AN ENHANCED FUSION BASED REGION SELECTION FOR CO-SALIENT DETECTION

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ABSTRACT

Human eye is perceptually more sensitive to certain colors and intensities and objects with such features are considered more salient. Co-saliency is a term for common visual attention point. Co-saliency detection aims at discovering the common salient objects existing in multiple images, which is a relatively under-explored area. Most existing methods combine multiple saliency cues based on fixed weights, and ignore the intrinsic relationship of these cues. In this paper, it proposes a method for finding salient region for single image, and co-salient region for pair of images as well as multiple images. And it provide a general saliency map fusion framework, which exploits the relationship of multiple saliency cues and obtains the self-adaptive weight to generate the final saliency/co-saliency map. Previous methods sometimes inaccurately predict the background as common salient object in case of complex images. The feature representation of the co-salient regions should be both similar and consistent. Therefore, the matrix jointing these feature histograms appears low rank. By considering the low-rank matrix of features, which defines the independence of the features of the co-salient region, it can find energy. This energy will further use to determine the co-saliency map. It helps to determine the co-salient map for complex images efficiently. Detection of Co-salient image regions is useful in applications such as co-segmentation, common pattern discovery, co-recognition, Image retrieval etc.

Keyword: - *Co-saliency, salient region, cues, co-segmentation, super pixels*

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1. INTRODUCTION

Detecting salient or irregular objects in images can be considered as a fast pre-processing step for image analysis, and has been shown to be useful in various applications, for ex- ample, human detection , defect detection, data visualization, texture segmentation, and visual tracking. Despite the importance and benefit of saliency detection, the problem itself is not well defined, and the validity of a solution to the problem is not easy to evaluate or justify. Generally, the likeliness of an image region being salient or not may depend on the context in the image. Saliency detection could be made more specific if we introduce additional information. Given a pair of input images, we are asked to find the common salient object that appears in both images. Such problems might be solved using some unsupervised algorithms to find automatically the common parts among all possible correspondences between two candidate sets. Besides co-saliency detection, similar settings that take a pair of images as the input have also been employed in object recognition (co- recognition) and image segmentation (co-segmentation).

Visual attention is an effective simulation of perceptual behavior, which aims to find a salient object from its surroundings by computing a spatial saliency map. Co saliency is fundamentally distinct from traditional definitions of image saliency because it is a property of an image set rather than a single image. A salient object in a single image may not be co-salient in an image set if it does not change in an interesting way. Likewise, a co-salient object may not be salient without the context of the second image. Visual co-saliency is a subjective perceptual quality that makes similar objects in a group of images stand out from their neighbors and grab our attention by visually co-salient stimuli. A co-salient region usually exhibits the following properties, i.e., 1) A salient region in an image should be prominent or noticeable with respect to its surroundings. 2) High similarity can be observed for such regions with respect to certain features (e.g., intensity, color, texture or shape). Co-saliency detection is a key attention mechanism by allocating the perceptual.

Most of existing saliency algorithms formulate on detecting the salient object from an individual image. When it thinks for common salient regions, single image saliency lead to co-saliency concept and considered common visual attention seeking regions in a pair of images. Given an image pair, co-saliency is closely related to how we perceive visual stimuli and fixate on the most valuable information from the image pair. Compared with image co-segmentation that partitions an image pair into different segments (i.e., similar regions and backgrounds), saliency as a concept from human vision implies a selection and/or ranking by importance. More precisely, co-saliency is the subjective perceptual quality that makes similar objects in an image pair stands out from their neighbors and capture our attention by visually salient stimuli.

Co-saliency detection is firstly defined as discovering the unique object in a group of similar images. However, the requirement of the similar images, captured within the same burst of shots, narrows its applications. An alternative concept is more favorite, which targets to extract the common saliency from the multiple images with which non similar backgrounds. Also in the first methods they deal with the images with simple background. But some new methods also consider the images with complex background. Some methods use the previous saliency detection methods to effectively find the co-salient region.

