Saliency Detection using Geometric Context Contrast Inferred from Natural Images

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Abstract: Image saliency detection using region contrast is often based on the premise that salient region has a contrast with the background which becomes a limiting factor if the color of the salient object background is similar. To overcome this problem associated with single image analysis, we propose to collect background regions from a collection of images where generative property of, say, natural images ensures that all the images are spun out of it hence negating any bias. Background regions are differentiated based on their geometric context where we use the ground and sky context as background. Finally, the aggregated map is generated using color contrast between the superpixels segments of the image and collection of background superpixels.

1 INTRODUCTION

Salient object detection has many useful applications in image understanding, image summarization, and object detection. The goal for single image salient object detection is to highlight pixels that stand out. We explore the view that for an object to be salient it should not only be salient in the image itself but it should be salient in a larger context of similar images. In this paper we propose use of background geometric context regions derived from similar images to highlight a salient object.

In color comparison based salient object detection algorithm, color comparisons are done between regions in a single image. The major drawback of this approach is if the salient object and background has similar color profile the comparison based algorithm fails to detect the salient region correctly. To overcome that problem we propose the use of salient features derived from a large collection of similar natural images. The advantages of using natural images are its generative property (Hyvärinen, 2009) ensures that all images can be seen as being spun out of it and natural images have closeness to evolutionary visual process which is developed in the visual cortex of primates.

For a given input image we first find the similar natural images derived from its scene category and GIST descriptor based distance. For these natural images we find their geometric context (Hoiem *et al.*, 2005). The geometric context divides an image into three regions, namely sky, ground and verticals. Geometric context helps to find only similar background regions (sky or ground). The regions here are represented using superpixels (Veksler *et al.*, 2010) as each of them is more or less homogeneous in its color property.

Figure 1: Input Image, Saliency Map, and Ground Truth.

We experimentally show that a salient region can be effectively highlighted when the salient region is compared to a large set of background superpixels from a similar collection of natural images. The main contributions of this paper are as follows. i) we show that an object is salient in a context of similar natural images, ii) a collection of natural images can be used to aid saliency detection and, iii) geometric context plays a useful role in comparison based saliency detection.

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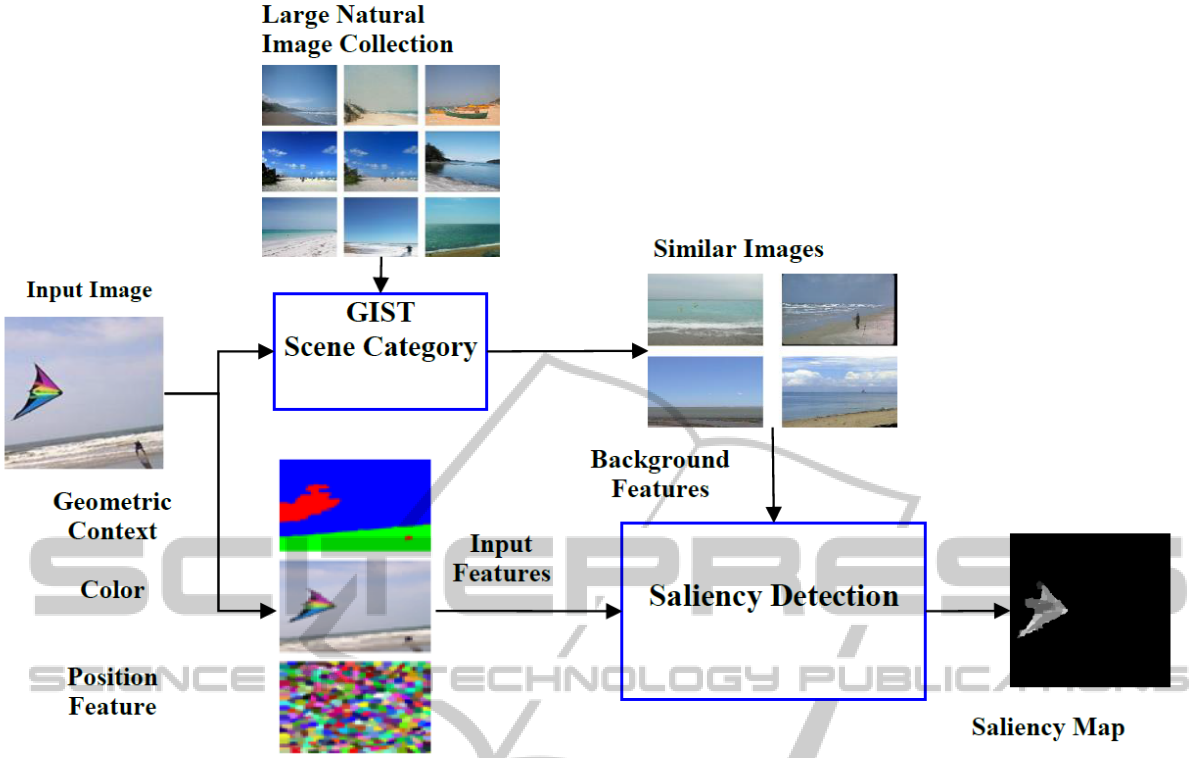


