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Saliency Detection from Geometric Attributes and Region Centerness

[1]Dr.P.Harish,[2]S.Sai Chandu [3]D.Saikeerthi,[4]G.Venu Gopala Krishna[5] P.Reddy Ganesh
[1]Associate Professor, Department of ECE, Annamacharya Institute of Technology and Sciences, Tirupati,A.P. India.
[2,3,4,5]B.Tech Student, Department of ECE, Annamacharya Institute of Technology and Sciences, Tirupati, A.P. India.

***Abstract*- Recent years have seen many complex models proposed for salient object detection and progressing results. However, less has been done to justify the need for such complex models as there lacks sufficient comparison to simple baselines on more challenging datasets. In this work, we propose a new baseline method for saliency detection. It simply considers a large region close to the image center as salient, and defines the saliency of a region as the product of its size and centerness. As accurate image segmentation problem is difficult by itself, we propose novel techniques that can estimate these attributes using superpixels in a soft manner, without the need to perform hard image segmentation. Our approach is based on very simple concepts and implementation, but already achieves very competitive results, especially on challenging datasets. Therefore we believe our method serves as a strong baseline and would enhance the problem understanding for future work.**

***IndexTerms*- saliency detection, geometric attributes region centernessetc.**

1. INTRODUCTION

Salient object detection [1] has attracted a lot of research interests in recent years . The problem is inherently ambiguous since there lacks common definitions and criteria of "what a salient object is". Consequently, the research in this area presents a great amount of diversity, from low level features to high level methodologies [14]. While many new methods have been proposed and steady improvements in evaluation have been shown, it is still unclear to tell how well and to what extent this problem has been solved.

We observed two issues in the current field: complex methodologies and insufficient evaluation. First, recent work uses more complex models. highlight the model has evolved from the previous simple contrast-based method [3,4].

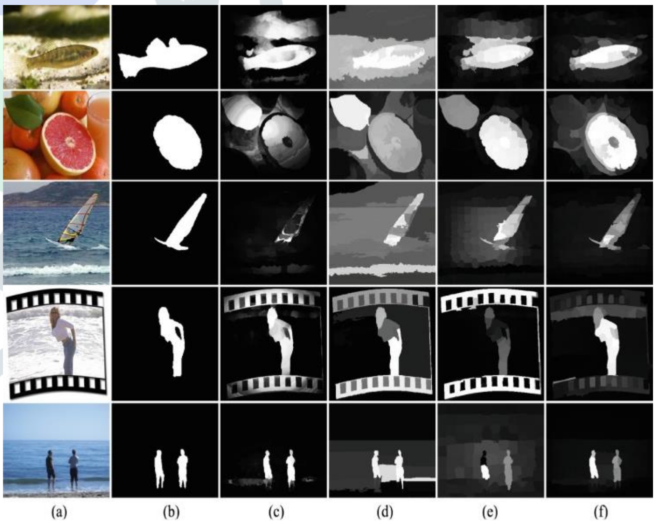

Fig.1: Excellent recognition results in a challenging example. (A) Input image; (b) Ground Truth; (c)-(e) Prior art results; (f) Our results.

From frequency analysis-based methodsto more complex methods such as Gauss Mixture appearance model , low-ranked matrix recovery , multiscale segmentation and optimization , graph-based manifold ranking , Submodular optimization , hypergraph modelling , Markov chains , Learning-based and fusion of multiple models . All these models Motivated, explained, and presented from a unique perspective I did it well. However, size and location are important due to the high complexity and wide variety. New baseline for prominent object detection.

It's very difficult to understand how the different methods are related and what they really are It can be used for highlight detection. In other words, it's unclear if it's expensive Is complexity essential. The second problem is that the evaluation is primarily performed on a simple ASD [7]. Or an MSRA [2] record. It is generally accepted that these datasets are biased

A large object near the center of the image that has a strong contrast [5] with what is included. The background is too simple. Although some other more sophisticated datasets SED1 [17], SED2 [17], SOD [18], ECSSD [10], etc. have been proposed. They are rarely used in evaluations. During a performance with a simple ASD Recent datasets are almost saturated, but it's relatively unclear if that's a good thing. ASD models can be generalized to more sophisticated datasets.