2. LITERATURE SURVEY

Jacobs et al. [1] firstly propose co saliency detection searching the unique object in a series of similar images. First step is to find Standard thumbnails for the input image pair. It finds the product of nearest neighbor patch error, gradient magnitude of nearest neighbor offsets and Jude saliency as features. Then use the goal map and the above features to calculate the co-saliency map. With the help of this, it will find a co-saliency value and use it to create the image triage by cropping the appropriate important region. In this work, it explore the importance of local structure changes e.g. human pose, appearance changes, object orientation, etc to the photographic triage task. This allows creating collection-aware crops that can augment the information provided by existing thumb-nailing techniques for the image triage task. The main advantage was that it proposes the method to detect the Common visual attention from a pair of images. And the main problem is that it is limited to only for a pair of images.

After that Hwan-Tzong et al. [2] proposed a pre-attentive method to find the co-saliency. This algorithm does not need to perform the correspondence matching between the two input images, and is able to achieve co-saliency detection before the focused attention occurs. Extract sparse features from the images. Build feature distributions from filter response. After that it compares the feature distributions with the Kullback-Leibler divergence. Then update the distributions for a number of steps. The final saliency weight will reflect the locations of the co-salient object within the 2 input images. The joint information provided by the image pair enables the algorithm to inhibit the responses of other salient objects that appear in just one of the images. This algorithm is effective in identifying the common salient objects inside pairs of input images. The computation of pre-attentive co- saliency detection m is straightforward and fast. It expects that the algorithm can also be readily incorporated into other applications such as video analysis as a pre-processing step.

Co-segmentation is an extended application of co-saliency. Kai-Yueh Chang et al. [3]. In his paper discuss about the use of co-saliency in co-segmentation. The main methodology is Use 2 properties Distinctness and repeatedness. Find image pixels whose saliency value is greater than a specific threshold. In such distinct areas sample a point and describe it by SIFT feature. Find the weight (repeatedness) of the point. The weight of the remaining points can be calculated by interpolation. The algorithm extends the concept to multiple images. The main problem is the increased complexity.

An effective method for pair of images was proposed by Hongliang Li A et al. [4].First of all; find the single image saliency map. And then find the multi image saliency in a number of steps. It will do pyramid decomposition of an image pair, region feature extraction, co- multilayer graph representation, and normalized sim rank similarity computation. Then compute the global multi image saliency map for the co-saliency calculation. It has a high precision and recall value.

There is an efficient and effective cluster-based co-saliency detection method [5].This method, as an automatic and rapid pre-processing step, is useful for the many vision applications. Global correspondence between the multiple images is implicitly learned during the clustering process. Three visual attention cues: contrast, spatial, and corresponding, are devised to effectively measure the cluster saliency. The final co-saliency maps are generated by fusing the single image saliency and multi-image saliency. There is no need of heavy learning for this algorithm. It is simple, general, efficient and effective. The algorithm works for both single image and multiple images and also works for different background images. The main problem is that we need to know the number of clusters. It is difficult to determine how much does the misclassified pixels are.

Another method for co saliency detection for multiple images is by Hongliang Li et al. [6]. Find intra image saliency and inter image saliency for detecting common salient region. For that first do multi scale image segmentation, and then do voting for each pixel. The highest vote gaining pixel will be more salient. Find inter image saliency using Feature extraction. The main features are color, co-occurrence, and shape. Use minimum spanning tree and pair wise image matching for computing inter image saliency map. Co saliency map created with the inter and intra image saliency maps. It work well for complex images. But the false detection will occur when the object have no clear shape or color within the image group.

Zhiyu Tan et al. [7] Proposed another method based on affinity matrix. The input is a pair of images. It uses the inter and intra super pixel affinities. It will compute bipartite super pixel matching on intra affinity matrix which produces sparse and reliable affinities. Update the affinity matrix via super pixel affinity propagation and generate co-saliency map based on this. It gives better performance compared to previous methods.

Co-saliency detection via base reconstruction [8] is another method. Select the reconstruction base by evaluating the occurrence rate on all images. The clusters with low occurrence rate will be discarded. After that reconstruct each image with common/center cues. Compute reconstruction error and also a pair of saliency maps. Final co-saliency map is computed by gathering the 2 saliency maps. It have a high precision, recall value and F-measure.

There is a hierarchical segmentation based model [9] proposed by Zhi Liu et al.Do coarse and fine segmentation and find regional histogram ,object prior and intra saliency map. These features are used to find the co-saliency map. It gives a better computational efficiency. Some backgrounds may not suppress efficiently if the object and background have similar color.