Figure 2: Flow diagram for proposed method.

This paper is organized as follows. We begin by reviewing related work in Section 2. In Section 3, we describe our algorithm by briefly introducing how similar natural images are found followed by image features required for saliency detection. We then describe in details the method for computing visual saliency detection using large collection of background superpixels. In Section 4, we present our experimental results. Finally, we draw our conclusions in Section 5.

2 RELATED WORK

There are two general directions for saliency detection, the first being biologically inspired where the focus is to mimic eye-tracking which in practice is not very useful for other computer vision applications (Cheng *et al.*, 2011). The second one is that of salient object detection where the main goal is to highlight the salient object in the image which is mostly found using region based color contrast (Singh *et al.*, 2014; Goferman *et al.*, 2010; Cheng *et al.*, 2011). The contrast based methods mainly differ on how the color representation is chosen. Once the color representation is established saliency is found by contrasting between regions. The line of work that are similar to our work is that of co-saliency where an image-saliency pair is used to guide saliency of a new image.

Co-saliency between images is learnt by combining features using weights of a linear SVM as a feature mapping technique between two image pairs (Toshev *et al.*, 2007). Co-saliency discovers the common saliency on the multiple images where the contrast, spatial and correspondence cues are compared between clusters to find the co-occurrence of an object in dataset. Co-saliency (Cheng *et al.*, 2011) is found as a product of saliency and repeatedness. Co-saliency for salient object is found using co-segmentation. An energy function is minimized to get segmentation of an object from two different images using a joint-image graph (Jacobs *et al.*, 2010). Co-segmentation (Mukherjee *et al.*, 2009) can be inferred with a penalty on the sum of squared differences of the foreground region's histogram.

Our method is different from others methods in a way that we use only background regions from similar images because a region should be salient in a larger background and not just in the image.

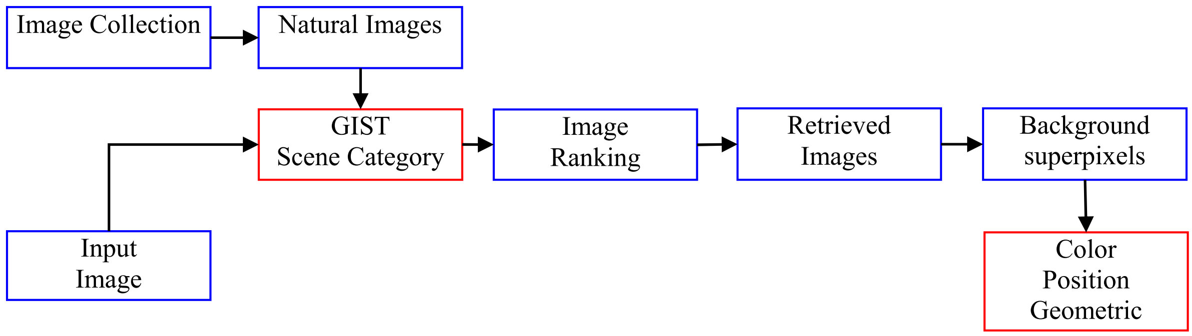


Figure 3: Pipeline for retrieving similar images and their background features.