This work is an attempt to address the above two issues by proposing a simple one. It shows the baseline method and strong results. Our method uses only two basic ones Concept: The size and location of the area to determine its excellence. Clock Defines large image areas near the center of the image to be more prominent Its size and regional excellence as a central product. Our definition Intuitive and compatible with human vision. How the problem is Make sure to calculate such a concept.Region sizes are obviously beneficial, but they have rarely been used so far. This is probably because accurate image segmentation problem itself is difficult and there is no good enough segmentation algorithm. While region center has been well known to be useful for saliency estimation, its usage in previous work is usually overly simple, nonadaptive (such as a gaussian centered on the image) and does not work well for images with different spatial object/background compositions. Our approach is based on a key observation that geodesic distances between image superpixels essentially encode the segmentation information. We therefore propose a superpixel based and unified geodesic filtering [9] framework to compute these concepts in a simple and robust manner: (1) it computes approximate region sizes without actually performing image segmentation; (2) it estimates relative region locations with respect to the image center adaptively.

We treat it as an approach-based approach because both the concept and the implementation are simple and can be easily extended or combined with others. A sophisticated model. Nevertheless, our results are very powerful and encouraging. Extensive experimental comparisons of all the above datasets This method is often compared to many modern, state-of-the-art complex models. Especially the best in SED2 [17] and SOD [18], the second best SED1 [17]. Example of the figure. 1 shows the various challenges of the previous method. Low contrast objects (fish, boats), high contrast but eccentric background Areas (green leaves), complex object / background composition (movies), and multiple small objects (beach). Our method works well for such difficult cases The previous method gives noisy results.

The second promising result is simply after combining the results The other method is a significant improvement over all previous methods with new, cutting-edge results. In addition, the gap between them before combining is reduced. This makes it clear that these concepts underlie our concepts. The approach is very effective and complements previous work.

In summary, this task uses the basics to address the highlight detection issue. Principle: Large and central area stands out. Our baselines are compared favorably It also highly complements much more sophisticated models across different datasets. The combination of simplicity and powerful results convinces us The proposed concept makes the essence of the highlight detection problem clearer It casts doubt on the need to adopt more complex models. In addition to technical contributions, we also hope that this work will inspire and encourage this area. A beneficial change in thinking.

The whole paper is organized as explained Literature Survey in section II, Section III discusses the types of diseases detection,. Section IV shows the methodology of the project, Section V shows the Simulation Results The conclusion has been given of the discussed in Section VI.

2. LITERATURE SURVEY

Geometric attributes such as the size and position of the image area are important in determining their excellence. However, extracting the appropriate image area is not possible. It's a challenging problem in itself. All commercial image segmentation algorithms There is a similar problem with how to automatically select the appropriate parameters. Usually the same parameters can produce different results through different results The image and this causes unstable area attributes.

Here's an easy way to estimate the size and position of an image Create an area without actually performing image segmentation to mitigate the above problem. Works with normal superpixel image representation. Or The parameters are easy to set and the results are stable. It is continuously based A measure of how well twosuperpixels are spatially connected is called a geodesic. Connectivity of this work. Further define based on connectivity measurements A basic operation called geodesic filtering. The image is initially split into hundreds of superpixels (200 inches). Our implementation) using the latest ones with similar size and normal boundaries SLIC algorithm [20]. Joining produces an undirected weighted graph Adjacent super pixels. Edge weights wi and j between superpixelsi and j Euclidean distance between averagecolors of CIELabcolorsuperpixels place. Geographical distance or length of shortest path between any The two superpixelgeodists (i, j) .

