

A Pertinent Region Estimation By Using Global Large Dimensional Color Transform and Local Constructional support

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ABSTRACT: An approach is described which significantly detect pertinent region in an image. Pertinent region is the main focusing part of a digital image that draws human attention. This approach considers global and local features. For pertinent region detection, first over-segmentation of a digital image is performed to form superpixels and then initial pertinency trimap is generated to build feature vectors. After that, global large dimensional color transform (LDCT) and local regression based (LRB) methods are used. In LDCT, colors of pertinent regions and its backgrounds are distinctively gets separated and in LRB, local structural relations and color contrast between superpixels are considered. The resulting detections of both the methods are combined to form final pertinency map. LRB method has low computational complexity and is an excellent match for LDCT method. Here, State-of-the-art pertinent region detection methods are compared with proposed approach. Proposed approach outperforms the state-of-the-art algorithms both on ground truth evaluation and low computational complexity.

KEYWORDS: Pertinent region detection, Superpixel, Trimap, Large-dimensional color space.

I. INTRODUCTION

Pertinent region detection is essential in image learning and dissection. Its objective is to find out pertinent regions in an image in terms of a pertinency map, such that, the drawn regions would gain 'human' attention. Many researchers have shown that pertinent region detection is advantageous, and it has been utilized in many applications including segmentation [1], object recognition [13], image retargetting [4], video compression [5], and image quality assessment. The encouragement behind pertinent region detection is people's visual recognition. As color is an essential visual clue to human, many pertinent region detection methods are based on distinguishing color detection from an image.

An advance proposal is described to significantly detect pertinent regions in an image. A tree-based classifier is used to evaluate proximate locations of pertinent regions. Classification of a superpixel into foreground, background and unknown is done through this classifier. This classifier classifies foreground and background regions as pertinent and non-pertinent regions. The regions with uncertain features are classified as unknown regions. An initial trimap is formed by foreground, background and unknown regions, and objective is to solve the uncertainty in the unknown regions to evaluate correct pertinency trimap. Two separate methods are described, to evaluate the pertinency map from the trimap, large dimensional Color Transform (LDCT) based method and local regression based (LRB) method. The resulting two pertinency maps are merged through a supervised weighted sum-based fusion.

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II. RELATED WORK

This section represents reviews of state-of-the-art salient region detection methods.

1. Local-contrast-based approach: This approach detects salient region by detecting rarity of image features in a small local region. Itti et al. [14] proposed a saliency detection method which utilizes visual filters called “center-surround difference” to calculate local color contrast. Harel et al. [15] suggested a graph-based visual saliency (GBVS) approach which is based on the Markovian approach on an activation map. This approach checks the dissimilarity of center-surround feature histograms. Hou *et al.* [3] used the term “information divergence” which expresses the non-uniform distribution of the visual information in an image for saliency detection. Klein and Frinrop [16] utilized information theory and defined the saliency of an image using the Kullback-Leibler divergence (KLD). The KLD measures the center-surround difference to combine different image features to compute the saliency.
2. Global-contrast-based approach: This approach uses color contrast to detect salient regions. These approaches provide little computational complexity. Achanta et al. [6] proposed a frequency-tuned method to determine the centre-surround contrast using the color and luminance in the frequency domain as features. Shen and Wu [7] divided an image into two parts—a low-rank matrix and sparse noise—where the former explains the background regions and the latter indicates the salient regions. Cheng et al. [8] described a Gaussian mixture model (GMM)-based abstract representation method that simultaneously evaluates the global contrast differences and spatial coherence to capture perceptually homogeneous elements and improve the salient region detection accuracy.
3. Statistical-learning-based approach: This approach detects saliency region. Wang et al. [9] proposed an approach that evaluates jointly the segmentation of objects learned by a trained classifier called the auto-context model to enhance an appearance-based energy minimization framework for salient region detection. Yang et al. [10] ranked the similarity of image regions with foreground clues and background clues using graph-based manifold ranking based on affinity matrices and successfully conducted saliency detection. Siva et al. [11] used an unsupervised method to learn patches that are highly likely to be parts of salient objects from unlabeled images and then sampled the object saliency map to find object locations and detect saliency regions.

III. PROPOSED METHODOLOGY

Following figure Fig.1 shows an overview of proposed methodology.

