A High Dimensional Color Transform and Learning Based Approach for Dominant Area Detection

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Abstract:
An approach is described that significantly detect dominant region in an image. This approach considers global and local features, which is used to compute a dominancy map. First a dominancy map of an image is created by using a linear combination of colors in a high dimensional color space. This is based on observation that dominant regions have distinguishing colors compared to backgrounds in human vision. The small-dimensional red, green, and blue color are mapped to a feature vector in a high dimensional color space, an detailed dominancy map is composite by finding the excellent linear combination of color coefficients in the high dimensional color space. Secondly, the performance of dominancy estimation is raised by applying relative location and color contrast between superpixels to from a trimap via regression algorithm. The test results of two benchmark datasets found to be effective.

Keywords : Dominant region detection, trimap, superpixel, high-dimensional color space.

I. INTRODUCTION

Dominant region detection is essential in image learning and dissection. Its objective is to find out dominant regions in an image in terms of a dominancy map, such that, the drawn regions would gain ‘individuals’ deliberation. Many researchers have shown that dominant region detection is advantageous, and it has been utilized in many applications including segmentation, object recognition, image retargeting, photo rearrangement, image quality assessment, image thumbnailing, and video compression.

The encouragement behind dominant region detection is people’s visual recognition. As color is a essential visual clue to human, many dominant region detection methods are based on distinguishing color detection from an image. An advance proposal is described to significantly detect dominant regions in an image. A tree-based classifier is used to evaluate proximate locations of dominant regions.

Classification of a super pixel into foreground, background or unknown is done through this classifier. This classifier classifies foreground and background regions as dominant and non-dominant regions with great assurance. The regions with uncertain features are classified as unknown regions with little assurance. 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 dominance trimap. Two separate methods are described, to evaluate the dominancy map from the trimap, global high-dimensional Color Transform (HDCT)-based method and local learning based (LLB) method.

The outcomes of these two methods are combined to produce final dominancy map. For reducing computations superpixel level is considered. HDCT-based dominant region detection algorithm is used to evaluate the linear combination of various color spaces that separate foreground and background regions. The local learning based (LLB) dominancy detection method takes into account local spatial relations and color contrast between superpixels. local learning based algorithm has little computational complexity and is a magnificent aggregation to the HDCT-based global dominancy map evaluation method. The resulting two dominancy maps are merged through a supervised weighted sum-based fusion.

II. RELATED WORKDONE

• Local-contrast-based approach:

This approach detects salient region by detecting rarity of image features in a small local region. Itti et al. [1] proposed a saliency detection method which utilizes visual filters called “center-surround difference” to calculate local color contrast. Harel et al. [2] 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. Goferman et al. [3] combined global and local contrast saliency to improve detection performance. Klein and Frintrop [4] 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.

• Global-contrast-based approach:

This approach uses color contrast to detect salient regions. These approaches provide little computational complexity. Achanta et al. [5] proposed a frequency-tuned method to determine the center-surround contrast using the color and luminance in the frequency domain as features. Shen and Wu [6] 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. [7] 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.

- Statistical-learning-based approach:

This approach detects saliency region. Wang et al. [8] proposed a approach that jointly evaluate 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. [9] 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. [10] 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. Li et al. [11] described a saliency measure via dense and sparse representation of each image region using a set of background templates as the basis for reconstruction, and they constructed the saliency map by integrating multi scale reconstruction errors.

III. PROPOSED METHODOLOGY

In this approach, an input image is taken from standard dataset and over segmentation is performed on it to divide image in superpixels. Then Initial dominancy trimap for the image is generated. To obtain final dominancy map from initial dominancy trimap, two methods are used first is Large dimensional color transform (HDCT) and second is local learning based. Summation of both the results provide final dominancy map. FIGURE 1 shows overview of proposed scheme and corresponding steps are as follows.

- **Input Image:**
  Input image ‘I’ is a digital color image of size 128*128 from standard dataset namely MSRA-B, ECSSD, PASCALS-S. These datasets are obtained from internet.

  1) **MSRA-B:**
  The MSRA-B salient object dataset contains 5,000 images. In this dataset color of background and foreground are totally distinctive so detecting dominant region from its is less challenging.

  2) **ECSSD:**
  The ECSSD salient object dataset contains 1,000 images. This dataset contains structurally complex background, making it more challenging dataset.

- **Over-segmentation:**

  For input image, over segmentation is performed to form superpixels X = {X1, . . . , XN }. Superpixel is a polygonal part of digital image, larger than a normal pixel. Superpixels makes computations complexity low.