Implicit rank-sparsity decomposition [10] is another method for co saliency detection. Input is a pair of images. In this create feature matrices for both images by dividing images into patches. Estimate the low-rank matrices and the concatenated support from this feature. Both intra and inter patch similarity are considered to find the co-saliency map. Compute the weight matrix W and the weight is used to find the co-saliency score. It is more efficient than previous methods. is possible to find both saliency and co-saliency using this method. It detect fewer non-salient regions as compared to previous methods. But it treats only for a pair of images.

Salient shape from a collection of images [11] is also proposed by Yi-Lei Chen et al. Input a text and a sketch. Then retrieve candidate images by per-filtering using keywords. The co-salient regions from maps are generated using GMM. Then find rank for each saliency cut with the measures: circularity, solidity, Fourier descriptor and shape context. Find the global prior by GMM. After that estimate global saliency based on global color prior. Do saliency segmentation according to it. The main advantage is that it work well for large set of datasets. Also it have a high precision and recall value. It can handle heterogeneous data from various internet sources. Also give better result for images with cluttered background. It need a keyword to filter out the candidate set and use labeling and related information to improve the saliency detection and segmentation.

3. METHODOLOGY

In this method, employ the rank constraint to integrate the superiority of each cue by weighting it self-adaptively. Self-adaptively weights each saliency map that participates in fusion process under the rank constraint. Fig. 1 shows the flow chart of the process.

Fig. 2 shows the flowchart of the method, consisting of six steps. The first two steps (b), (c) generate saliency maps and super pixels for all the images, respectively. Various saliency detection methods are used in this framework, and their outputs are employed as the elemental saliency maps. Next, perform saliency thresholding to extract the salient regions for each image, by selecting salient super pixels based on different maps. The salient region results are shown in Fig.2(d). The histogram is utilized to represent the feature statistics of the salient region. As in Fig.2(e), stack all the histograms to form a feature matrix [19], which is used to calculate the consistency energy of each elementary map. Finally, combine all the maps with self-adaptive weights decided by the energy values to generate the raw co-saliency map, and then refine the raw map to obtain the final one.

3.1 Saliency Generation

It can have input as a single image, a pair of image or multiple images. For calculating the co saliency it need to find the saliency map first of all. Various saliency detection methods are used in this framework. Single saliency map as well as previous co-saliency maps are used in this stage. As an improvement we add GMM based saliency map and also the content aware saliency map. The saliency methods used are Saliency detection via graph based manifold ranking - MR [13], Hierarchical saliency segmentation- HS [14], Global contrast based salient region detection- RC,HC [15], A unified approach to salient object detection via low rank matrix recovery- LR [16], Graph based visual saliency - GB [17].

