Symmetry Integrated Region-based Image Segmentation

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Abstract

Symmetry is an important cue for machine perception that involves high-level knowledge of image components. Unlike most of the previous research that only computes symmetry in an image, this paper integrates symmetry with image segmentation to improve the segmentation performance. The symmetry integration is used to optimize both the segmentation and the symmetry of regions simultaneously. Interesting points are initially extracted from an image and they are further refined for detecting symmetry axis. A symmetry affinity matrix is used explicitly as a constraint in a region growing algorithm in order to refine the symmetry of segmented regions. Experimental results and comparisons from a wide domain of images indicate a promising improvement by symmetry integrated image segmentation compared to other image segmentation methods that do not exploit symmetry.

1. Introduction

Since most natural objects exhibit different levels of symmetry, symmetry detection has become a major research topic in computer vision and pattern recognition. Research on image symmetry can be mainly divided into two schemes: local symmetry detection [1, 2], and global symmetry detection [3, 4]. The earlier work on local symmetry detection explored symmetry by local features such as edges, shapes, contours or boundary points. However, these methods can only detect local symmetry properties without considering the whole image. To solve this problem, recent global symmetry detection methods basically treat the entire image as a signal from which symmetry properties are discovered. These approaches successfully detect symmetry information from complex image patterns in either a discrete or a continuous symmetry detection framework. Current *global discrete* symmetry detection approaches are reviewed in [11].

More recently, the use of symmetry as an important feature has been a topic with significant attention in new applications. The research has been done to apply symmetry into the areas of pattern classification [5] and object recognition [6]. The symmetry feature along with other features has been used as one of the key multiple cues.

In this paper, we use symmetry to improve image segmentation, which establishes a broad new domain of image analysis. The objective of our work is to enforce symmetry constraints into a region-based image segmentation algorithm to improve its performance.

Since *global* symmetry detection has advantages of freedom from *a priori* model, and robustness to complex patterns and distortions, it is suitable for our region-based image segmentation scheme. Moreover, *discrete* symmetry detection is necessary in order to enforce symmetry into region-based image segmentation methods such as region growing, meanshift and watershed. Although these segmentation methods vary in how to obtain the regions, all of them have one thing in common – they all define a *discrete* threshold setting, which can be used to utilize the symmetry criterion that is also *discrete*. Meanwhile, since region-based image segmentation accepts multiple clustering criteria, previous work successfully integrated numerous criteria like color, texture and shape prior. For our work, symmetry is combined as a new efficient criterion.

The rest of this paper is organized as follows. In section 2, we give an overview of related work and provide our contributions. In section 3, the technical approach of our work is proposed. Section 4 provides experimental results and discussions. Finally, conclusions are given in section 5.

2. Related Works and Our Contributions

The approaches in [1, 2] mainly detect symmetry by local shapes. In these papers, the local feature is the source of limitations, because of its sensitivity to pattern complexity and distortion. The intuition of symmetry grouping is proposed in [5], which is robust to more complex shapes. However, they are only used in images with limited pattern classes. Recently, some researchers in [3, 4, 7] have taken a global approach to solve the above problems, where they investigate symmetry cues based on an entire image. These kinds of approaches, also used in our method, are relatively more robust to complex and distorted data.

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The progress in symmetry detection enables us to exploit symmetry to other areas. However, only a few papers are found in application of symmetry to areas such as image segmentation. Two publications on symmetry enhanced image segmentation are found in [8, 9]. However, both of these papers have several limitations as given below:

Limitation 1: They combine symmetry with only a single segmentation criterion, namely the edge criterion, such as active contour [8] and edge weights [9], that aims to find the contour of the symmetric region. They segment the image into only two kinds of regions: symmetric region inside the contour and non-symmetric background region outside the contour, that do not segment the image into regions with different properties such as color, texture and shape.

Limitation 2: These methods use local features to segment symmetric regions. Since local features are sensitive to non-symmetric distortion and noise, they have difficulties with the segmentation of symmetric regions with ambiguous, complex and noisy patterns. And local features always fail to detect global dominant symmetry property of the whole image.

As compared to the above limitations, our approach demonstrates the following contributions:

1. Whereas most other research work stops at detecting symmetry, we go further to use symmetry to improve image segmentation. Symmetry and segmentation are improved simultaneously with a satisfactory performance.

2. Our method solves the problem of *limitation 1*, by using multiple criteria (rather than a single criterion) integrated with symmetry. As a result, regions with different properties like color, texture and symmetry are segmented simultaneously.

3. Our method solves the problem of *limitation 2*, by using global symmetry detection, instead of local symmetry detection. Hence our approach is more robust to ambiguous and complex non-symmetric distortions.

3. Technical Approach

The overall procedure is summarized in Fig 1:

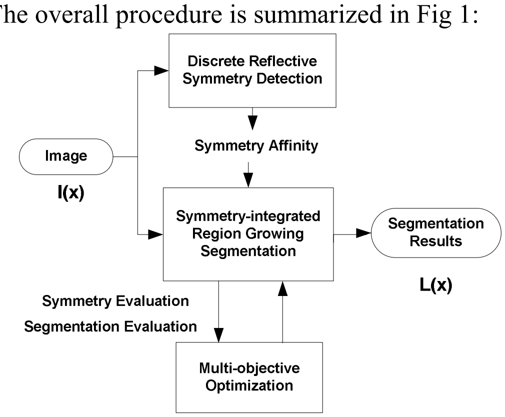


Fig 1. System diagram for symmetry integrated segmentation.