- **Initial dominancy trimap:**

  In Initial dominancy trimap, feature vectors are build by concatenating location feature color features, color histogram features, color contrast features, texture and shape features for each superpixels. The histogram features of the superpixel

  \[ DHi = \sum_{j=1}^{N} \sum_{i=1}^{1} \frac{(hik - h jk)^2}{(hik + h jk)} \]  

Equation (1) demonstrates this construction.

  \[ DGi = \sum_{j=1}^{N} d(ci, c j) \]  

Equation (2) represents global contrast DGi of superpixel.

  \[ DLi = \sum_{j=1}^{N} \omega d(ci, c j) \]  

Equation (3) demonstrates local contrast DLi of superpixel.

  \[ \omega_{ij} = \frac{1}{Zi} \exp \left( -\frac{1}{2\sigma^2} \| p_i - p_j \|^2 \right) \]  

Equation (4) denotes the normalized position of the \( i^{th} \) superpixel and \( Zi \) is the normalization term.

Random forest classification algorithm is applied after getting feature vectors for every superpixel. This algorithm is performed to check whether each region is dominant. From the outputs of the random forest, three-class classification is used to generate an initial dominancy trimap. Trimap performances considers foreground background and unknown candidates.

- **Global dominant region detection via HDCT:**

  From the trimap, global dominancy detection is done by High-dimensional color transform (HDCT) based method. In HDCT detection method, a linear combination of color coefficients in the HDCT space is found such that the colors of dominant regions and those of backgrounds can be distinctively separated. To build HDCT space, different nonlinear RGB transformed color space representations are concatenated. Here, only the nonlinear RGB transformed color spaces are concatenated, because the effects of the coefficients of a linear transformed color space such as YUV/YIQ will be cancelled when linearly combine the color coefficient to form map. The
color spaces concatenated include the CIELab color space and the hue and saturation channel in the HSV color space. Also color gradients are included in the RGB space as human perception is more sensitive to relative color differences than absolute color values. But this detection has limitation also that it is easily affected by the texture of dominant region and hence it has relatively high false negative rate too. To enrich power of HDCT method, power law transformations is applied to each color coefficient after normalizing coefficient between [0,1]. Equation (5) demonstrates the resulted high dimensional matrix.

\[ K = \begin{bmatrix} R_{f_1}^1 & R_{f_1}^2 & R_{f_1}^3 & G_{f_1}^1 & \cdots \\ R_{f_2}^1 & R_{f_2}^2 & R_{f_2}^3 & G_{f_2}^1 & \cdots \\ \vdots & \vdots & \vdots & \vdots & \ddots \\ R_{f_{n}}^1 & R_{f_{n}}^2 & R_{f_{n}}^3 & G_{f_{n}}^1 & \cdots \\ R_{b_1}^1 & R_{b_1}^2 & R_{b_1}^3 & G_{b_1}^1 & \cdots \\ \vdots & \vdots & \vdots & \vdots & \ddots \\ R_{b_{n}}^1 & R_{b_{n}}^2 & R_{b_{n}}^3 & G_{b_{n}}^1 & \cdots \end{bmatrix} \in \mathbb{R}^{N 	imes i} \tag{5} \]

in which \( R_i \) and \( G_i \) are the test image’s superpixel’s mean pixel value of the \( R \) color channel and \( G \) color channel, respectively. To obtain dominancy map, least square regularizer formula is used, refer to (6).

\[ \min \| U - \tilde{K} \|^2 + \lambda \| \alpha \|^2 \tag{6} \]

Where,

\[ \tilde{K} = \begin{bmatrix} R_{f_1}^1 & R_{f_1}^2 & R_{f_1}^3 & G_{f_1}^1 & \cdots \\ R_{f_2}^1 & R_{f_2}^2 & R_{f_2}^3 & G_{f_2}^1 & \cdots \\ \vdots & \vdots & \vdots & \vdots & \ddots \\ R_{f_{n}}^1 & R_{f_{n}}^2 & R_{f_{n}}^3 & G_{f_{n}}^1 & \cdots \\ R_{b_1}^1 & R_{b_1}^2 & R_{b_1}^3 & G_{b_1}^1 & \cdots \\ \vdots & \vdots & \vdots & \vdots & \ddots \\ R_{b_{n}}^1 & R_{b_{n}}^2 & R_{b_{n}}^3 & G_{b_{n}}^1 & \cdots \end{bmatrix} \]