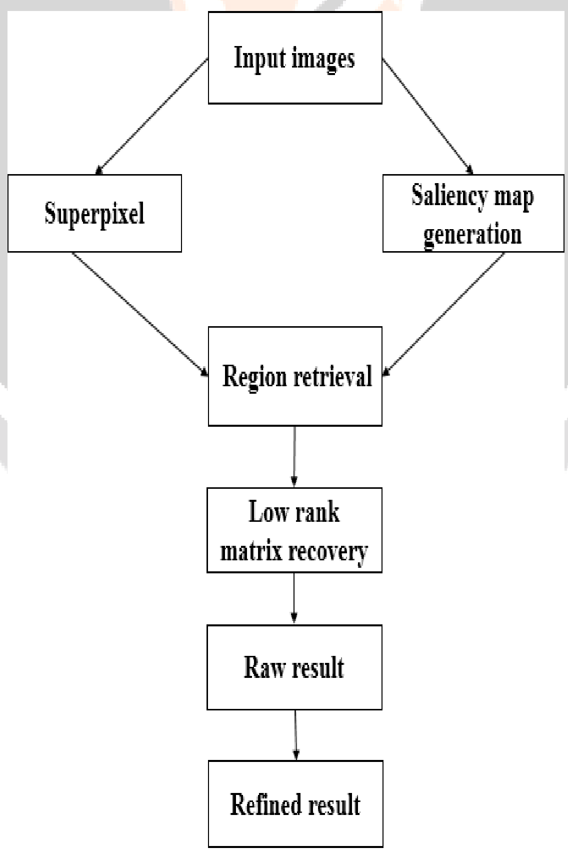

Fig -1: Flowchart

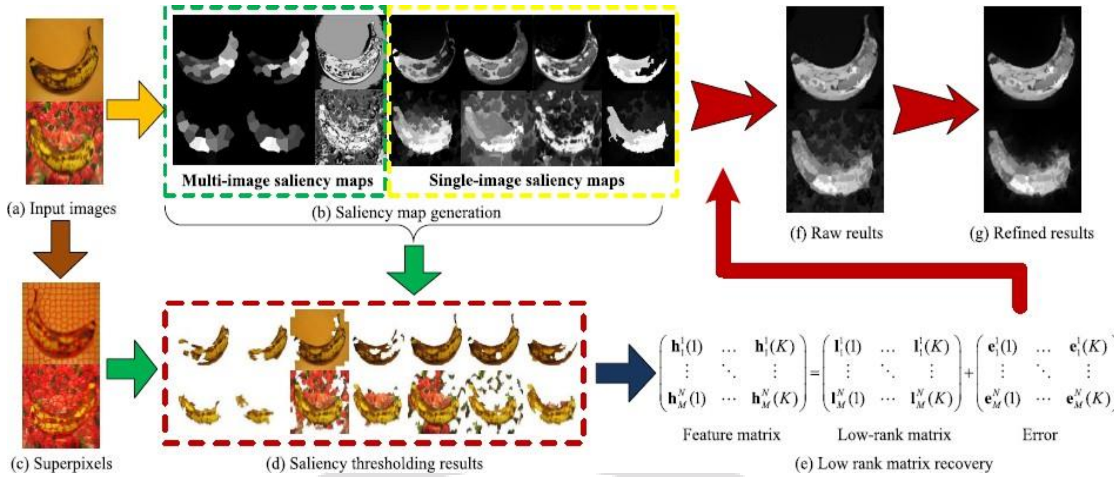

Fig -2: Framework

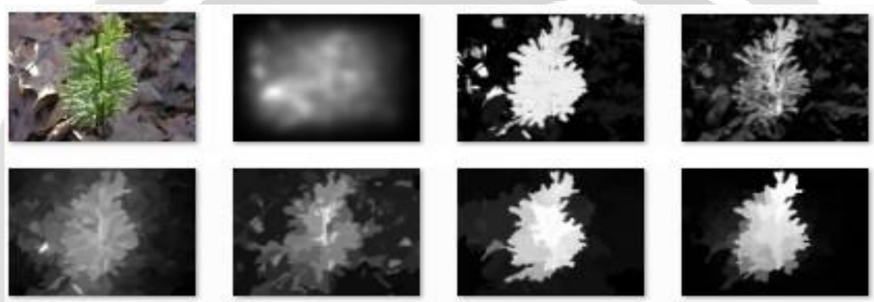

Fig -3: Saliency maps for fusion

These are single image saliency methods. And the multi image saliency methods include a co-saliency model of image pairs- CC, CP [4] and Cluster [20] based co-saliency detection-SP [5]. These single image saliency elementary maps and co-salient multi image maps are combined in the fusion step. Figure 3 shows a single image and 7 saliency maps of it.

3.2 Super pixel segmentation

Perform over segmentation to image by SLICE super pixel segmentation algorithm. SLIC (Simple Linear Iterative Clustering) that clusters pixels in the combined ve-dimensional color and image plane space to efficiently generate compact, nearly uniform super pixels. SLIC uses the same compactness parameter (chosen by user) for all super pixels in the image [21]. If the image is smooth in certain regions but highly textured in others, SLIC produces smooth regular-sized super pixels in the smooth regions and highly irregular super pixels in the textured regions. So, it become tricky choosing the right parameter for each image. It decompose image into a set of super pixels $\mathcal{X}^i = \{x_k^i\}_{k=1}^{n_i}$, where n is the number of all the super pixels in image I_i. Then and a binary map with the help of some thresholding. The saliency thresholding aims at extracting the salient region detected by a saliency map. A binary map B_j^i is defined by thresholding on S_j^i.

$$B_j^i(x) = \begin{cases} 1, & mean(S_j^i(x)) > T_j^i \\ 0, & otherwise \end{cases},$$