3 SALIENCY DETECTION

Our goal is to highlight a salient region using background geometric context (sky and ground) from similar set of natural images. Figure 2 shows the flow diagram for the computation of the proposed saliency detection algorithm. In order, we describe superpixels generation, retrieving similar images, image features computation, and saliency computation.

3.1. Image over Segmentation

To highlight a salient region in an image we want to compare and contrast it against a collection of similar images. Comparison step is of quadratic order hence comparing pixels is computationally expensive it is suitable to divide the images into regions. Superpixels are a good representation of regions. They are usually homogeneous and their boundaries fall on image edges making them true segments. Superpixels can be generated by clustering of pixels based on similarity or defining them as a labelling problem and solving it using an energy minimization framework.

3.2 Similar Image Search

A salient image regions stands out in the context of other similar natural images. To find similar images we use a collection of publicly available natural image datasets. For an input image we find the image category that matches closet to it. This ensures images are extracted based on the most similar category. Next, using images from a similar category we find the GIST descriptor to retrieve N closest image. Figure 3 shows the pipeline of retrieving similar images and their background features.

3.2.1 Natural Image Category

The SUN database (Xiao *et al.*, 2010) is the most extensive scene category database where there are three types of broad scene hierarchy as indoor, outdoor man-made, and outdoor natural. We pick the outdoor natural category as the source of natural images. The outdoor category gives a generic set of similar images for the input image.

3.2.2 Similar Image Search

Image categories can have results in thousands of images and it is not feasible to compare using all of them. Each category itself will have various types of images. To get images that are most similar from the chosen category to input image we use GIST descriptors. Similar scene images provide a dual advantage as in they are not semantically different and yet they provide discriminant background information.

GIST (Oliva and Torralba, 2001): GIST is one of the first scene recognition descriptors. It has been widely used for scene completion and image retrieval applications. These descriptors are based on perceptual properties of the natural images and it summaries these images into low dimensional representation. The GIST descriptor computes the output energy of a bank of 24 filters. The filters are Gabor-like filters tuned to 8 orientations at 4 different scales. The square output of each filter is then averaged on a 4×4 grid. GIST summarizes the scene (image) well and as a descriptor makes it very useful for finding similar images.

Image Ranking: We rank category images based on the closeness between their GIST descriptors and input image descriptors. The ranking ensures similar the images have a higher rank. We choose N most similar images where N is empirically set at 20 based on image ranking.

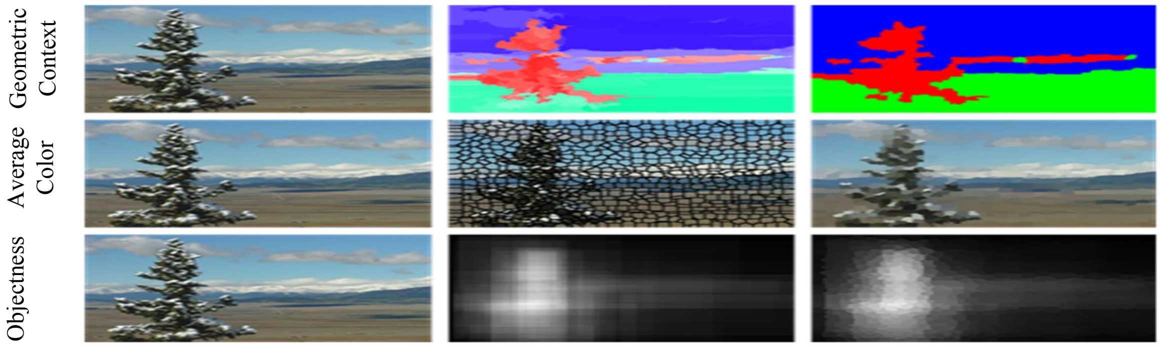


Figure 4: Image Features.