Geodesy distance measures the cumulative difference in appearance. It also characterizes the geodesic connection between the two superpixels They are spatially connected. For the same type of superpixel Area, geodetic distance is close to 0, connection is close to 1. Otherwise, the geodetic distance is large and the connection is close to zero. Superpixels have a large connection value only forsuperpixels in the same area of the same kind, and have near zero connection values for other superpixels. With that in mind, geodetic connectivity measurements actually encode information. Implicit and soft image segmentation [8]. Intuitive, easy to implement, and stable. The only important parameter is σ. We, When σ ∈ [10, 20], the power is stable. Empirically set to 15 Next, define a geodesic filtering process for measuring image properties.Area of superpixels. Suppose you have a feature map M for the primitive region. In superpixel representation, that is, M (i) is the property value of the superpixel. i, geodetic filtering calculates the properties of the area of superpixeli

A global filtering of feature map M using geodetic connections as weights. It aggregates and smoothes property values Same homogeneous area. After filtering, all have superpixels in the same area Similar property values for this area. By removing the normalized part (Get the filtering of the (3) non-normalized version of the denominator) expression.

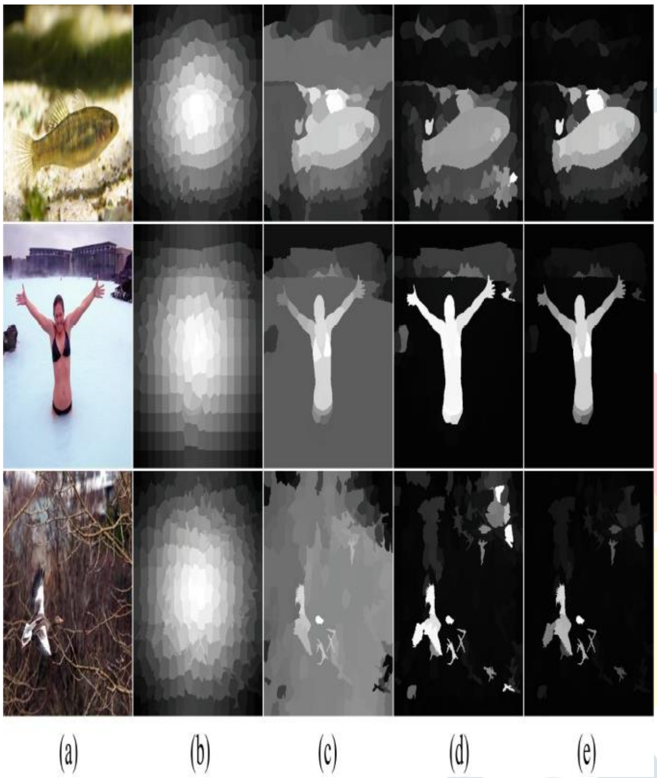

Fig. 2: Display of centering calculation. (A) Input image; (b) Super pixel base Gauss map Cgau; (c) Geographically filtered Gauss map SCgau of equation (1). (4); Image boundary-based centrality map Cbnd in equation (d). (5); Final centering map C of equation (e). (6).

It is represented by GF ~. Perform sums instead of averaging. Compared to use Hard image segmentation, our method usually produces smoother and more Stable results. Sample results before and after geodetic filtering are displayed Figures 2 (b) and (c).

Note that the geodesic propagation approach in [21] is somewhat similar to our work, as it essentially applies geodesic filtering. Improved input rough symptom map. Therefore, it can be considered as a post-processing and as a special case from us. In contrast, our approach is motivated derived from a more general perspective: analyze geodesic relationships Distance and segmentation, and generalization of geodetic filtering as a framework To calculate more useful area characteristics (size and mean) for saliency estimation. This is novel and effective.

3. METHODOLOGY

1. Adaptive Computation of Region Centerness

Many enhancement methods are designed to assign higher enhancement to the central area of the image. However, with the previous method [6], the average is Image centerand fixed radius. Such maps do not take image content into account and are problematic for off-center objects and multiple objects. Several ways Re-estimate the mean and radius of the Gauss map from the initial saliency map Then improve the saliency map accordingly. This strategy is not yet suitable It is a multi-object and is highly dependent on the quality of the original saliency map.