Where x 2 X_i, mean(:) computes the mean saliency score of all pixels in super pixel x by saliency map S_j^i, and the threshold T_j^i is computed by:

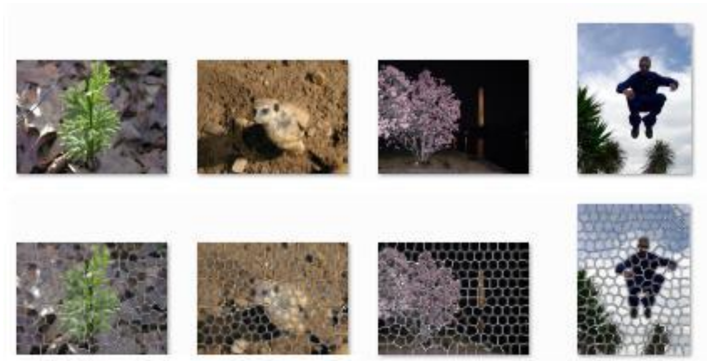

Fig -4: Super pixel segmentation for single images

Fig -5: Superpixel segmentation for multiple images

$$T_j^i = \alpha \cdot \max\{mean(S_j^i(x_k^i))\}_{k=1}^{n^i},$$

Where T^i_J is used to control the threshold.

Figure 4 and 5 shows the input images and their corresponding SLIC super pixel segmented images

3.3 Salient region detection

Here the salient region is a set of super pixels in an image and may not be spatially connected, which slightly di ers from the general concept of a connected region [22]. The salient region F_j^ican be defined as a set of candidate salient super pixels decided by the j^{th} saliency detection method in the image I^i , and it is obtained by:
$f_j^i = I^i{:}B_j^i$

where f_j^i may not be spatially connected. Each saliency map set S^i has a group of salient regions $F^{\,i} = f_j^{iM}{}_{j=1}$ and each Sj is corresponding $F^{\,j} = f_j^{iN}{}_{i=1}$. Depend on the salient region created the efficiency of calculating the weight will change. Here the binary map created by the thresholding is used to build the salient region. Also the selection of saliency maps also affect the quality. The more the feature related elementary maps used, it will get more quality.

3.4 Low rank matrix recovery

First, based on the definition of co-saliency in this work, the salient regions in F_j should exhibit similarity and consistency property. To measure this property, a 3-D color histogram is employed to represent each salient region, F_j^i, as a K-bin histogram. The 3-D color histogram is computed based on the three channels of the RGB color space. In detail, each color channel is uniformly quantized into 10 bins, and there is a total of $K = 10^3$ bins. Then, stack the

N histograms of the salient regions in F_j to get the matrix H_j, where $H_j = [h^1{}_j h^2{}_j{:}{:}{:}h^N{}_j\ ]^T$ 2 R(N xK). How much the j^{th} method contributes to the co-saliency detection could be measured by the consistency of rows in the feature matrix H_j . Create the feature matrix H_j. It is done by combining the color histogram of each salient region.

Since the salient regions in F_j should be similar, the rank of H_j is expected to be one ideally. In practice, saliency thresholding is unable to precisely separate the salient regions from original images. In addition, the color feature representation of the co-salient regions is sensitive to noises. Therefore, H_j is a low rank matrix. Formalize this property as rank constraint. An important benefit of this constraint [23] is that it transforms the consistency measure into measuring the rank of the feature matrix. Find the rank-one energy to calculate the consistency of H_j , which decides the self-adaptive weight of each map in the map set S_j .The similarity exists not only in F_j, but also in $F^{\ i}$. The feature matrix H^i is utilized to denote $F^{\ i}$, where $H^i = [h^i{}_1 h^i{}_2{:}{:}{:}h^i{}_M\ ]^T$ 2 R(M xK). Since the salient regions in $F^{\ i}$are used to represent the same salient object from the image I^i, rank constraint is also applicable forH^i . F = F $^{iN}{}_{i=1}$, and is described by the feature matrix H:

$$\mathbf{H} = \begin{bmatrix} \mathbf{H}^1 \\ \mathbf{H}^2 \\ \vdots \\ \mathbf{H}^N \end{bmatrix}$$

After that it will perform a singular value decomposition which will select the maximum variant rows from it. Suppose we know the SVD of a matrix. The key is in the singular values. Singular values are arranged in decreasing order so the rst singular value is big and the next after is smaller and smaller. Then some singular values are extremely small. It will consider only the k rows which are seem to be relatively more independent. The dependency [24] shows the common salient region. Since we use the thresholding we will not get a rank one matrix. So it will be a low rank matrix. Thus we need to nd the most independent part. It can be select by the singular value decomposition.