3.3 Image Features

For each superpixel region we would like to compute features that are used for saliency computation. For our algorithm we use geometric context, color difference, position difference and objectness measure. In this section we will describe each of the features in detail. Figure 4 shows example of image features at pixel level and superpixel level.

3.3.1 Color Difference

Color is most dominant attribute for the salient region. A salient region is highly discriminative in the color space. The color space used is CIE *L*a*b** which is closest to human visual system. To summarize a region most commonly used method is to find the average color in each channel. Other methods to summarize a region use quantized color histogram (Cheng *et al.*, 2011) and dominant color descriptor (Singh *et al.*, 2014). We use average color as it is simple to compute and superpixels are mostly homogeneous with respect to color.

3.3.2 Geometric Context Feature

Saliency detection as an early process is used to assist higher level vision tasks like object detection. It was found by (Torralba *et al.*, 2003) that context plays a very important role in object detection for real world scenario. Conventional saliency detection algorithms largely ignore the geometric context while estimating the distinct pixels in an image. We explore the use of context for saliency detection.

Any outdoor natural image can broadly be divided into three contexts viz. sky, ground and vertical objects. These three context categories are relative to the 3D orientation of a region with respect to camera. Dividing the image into geometric context of the images by learning on image features for a segment like color, texture, location, shape and 3D geometry was first proposed by (Hoiem *et al.*, 2005).

For saliency detection geometric context can be used to compare between contrasting contexts. Most salient regions are highly likely to be in the vertical context while non salient background regions are likely to be in sky and ground context. We propose to use geometric context as a feature where only background contexts (sky and ground) are used of comparison.

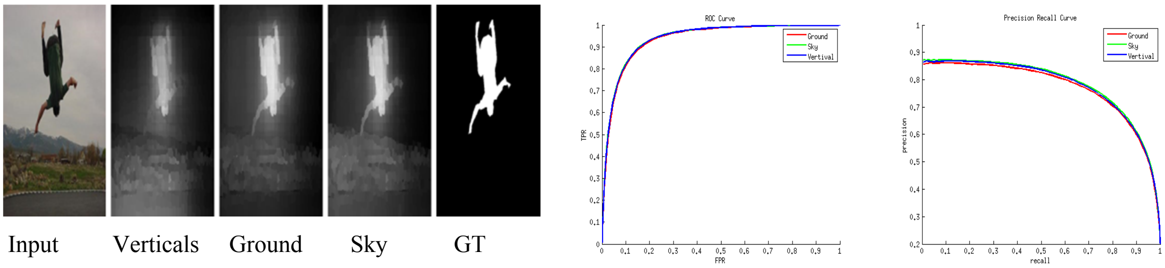
The learning algorithm can learn more than one context for the pixels within superpixel. To compute geometric context for each superpixel is done by estimating which context that has the maximum influence. Maximum influence is the context with the most number of pixels to it:

$$\mathrm{geo_r} = \begin{cases} \mathrm{gc_{sky}}, & \text{if mc = sky;} \\ \mathrm{gc_{grd}}, & \text{if mc = ground} \\ \mathrm{gc_{vert}}, & \text{if mc = vertical} \end{cases} \quad (1)$$

where, $\mathrm{geo_r}$ is the geometric context for superpixel r; the terms $\mathrm{gc_{sky}}, \mathrm{gc_{grd}}$, and $\mathrm{gc_{vert}}$ are categorical labels associated with the context; and mc is the maximum influencing context.