Propose a simple adaptation method[25] for calculating image centers Areas that mitigate the above problems. Start with a Gauss falloff map with a mean in the center of the image and a standard deviation of 10% for the image. Dimensions (shorter image width and height). This Gauss map Convert to Super Pixel Based Version: Include All Pixels in Same Super Pixel Those values were averaged. A superpixel-based Gauss map is called a Cgau. An example is shown in the figure. 2 B). This map is blocky, homogeneous and non-uniform Image area. Then it is smoothed by geodesic filtering.

The smoothed map is shown in Figure 2 (c). It's much better, but it's still not enough because the large background area usually covers the central part. It is a Gauss map and still has a large "centrality" value. To reduce such errors, we also have a large background area The border of the photo. However, special attention should be paid to the object. I often do so. You can also see that the background area is more distributed than the objects (objects) and is more closely related to the boundaries of the image. You rarely touch different sides of an image, but the background is usually To do. Next, we define a new centrality map Cbnd for the four sides of. Image boundaries where the value of superpixeli is calculated by display Geodesic distance to all four sides,

Where L (i), T (i), R (i), and B (i) are from the superpixeli. Left, top, right, bottom border. Add a small constant The four distance values avoid degeneracy when equal to zero. Figure 2 (d) shows the sample results of Cbnd. Large background area coward. 2 (c) is suppressed accordingly.

The measured value of the equation. (5) It differs from the work of [11,22] in that it is tricky but important. Method. This is shown in Figure 3. Method [22] simply uses geodesics The distance of the superpixels to the entire edge of the image. It's very sensitive When touching a bounding object, as shown. 3(b). The method in [11] uses the four boundaries separately in its first stage. However, it does not exploit the concept of geodesic connectivity but uses a complex optimization based on manifold ranking. This usually produces results that are hard to understand, as shown in Fig. 3(c). In contrast, our approach better preserves the boundaries that touch the object and removes the largest background, as shown in Figure 3 (d).Two central maps of the expression. (4) and (5) are complementary. Our final The centrality map is obtained as the product of the two.

An exemplary centering map is shown in Figure 2 (e). Wise than that Maps in Figures 2 (c) and (d): The value of the object in the center of the image is high Large backgrounds will be removed.

Expression centering measurement. (6) Very adaptable to image content. It Can naturally detect off-center objects [16] or multiple objects, as shown in Fig 1, 2, 3. This is the main reason why our approach is superior to the previous method. An image that contains multiple objects.

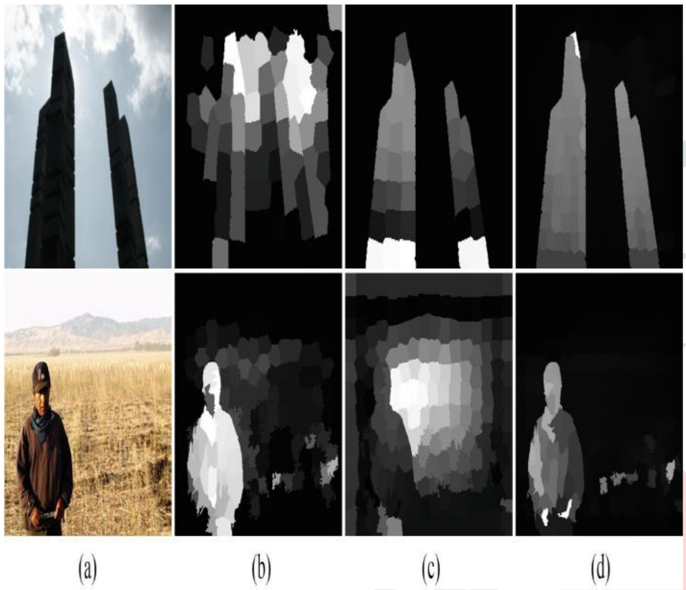

Fig.3:It will explain the advantages of CenternessCardCbnd. (A) Input image; (b) The result is [22]. (C) The result of the first stage of [11]. Result from Cbnd in equation (d). (Five).

2. Approximate Computation of Region Size

The concept of range size is intuitive, but rarely used in previous versions. work. The possible reason is that it is almost impossible to calculate the area.The size is accurate as the image segmentation can be unstable and inaccurate. area.