The rank-one energy focuses on the consistency of a set F_j. It is too strict to approximate the whole salient regions F. Thus the low-rank energy to describe the rank constraint as a more general version. The feature matrix H is utilized to represent the feature statistics of F. Hence, H could be decomposed as a sum of two parts H = L + E . Where, H: Feature matrix

L: Low rank matrix corresponding to salient region

E: residual backgrounds.

Then nd the energy by computing the norm of the error.

The matrix E is regarded as an error matrix between H and the low rank matrix L, where E 2 R(N M K); Ei = $[e^i{}_1 e^i{}_2{:}{:}{:}e^i{}_M\ ]^T$ 2 R(M xK), and $e^i{}_j$ 2 R(Kx1); 1jM; 1iN: E^i is the error matrix of image I^i . Based on the rank constraint, the matrix H should be low rank, and the consistency of the whole salient regions F could be computed by the error E. It need to perform the RPCA to reduce the time complexity.

In detail, the low-rank energy $_j{}^i$ of the saliency map $S_j{}^i$ is de ned as a histogram distance between the corresponding feature histogram $h^i{}_j$ and the recovered $I_j{}^i$in L. After a normalization of E, we calculate this distance by:

$$_j{}^i = e^i{}_j jj$$

The higher low-rank energy $_j{}^i$ indicates that the salient region detected by $S_j{}^i$ is more likely to be the true co-salient region.

3.5 Raw Result Formation

The energy so nd is utilized to find the co saliency map. The co-saliency map of I^i is obtained by combining each map $S_j{}^i$ in the map set S^i with its own self-adaptive weight.

The consistency energy $_j^i$ (i.e., rank-one energy or low-rank energy) of S_j^i is utilized to de ne the self-adaptive weight by finding the norm value.

The exponential of the weight value is used to find the weight. After that the co-saliency map CS^i of image Ii is calculated as follows:

$$CS^i = \quad W_j^i{:}S_j^i$$

The created co-saliency map is the raw co-saliency map. Moreover, the proposed method is also applicable for single image saliency detection. Suppose N = 1, and we only have the map set $S^1 = S_j^{1M}{}_{j=1}$. Since the rank-one energy is computed by the consistency of a group of images, it is inapplicable for a single image. However, can utilize the set F_1 to calculate the low-rank energy [25] of each map in S^1. In the fusion framework, single saliency map is obtained by recovering the common salient region shared by all the M elementary saliency maps, which could be also computed by the above equation with the low-rank energy and i=1.

3.6 Refined Results

The created raw map may not be the actual co-saliency map since there is a chance of background effects in the final map. Because the co saliency weight is calculated using different saliency map. So it need a refinement stage which re ne the raw result. The refinement stage process is doing simple normalization [26] method to avoid the background clutter effectively.

4. EXPERIMENTAL RESULTS AND ANALYSIS

In this section, test this method on single image saliency detection, image pair co-saliency detection, and multiple image co-saliency detection, respectively. Our following results are based on the low-rank energy by default, since it is more general than the rank-one energy. For each input image it needs to nd a set of saliency map which has a major role in the development of co saliency detection effectively.

4.1 Experiments on Single Images

First verify the performance of the method for single saliency detection on the MSRA-B dataset. Take 4 images one by one. And 6 saliency map of each image separately. As an experiment also add two more saliency maps in fusion of the maps. A content aware saliency map and GMM based saliency map. So that it will aware of more features. And thus it helps to and the salient regions more efficiently. Hence formed weights leads to clearer saliency map which occlude the non-salient region. Figure 6 shows the set of single images. The output saliency maps for the 4 input images are shown in figure 7.

