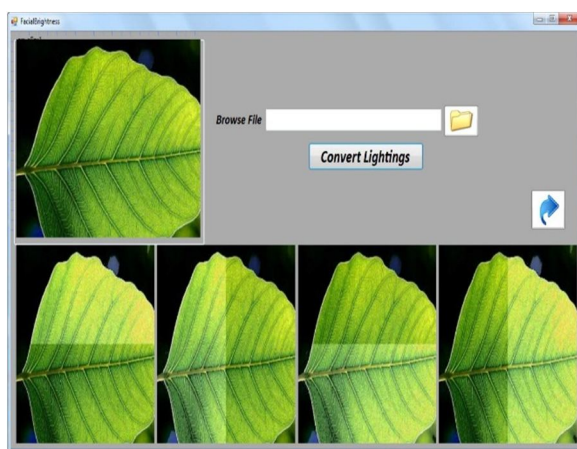


Fig6.3 Converting lightings

7. CONCLUSION

Proposes a promising saliency detection approach, which can generate accurate saliency maps with well-defined object boundary. To avoid deficiency of pixel representation in large salient region detection and tolerate noise, our method employs adaptive mean shift algorithm to extract perceptually and semantically meaningful super pixels as features. We also refine the saliency values by a modified Page Rank algorithm for propagating saliency between similar clusters. Experiments show that these two strategies can improve the saliency detection. To better encode those salient regions, which usually correspond to the objects, we propose a feature importance-based feature coding technique: weighted sparse coding. The weighted sparse coding can learn a discriminative codebook, which favors the coding of those more important object regions. We also propose a saliency weighted max pooling for image representation.

8. FUTURE ENHANCEMENTS

Besides features from spatial domain, characteristics from frequency domain are also investigated for saliency detection. Hou and Zhang calculated saliency on frequency domain based on spectral residual. Later, Guo *et al.* pointed out that it is not the amplitude spectrum but the phase spectrum that contributes to saliency detection. They make use of phase spectrum to detect saliency and extend 2-D Fourier transform to a quaternion Fourier transform for spatiotemporal saliency detection.

9. REFERENCES

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