Keep in mind that accurate segmentation may not be required. Since then The size and shape of superpixels are similar. The basic idea is to count. Use the number ofsuperpixels in a uniform area as an approximate size. region. This is done smoothly using the geodesic filter approach. Sect. 2. N is the number of superpixels and U is called uniform mapping. Has the same normalized region 1 N for all superpixels. Calculate the region As a size map.

Note that you are using an unnormalized version of geodetic filtering. Superpixel It "sums" all superpixels from there within the same homogeneous area Region size. Our "soft" compared to hard image segmentation methods The approach[25] leads to more stable and smooth results. This is an example of Figure 4. [23] tested one of the most widely used image segmentation methods. There are several parameters. I tried different values and found it difficult to find General parameters that give reasonable results for different images. we We also tried a normalized cut and mean shift segmentation algorithm, Similar problem. In contrast, our method calculates a stable and smooth area There are no difficult issues with size maps and parameter selection.

The final saliency map is the area size and middle,

Note that we are using the square root of the area size to reduce the sensitivity of the product About range sizes found to be heuristically useful.

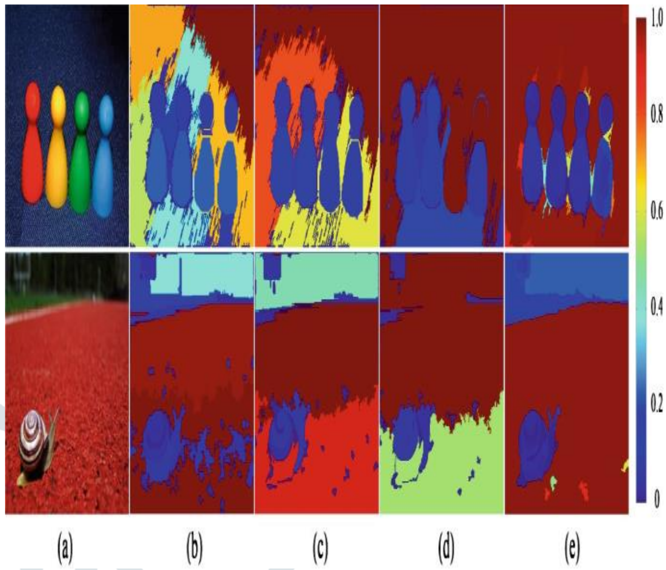

Fig. 4: An example of the result of calculating the size of the area (which looks good in color) Segmentation method and our method. (A) Input image; (b) – (d) Regional size map Use the segmentation method of [23] with various parameters. (E) Regional size map Our way. Area size values are normalized to [24] and visualized in color (Online color illustration).