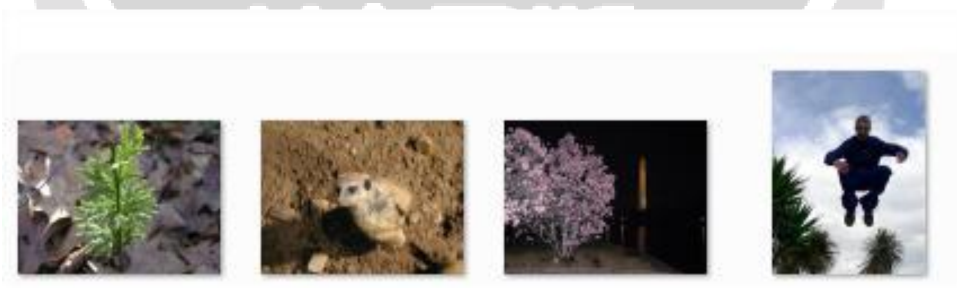

Fig -6: Single Image Input

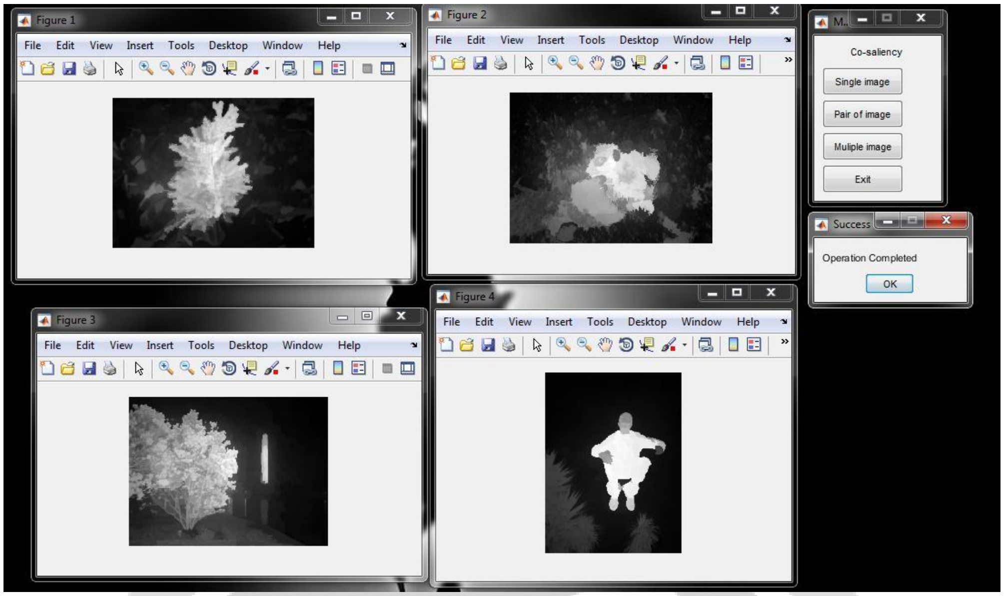

Fig -7: Single Image Output

Fig -8: Pair of Images Input

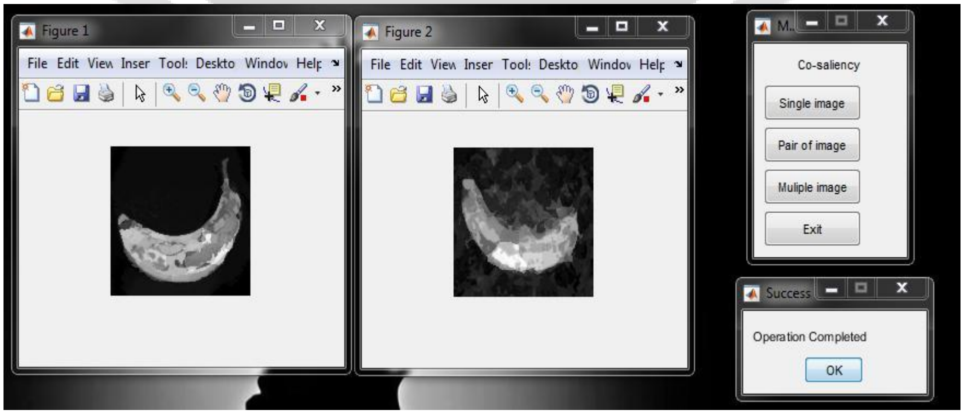

Fig -9: Pair of Images Output

4.2 Experiments on Pair of Images

This self adaptive weight method achieves co-saliency detection via integrating various single-image saliency maps and multi-image saliency maps under the rank constraint. The self-adaptive weight helps to create the maps, that extracting the common salient regions more accurately. Figure 8 shows the pair of images. It uses 9 saliency maps for creating the co saliency. Here it needs to find the co-saliency map of the two images instead of the single saliency map. For the experiment take a pair of images of bananas as a sample and created its saliency maps. Then find the salient region and corresponding self adaptive weight. This weight will further use to nd the co-saliency map. The output of image pair is shown in the figure 9.