3.3.3 Position Difference

The spatial position of each superpixel in image plane is given by calculating the mean position value of all the constituent pixels in the superpixel. For saliency detection purpose it gives the correct estimate for the spatial location of superpixel in the image plane. In our saliency model the motivation is to show that salient superpixels are closer to each other and background is all over the place.



5a: Visual comparison. 5b: ROC curve. 5c: Precision Recall curve.

Figure 5: The sky and ground geometric context used as background gives better performance over the vertical context.

3.3.4 Objectness Measure

The objectness map of an image is the probability of occurrence of a generic object in a window (Alexe *et al*., 2012). Sampling for object windows gives the notion of objectness (Sun and Ling, 2013) which ensures higher objectness measure for a pixel if there is a higher probability of occurrence of an object. Objectness for a superpixel is computed by summing and averaging the objectness value of all the pixels under each superpixel and is given by

$$\mathrm{objectness}_i = \frac{1}{J}\sum_{j=1}^{J}\mathrm{Pob}_r(x_j, y_j) \qquad (2)$$

where, $\mathrm{objectness}_i$ is the objectness for superpixel *i*, J is the total pixels in superpixel r, Pob_r is the probability of occurrence of an object. We use objectness as noise reduction, bias and focus. It effectively reduces low level responses attributed to non object pixels.

3.4 Saliency Computation

First step in our saliency computation is quantization of background features derived from natural images. We extract sky and ground geometric context superpixels from the similar natural images. These superpixels are most likely to contribute to background region as compared to vertical regions. Since a large number of superpixels are collected we quantize them into groups by using k-means clustering. K-means uses objective function which minimizes a measure to find cluster center. The objective function used is given as:

$$\underbrace{\min}_{\{c_1,\dots,c_j\}} \sum_{j=1}^{K}\sum_{i=1}^{N}\left\|x_i - c_j\right\|^2 \qquad (3)$$

where $\left\|x_i - c_j\right\|^2$ is the distance measure between a data point x_i and the cluster centre c_j. The total number of clusters is determined by the number of superpixels in the target image to ensure that the number of comparisons remains constant.

3.4.1 Color Contrast

Color contrast or comparison is one of most distinct ways of highlighting a salient region. Color contrast has been extensively used for saliency detection (Singh *et al*., 2014; Goferman *et al*., 2010; Cheng *et al*., 2011). We use average color to represent each superpixel. The color difference between two superpixels is given as:

$$\mathrm{Dcol}(sp_i, sp_j) = \sqrt{{L_{diff}}^2 + {a_{diff}}^2 + {b_{diff}}^2} \qquad (4)$$

where, $\mathrm{Dcol}(sp_i, sp_j)$ is color difference between superpixel sp_i and superpixel sp_j. The variables ${L_{diff}}^2, {a_{diff}}^2$ and ${b_{diff}}^2$ are color distance for *L*a*b** color channels respectively between superpixels sp_i and sp_j. The distance between centers of superpixels is used to find the spatial or position difference:

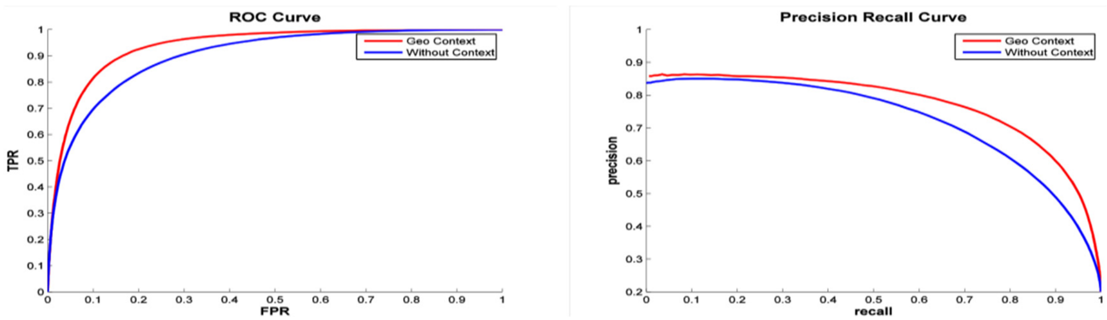
$$\mathrm{Dpos}(sp_i, sp_j) = \sqrt{(x_i - x_j)^2 + (y_i - y_j)^2} \qquad (5)$$

where, $\mathrm{Dpos}(sp_i, sp_j)$ is distance between centre x_i, y_i and centre x_j, y_j of superpixels sp_i and sp_j.