4. SIMULATION RESULTS

A. DATASET-1

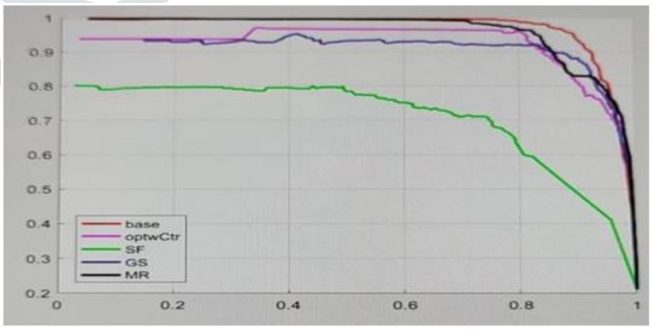

Fig.5:PRCurvefor Dataset –1

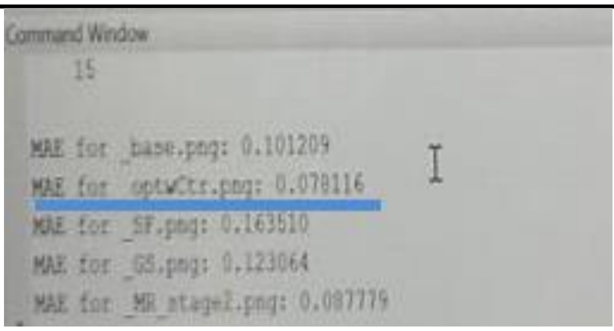

Fig.6: : Mean Absolute Errors for different methods from Dataset-1

B. Data Set 2

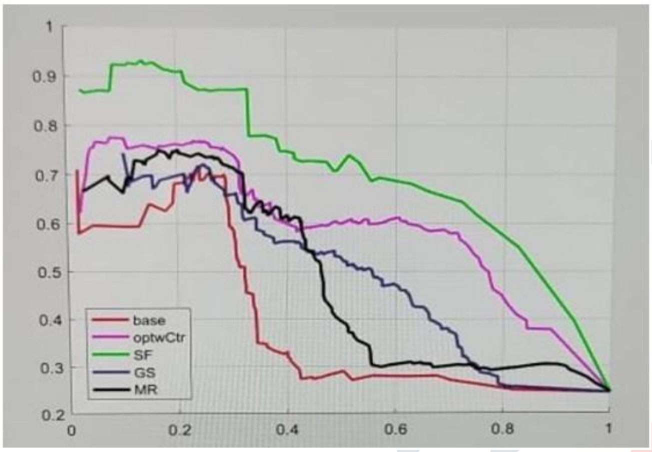

Fig.7:PRCurveforDataset-2

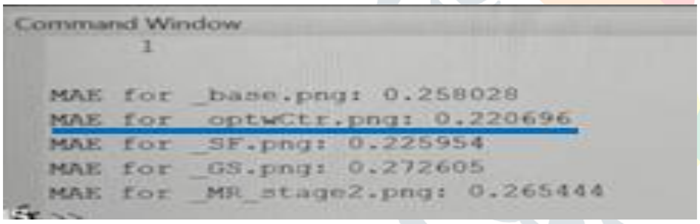

Fig.8:MeanAbsoluteErrorsfordifferent methods fromDataset-2

C. Dataset 3

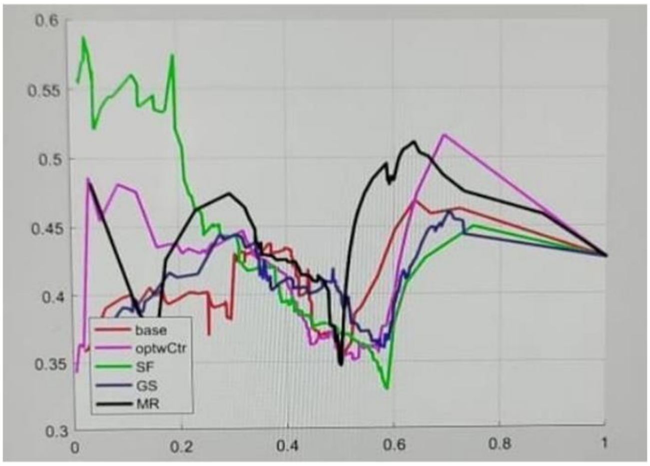

Fig.9:PRCurvefor Dataset-3

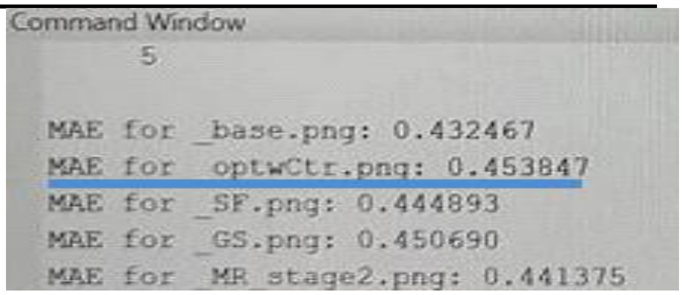

Fig.10:MeanAbsoluteErrorsfordifferent methods fromDataset-3

6. CONCLUSION

Presents a new baseline saliency technique. It uses basic principles and concepts Of the size and location of the area. I showed you how to evaluate these attributes With a simple technique without the need to perform image segmentation. our This method works well with a variety of datasets, including the most demanding datasets. It is well compared and well combined with state-of-the-art technology For further improvement. I hope this work can deepen your understanding. Solves prominent object detection problems and makes more work easier to use A well-generalized model.

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