where \( F_{Si} \) and \( B_{Si} \) are the foreground candidate superpixel among entire superpixels and the background superpixel among entire superpixels that are classified at the trimap generation step, respectively. \( M \) is the number of color samples in the foreground/background candidate regions and \( f \) and \( b \) denote the number of foreground and background regions, respectively, such that \( M = f + b \). \( U \) is \( M \) dimensional vector with value equal to 1 and 0 if a color sample belongs to the foreground and background candidate. The l2 regularized least squares problem is a well-conditioned problem that can be readily minimized with respect to \( \alpha \), for this refer to (8)

\[ \alpha^* = \left( \tilde{K}^T \tilde{K} + \lambda I\right)^{-1} \tilde{K}^T U \tag{8} \]

After obtaining \( \alpha^* \) the dominancy map can be constructed by (9).

\[ D_{G}(X_i) = \sum_{j=1}^{i} K_{ij} \alpha_{j}^* \quad i = 1, 2, \cdots, N \tag{9} \]

- **Local dominant region detection via LLB:**

From the trimap, local dominancy detection is done by local learning based (LLB) method. In Local learning based detection method, local spatial relations and color contrast between superpixels are considered and limitation of HDCT w.r.t texture effect is overcome in dominant region. LLB method uses random forest regression algorithm, which is effective for large high-dimensional data. Feature vectors are extracted using the initial trimap, and then, the dominancy degree estimated for all superpixels. For this local dominancy map, even those classified as foreground/background candidate superpixels in the initial trimap are reevaluated because they could still be misclassified. Although a superpixel located near the foreground superpixels tends to be a foreground, if the color is different, there is a high possibility that it is a background superpixel located near the boundary of an object. Two features are used in this method first, for each super pixel K-nearest foreground pixel and K-nearest background pixels are considered and for this Euclidean distance is calculated for this refer to (10).

\[ d_{FS_i} = \frac{\| P_i - P_{F_{Si}} \|_2^2}{\| P_i - P_{B_{Si}} \|_2^2} \quad d_{BS_i} = \frac{\| P_i - P_{B_{Si}} \|_2^2}{\| P_i - P_{F_{Si}} \|_2^2} \tag{10} \]

Second feature is color distance between superpixels. It is calculated by (11).

\[ d_{CF_i} = \begin{bmatrix} d(c_i, c_{F_{Si1}}) \\ \vdots \\ d(c_i, c_{F_{Si2}}) \\ \vdots \\ d(c_i, c_{B_{Si1}}) \\ \vdots \\ d(c_i, c_{B_{Si2}}) \end{bmatrix} \]

\[ d_{CB_i} = \begin{bmatrix} d(c_i, c_{B_{Si1}}) \\ \vdots \\ d(c_i, c_{B_{Si2}}) \end{bmatrix} \tag{11} \]

- **Final dominancy map:** The results of these two methods are combined in a principle way via a supervised weighted sum based fusion together to form final dominancy map. Equation (12) describes this operation.

\[ D_{sum} = \frac{1}{Z} (p(D_G) + p(D_L)) \tag{12} \]

in which \( Z \) is a normalization factor, \( p(.) \) is a pixel-wise combination function, \( D_G \) is the global dominancy result and \( D_L \) is the local result.

**IV. EXPERIMENTAL RESULTS**

This section shows results of proposed methodology for two datasets.

- **MSRA-B dataset:** Dominancy result for this dataset is shown in FIGURE 2. In this result first image (a) is original image from MSRA-B dataset and second image (b) is its dominancy region.

![Figure 2. Result of msra-b dataset](http://ijesc.org/)

- **ECSSD dataset:** Dominancy result for this dataset is shown in FIGURE 3. In this result first image (a) is original image from ECSSD dataset and second image (b) is its dominancy region.

![Figure 3. Result of ecssd dataset](http://ijesc.org/)
V. CONCLUSION

The proposed method of dominant region detection estimates the foreground regions from an initial dominancy trimap using two different methods first is global dominancy estimation via global High Dimensional Color Transform (HDCT) method and second is local dominancy estimation via local learning based (LLB) method. High Dimensional Color Transform (HDCT) detection uses HDCT algorithm and local learning based (LLB) detection uses regression algorithm. LLB method has low computational complexity and is an excellent complement for HDCT method. The trimap-based robust estimation overcomes the limitations of inaccurate initial dominancy classification. There is use of some most effective features that can be calculated rapidly, such as color, contrast and location features. So, the dominant 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.

VI. REFERENCES