We incorporate geometric context by computing two sets of maps for sky and ground context. A superpixel dissimilarity measure can be given by combining the above equations

$$D_{gc}(sp_i, sp_{gc}) = \frac{\mathrm{Dcol}(sp_i, sp_{gc})}{1 + \mathrm{Dpos}(sp_i, sp_{gc})} \qquad (6)$$

where, the variable $D_{gc}(sp_i, sp_{gc})$ is the geometric dissimilarity, $\mathrm{Dcol}(sp_i, sp_{gc})$ is the color difference between superpixel i from input image and superpixel sp_{gc} from similar images with $gc \in \{\mathrm{sky}, \mathrm{ground}\}$. The variable $\mathrm{Dpos}(sp_i, sp_{gc})$ is the



a: ROC curve. b: Precision Recall curve.

Figure 6: Geometric context gives better result than baseline average color.

position difference between superpixel centres. Aggregated dissimilarity is given as

$$\mathrm{Gsp_i} = \frac{1}{n}\sum_{j=1}^{n} d(\mathrm{sp_i}, \mathrm{sp_{gc}}) \tag{7}$$

where, the variable $\mathrm{Gsp_i}$ is aggregated dissimilarity measure for superpixel *i*, n is the number of superpixels and $d(\mathrm{sp_i}, \mathrm{sp_{gc}})$ is local geometric dissimilarity measure. Final map is given as an average of maps

$$\mathrm{sal_{final}} = w_1 * \mathrm{sal_{sky}} + w_2 * \mathrm{sal_{ground}} \tag{8}$$

where, $\mathrm{sal_{final}}$ is the average saliency map and $\mathrm{sal_{sky}}$ and $\mathrm{sal_{ground}}$ are the saliency map found using sky and ground geometric context. The weights w_1 and w_2 are set at 0.5.

3.4.2 Normalization Step

Every saliency map will have low-level responses as some regions attract less attention. Our approach focuses on salient object highlighting we would like to suppress the low level responses associated with non-salient regions. These low level responses are associated with non object regions which affects the connectedness of the saliency map. Normalization is achieved using objectness measure. The objectness measure gives a measure of occurrence of generic object in a scene. Finally the saliency map is normalized using objectness as follows

$$\mathrm{salNorm_i} = \frac{1}{2}(\mathrm{sal_i} + \mathrm{objectness_i}) \tag{9}$$

where, $\mathrm{salNorm_i}$ is the normalized saliency value and $\mathrm{sal_i}$ is final saliency value and $\mathrm{objectness_i}$ is objectness map value for superpixel *i*.

4 EXPERIMENTS

Algorithm 1. Saliency Detection

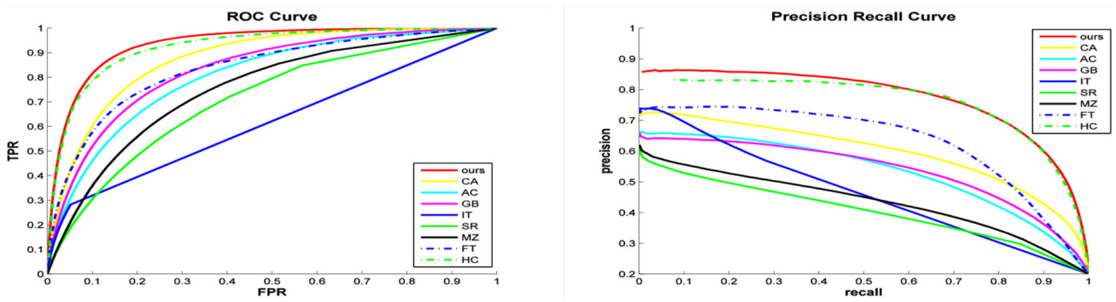
1. Divide the image into superpixels
2. Find N similar natural images
   a. Compute GIST descriptor
   b. Rank and Retrieve Images
3. Compute features for similar images and input image
4. Quantize the background superpixels using k-means
5. Compute saliency detection for image vs sky and image vs ground
6. Normalization for suppressing low-level responses