4.3 Experiments on Multiple Images

Most existing co-saliency detection methods focus on a pair of images, and only few co-saliency models are applicable for the multiple images. However, the iCoseg dataset is provided for the co-segmentation, where the objects are always along with the alike backgrounds. Therefore, previous methods are confused by the recurred backgrounds. Figure 10 shows the multiple set of images. Here it considers 7 saliency map of each image. And do some fusion process for the combined results. It takes 13 images of the statue of Christ and their corresponding saliency maps. MR, HS, RC, SP and the extra two saliency methods GMM and CA are the elementary maps and CO is the co-saliency map. It considers both single elementary maps and co saliency maps for fusion process. Then do the process as described in the previous section. The output co-saliency maps of the input images are shown in the figure 11.

Fig -10: Multiple Images Input

In summary, benefiting from the rank constraint, this co-saliency detection model inherits the advantages of all the fusion maps effectively. It utilizes multiple saliency cues to generate the final results. It proves that the rank constraint is effective to inherit the various merits of different saliency maps. The framework inherited the merits of the multiple saliency cues, and was more robust to few wrong detections. This was achieved by utilizing the consistency [27] properties among various saliency detection results. By adding more saliency maps, the quality of co-saliency map will get increased.

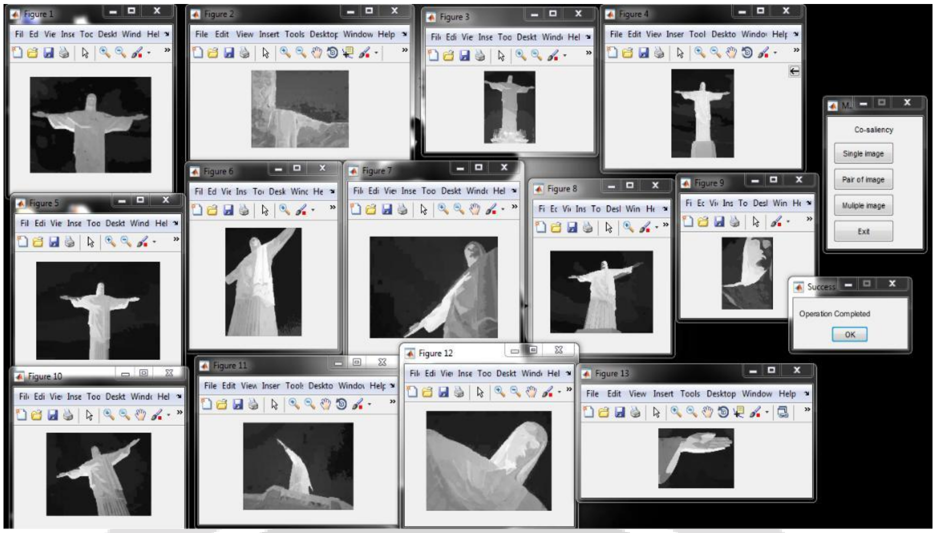

Fig -11: Multiple Images Output

5. CONCLUSIONS

In this paper, we provided a general fusion framework for both single saliency and co saliency detection. The framework inherited the merits of the multiple saliency cues, and was more robust to little wrong detection. This was achieved by utilizing the consistency properties among various saliency detection results. It creates self-adaptive weight for the co saliency detection. First of all it do some super pixel segmentation and then perform thresholding to find the salient region from each image. Then compute the Low-rank energy. Using this energy it will find a co saliency weight. This weight combined with the saliency map will generate the co saliency map. And it further go through a refinement stage for better result. It is an effective way to find both the single and multi-image saliency. Adding more saliency map will help to improve the result. And also can find the saliency map from different types of images. The main demerit is that the co-salient region depends on a number of saliency methods used in fusion.

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