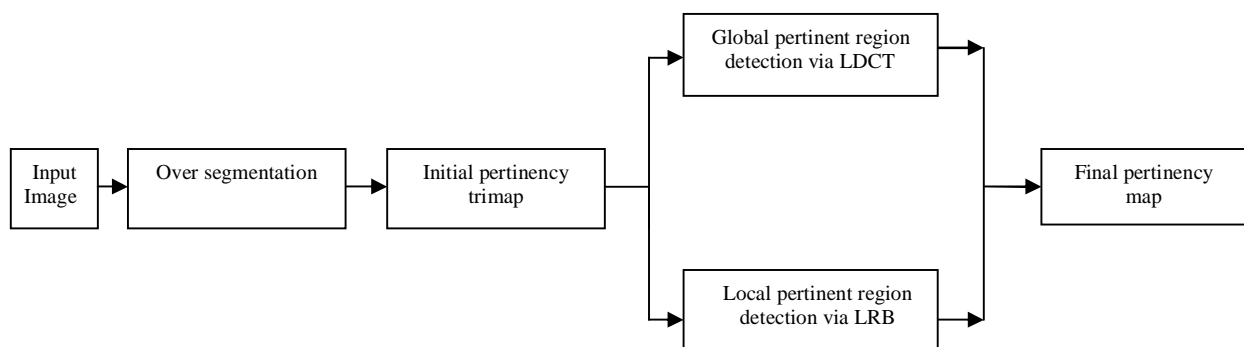


Fig.1. Overview of proposed methodology

In this approach, an input image is taken from standard dataset and over segmentation is performed on it to divide the image into superpixels in order to reduce computations. Here SLIC [2] superpixel is used due to its low computational cost and high performance. Then Initial pertinency trimap for the image is generated. To obtain final pertinency map from initial pertinency trimap, two methods are used one is large dimensional color transform (LDCT) and other is local regression based (LRB) method. Summation of both the results provide final pertinency map.

IV. EXPERIMENTAL RESULTS

This section shows results of proposed methodology and state-of –the-art methods.

1. Klein and Frintrap [16] have proposed salient region detection by “center surround divergence” method. Saliency system for this method is shown in Fig.2. In this method basic features of color, orientation and intensity are considered. Hue and saturation that represent polar co-ordinates in the HSL color space are converted into Cartesian coordinates, referred to as hue(x)- and hue(y)-layers. From these, average colors can be computed through integral layers. In HSL space, integral layers are built from input image to compute pyramid representations. These integral layers enable the calculation of summed and averaged values of arbitrary sized rectangular regions in constant time. The orientation feature computes partial derivatives from region-wise averages to determine the gradient direction on a given scale.

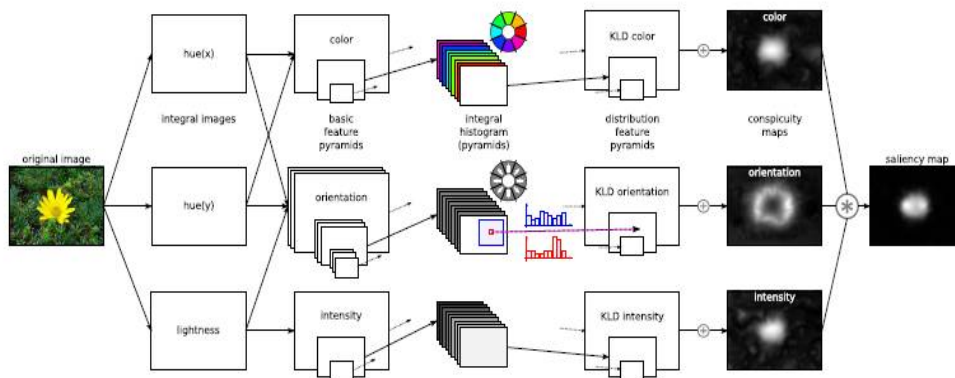


Fig.2. Saliency system

The above mentioned approach determines contrast of the center and the surround distribution of features for the dimensions intensity, color, and orientation. There is no need to scale the image data, but the feature size, which is an advantage in terms of speed but this approach fails to detect small red color boxes, as shown in Fig.3. In the output, green color boxes from input are more clearer than red color boxes. Red color boxes are not detected clearly.