Implementation: Algorithm 1 shows the steps for computing saliency map. Implementation of our saliency detection was done in C++ using the OpenCV library. Superpixels were generated using publically available code by (Veksler *et al*., 2010). We use the respective authors' implementations for objectness (Alexe *et al*., 2012), geometric context (Hoiem *et al*., 2005), GIST descriptors (Oliva and Torralba, 2001) and scene category (Xiao *et al*., 2010).

Data Set: We test our algorithm on the ASD data set (Achanta *et al*., 2008), which has 1000 images, each with an unambiguous salient object. The ground truth was generated by labelling only one salient object in the image.

Evaluation: We perform quantitative evaluations to shows (i) geometric context for sky and ground gives better results than verticals context, (ii) geometric context gives better performance than average color and (iii) our method outperform other state of art methods.

Evaluation metrics are consistent for all three sets of experiment and we use benchmark code



7a: ROC curve. 7b: Precision Recall curve.

Figure 7: Comparisons of our method ("ours") with other state-of-the-art methods (see Table 1) using the ROC and the Precision Recall curves.

Input Ours CA AC HC GB IT SR GT

Figure 8: Visual comparisons of our results ("ours") with other state-of-the-art methods. See Table 1 for method references.

given by (Borji *et al.*, 2012). We use ROC curve where area under the curve shows how well the saliency algorithm predicts against the ground truth.

Precision is defined as the ratio of salient object detected to ground truth thus higher the precision the more the saliency map overlaps with the ground truth while recall quantifies the amount of ground-truth detected.

Background Context Evaluation: The ROC curve in Figure 5b and the precision-recall curve in Figure 5c as well as the visual comparison in Figure 5a show that background context (sky, ground) gives better results than vertical context.

Geometric Context vs Average Color Evaluation: The ROC curve in Figure 6a and the precision-recall curve in Figure 6b show that use of geometric context improves results over baseline average color.

Table 1: Saliency detection methods for comparison.

Method	Reference
IT	(Itti *et al.*,1998)
SR	(Hou *et al.*, 2007)
MZ	(Ma *et al.*, 2003)
AC	(Achanta *et al*, 2008)
CA	(Goferman *et al.*, 2010)
GB	(Harel *et al.*, 2007)
HC	(Cheng *et al.*, 2011)
FT	(Achanta *et al*, 2009)

Comparison to State-of-the-art Methods: In order to compare our work we use ROC curve (Figure 7a), precision-recall curve (Figure 7b) and visual comparison (Figure 8) with other saliency detection methods (Table 1).

From the comparison result we can quantitatively establish that our methods out-perform other methods.

5 CONCLUSIONS

We present a novel method of detecting saliency using geometric context derived from a large collection of natural images. We give new direction for highlighting salient region by deriving background context from similar images. We experimentally show that our method out performs other state of art methods.

For future work we would like to include attribute based information in extracting background features along with attribute matching for image segments.

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REFERENCES

Achanta, R., Estrada, F., Wils, P., and S¨usstrunk, S., 2008. Salient region detection and segmentation. In *ICVS*, pp 66–75.

Achanta, R., Hemami, S., Estrada, F., and S¨usstrunk, S., 2009. Frequency-tuned salient region detection. In *IEEE CVPR*, pp 1597–1604.

Alexe, B., Deselaers, T., and Ferrari, V., 2012. Measuring the objectness of image windows. *IEEE Transactions on PAMI*, vol. 34, no. 11, pp. 2189-2202.

Borji, A., Sihite, D.N., and Itti, L., 2012. Salient object detection: A benchmark. In *ECCV,* pp. 414-429.

Chang, K-Y., Liu, T-L., and Lai, S-H., 2011. From co-saliency to co-segmentation: An efficient and fully unsupervised energy minimization model. In *IEEE CVPR*, pp. 2129-2136.

Cheng, M.-M., Zhang, G.-X., Mitra, N.J., Huang, X., and Hu, S.-M., 2011. Global contrast based salient region detection. In *IEEE CVPR*, pp.409-416.

Goferman, S., Zelnik-Manor, L., and Tal, A., 2010. Context-aware saliency detection. In *IEEE CVPR*, pp. 2376-2383.

Harel, J., Koch, C., and Perona, P., 2007. Graph-Based Visual Saliency. In *NIPS,* pp. 545-552.

Hoiem, D., Efros, A.A., and Hebert, M., 2005. Geometric context from a single image, In *IEEE ICCV,* vol. 1, pp. 654-661.

Hou, X., and Zhang, L., 2007. Saliency detection: A spectral residual approach. In *IEEE CVPR*, pages 1–8.

Huazhu. F., Xiaochun, C., Zhuowen, T., 2013. Cluster-based co-saliency detection. *IEEE Transactions on Image Processing*, vol.22, no.10, pp.3766-3778.

Hyvärinen, A., Hurri, J., and Hoyer, P. O., 2009. *Natural Image Statistics: A Probabilistic Approach to Early Computational Vision*, Springer-Verlag, London.

Itti, L., Koch, C., and Niebur, E., 1998. A model of saliency-based visual attention for rapid scene analysis. *IEEE Transactions on PAMI*, vol 20, no 11, pp. 1254–1259.

Jacobs, D. E., Goldman, D.B., and Shechtman E., 2010. Cosaliency: Where people look when comparing images. In *ACM UIST*, pp. 219-228.

Li, X., Lu, H., Zhang, L., Ruan, X., and Yang, M-H., 2013. Saliency detection via dense and sparse reconstruction. In *IEEE ICCV*, pp. 2976-2983.

Ma, Y.-F., and Zhang, H.-J., 2003. Contrast-based image attention analysis by using fuzzy growing. In *ACM Multimedia*, pages 374–381.

Mukherjee, L., Singh, V., Dyer, C.R., 2009. Half-integrality based algorithms for cosegmentation of images. In *IEEE CVPR*, pp.2028-2035.

Oliva, A., and Torralba, A., 2001. Modeling the shape of the scene: a holistic representation of the spatial envelope. *IJCV*, 42:145–175.

Singh, A., Chu, C.H., and Pratt, M.A., 2014. Multiresolution superpixels for visual saliency detection. In *IEEE CIMSIVP*.

Sun, J., and Ling, H., 2013. Scale and object aware image thumbnailing. *International Journal of Computer Vision*, vol. 104, no. 2, pp. 135-153.

Torralba, A., 2003. Contextual priming for object detection. *IJCV,* vol 53, no 2, pp. 169-191.

Toshev, A., Shi, J., and Daniilidis, K., 2007. Image matching via saliency region correspondences. In *IEEE CVPR,* pp.1-8.

Veksler, O., Boykov, Y., and Mehrani, P., 2010. Superpixels and supervoxels in an energy optimization framework. In *ECCV*, pp. 211-214.

Xiao, J., Hays, J., Ehinger, K.A., Oliva, A., and Torralba, A., 2010. SUN database: Large-scale scene recognition from abbey to zoo. In *IEEE CVPR*, pp. 3485-3492.

Zhai, Y., and Shah, M., 2006. Visual attention detection in video sequences using spatiotemporal cues. In *ACM Multimedia*, pages 815–824.