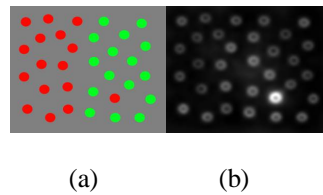


Fig.3. Failure: Red color boxes. (a) Input: image (b) Output: salient region

2. J.Kim [12] has proposed HDCT based salient region detection method. Salient region detection system by high dimensional color transform (HDCT) is shown in Fig.4. In this method, over-segmentation is performed on an input image to divide it into superpixels. Then initial saliency map for the image is generated. Threshold is done on initial saliency map, to obtain trimap where pixel colors within the definite foreground and the definite background regions will be used as initial color samples of the salient regions and background. Then low-dimensional color is mapped into the high dimensional color transform space and optimal linear combination of color channels is estimated through HDCT algorithm. Finally, color values in the high-dimensional color space are combined to obtain saliency map.

HDCT method fully don't coincide with human vision and it experience limitation of texture effect.

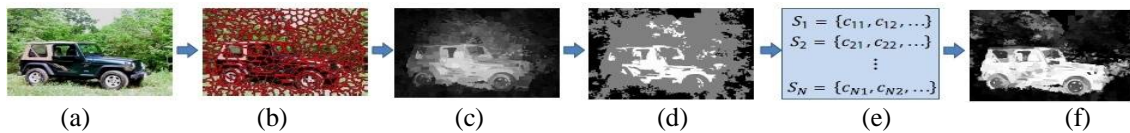


Fig.4. Overview of HDCT method. (a) Input image (b) Over-segmentation (c) Initial saliency map (d) Trimap (e) HDCT algorithm (f) Final saliency map.

3. Pertinent region detection by the proposed methodology is shown in Fig.5. In this methodology, over segmentation is done on input image to form superpixels. Then initial pertinency trimap composed of a foreground candidate, background candidate, and unknown regions is generated. LDCT method is applied on trimap to estimate global pertinent region and then LRB method is applied to estimate local pertinent region. Outcome of both the methods are combined to form final pertinency map.

In the proposed methodology, trimap-based robust estimation overcomes the limitations of inaccurate initial Pertinency classification. Also, it overcomes limitation of texture effect of HDCT by use of local regression based (LRB) method.

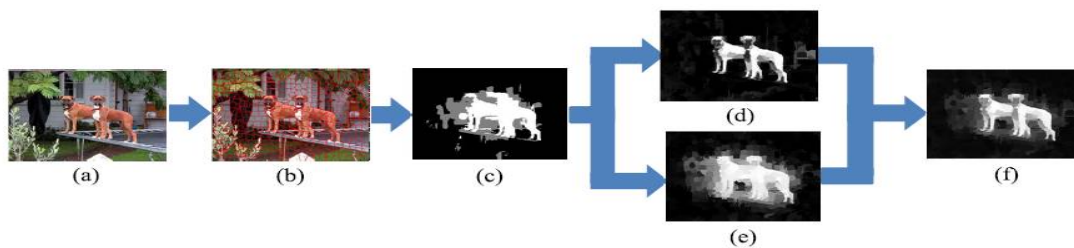


Fig.5. LDCT and LRB method. (a) Input image (b) Over-segmentation (c) Initial pertinency trimap (d) Global Pertinent region estimation via LDCT (e) Local Pertinent region estimation via LRB (f) Final pertinency map.

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V. CONCLUSION

The proposed methodology of pertinent region detection utilizes two different methods one is global pertinency estimation via large dimensional color transform (LDCT) method and other is local pertinency estimation via local regression based (LRB) method. LRB method has low computational complexity. It overcomes effect of texture from LDCT and hence it is an excellent match for LDCT method. The trimap-based robust estimation overcomes the limitations of inaccurate initial prominency classification. There is use of some most effective features that can be calculated rapidly, such as color, contrast and location features. So, the pertinent region can be found accurately using even a smaller number of features. Computations are performed in superpixel level. As a result, this proposed approach achieves good performance and is computationally efficient in comparison to the state-of-the-art methods. In the future, there is an aim to extend the features for the initial trimap to further improve algorithm's performance.

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