The key procedures are symmetry integration by symmetry affinity, and the multi-objective optimization. The first procedure realizes the symmetry constraint enforcement, while the second procedure refines the system through a closed-loop self-adjustable optimization procedure.

3.1. Discrete Reflective Symmetry Detection

We use *Global* Symmetric Constellations of Features in [7] to detect reflective symmetry presenting in natural images. Reflective symmetric pairs are first selected from SIFT points [13]. Pairs of points which pass this selection are then made to vote for dominant symmetry axis in Hough Space. A sample result is shown in Fig 2(b).

Once the symmetry axis is detected, it is utilized to compute a symmetry affinity matrix. Each point in affinity matrix corresponds to a pixel in an image, and its value is the pixel's symmetry level as it relates to its symmetric counterparts. We employ Curvature of Gradient Vector Flow (CGVF) [10], as a measurement of symmetry affinity:

$$Curv(\mathrm{x,y}) = \frac{1}{|V|^3}[(v_x + u_y)uv - u_x v^2 - v_y u^2] \tag{1}$$

Let the GVF of image be:

$$V = [u(x,y), v(x,y)] \tag{2}$$

In equation (1), $u_x = \partial u / \partial x$, $u_y = \partial u / \partial y$, $v_x = \partial v / \partial x$, $v_y = \partial v / \partial y$ are the first derivatives of pixel along x and y directions. Considering a pixel (x_i, y_i), we define its symmetry affinity as:

$$C(x_i, y_i) = |Curv(x_i, y_i) - Curv(x_j, y_j)| \tag{3}$$

where (x_j, y_j) is the symmetric counterpart of (x_i, y_i) by the symmetry axis. If the two points have locally symmetric fields, then values of $Curv(x_i, y_i)$ and $Curv(x_j, y_j)$ should be closer. Three other symmetry conditions are stated in [10], which can be combined with (3) to build the affinity matrix.

3.2. Symmetry-based Region Growing

The region growing segmentation has the advantages of simplicity, speed and the capability of parallel clustering, but has the limitations of over-segmentation and is sensitive to noise. Our method aims to solve these problems by integrating symmetry as a new constraint in region growing segmentation. The seeds for region growing are chosen by the SIFT operator as in section 3.1. The symmetry affinity matrix is used to compute the symmetry constraint.

Aggregation Criterion: Image segmentation concerns the partition of pixels into regions with uniform properties measured by homogeneity criteria, like color, texture, *etc.*

Let $\delta(x, y)$ denotes the homogeneity aggregation criterion for a region growing scheme. This criterion holds true when:

$$\delta(i, j) < \delta_m \quad (4)$$

that means pixel i will be aggregated into a neighboring region j if the homogeneity criterion between them satisfies a threshold δ_m. Naturally, common region homogeneity criteria used are color, texture and grayscale. In this paper, the aggregation criterion is modified so as to integrate the symmetry constraint. The modified criterion is defined as:

$$\delta(i, j) = \delta_R(i, j)\delta_S(i, j) \quad (5)$$

where we enforce symmetry constraint $\delta_s(i, j)$ along with region criterion $\delta_R(i, j)$. Symmetry constraint $\delta_s(i, j)$ will be introduced below. The region homogeneity criterion $\delta_R(i, j)$ is the combination of color and texture, that will be provided in Section 3.3. From this work, a new criterion is realized with multiple cues.

Symmetry Constraints: $\delta_s(i, j)$ in equation (5) is related to our new symmetry constraint, as shown below:

$$\delta_s(i, j) = \frac{\frac{\pi}{2} + actan(\sqrt{(1+C_i)(1+C_j)})}{\pi} + \frac{1 + |\sqrt{C_i} - \sqrt{C_j}|}{2} \quad (6)$$

C_i and C_j are symmetry affinities of pixel i and neighboring region j, using equation (3). Equation (6) provides the following symmetry constraints: the first term controls the symmetry level, which means that if both patterns i and j indicate low symmetry affinities (highly symmetric), they are more likely to be aggregated by decreasing the criterion $\delta_s(i, j)$; while the second term favors more similar symmetry affinities between the two patterns. Work in [9] uses symmetry criterion integrated into edge weight in image-cut segmentation, and its limitations are stated in section 2.

Region Merging Criterion: Initial segmentation by the aggregation criterion $\delta(i, j)$ is an over-segmentation result. Here the neighbored homogenous regions are merged by a measure of their HSV color similarity by equation (9). According to both aggregation and merging criteria stated above, we establish a 2D parameter search space used for segmentation optimization, as introduced in Section 4.1.

3.3. Color and Texture Aggregation Criterion

Our segmentation procedure abides both color and texture in the region homogeneity criterion $\delta_R(i, j)$, as given by equation (7). In particular, the weights of color and texture criteria can be adjusted dynamically during the region growing, depending on whether the region shows more uniformity on color or more on texture.

$$\delta_R(i, j) = W_{Color}\delta_{Color}(i, j) + W_{Texture}\delta_{Texture}(i, j) \quad (7)$$

Where $W_{Texture} + W_{color} = 1$. We employ HSV color space as the basis of color feature, that can be expressed as a 3D vector:

$$F_{Color}(i) = (v_i s_i \cos(2\pi h_i), v_i s_i \sin(2\pi h_i), v_i) \quad (8)$$

where h_i, s_i and v_i correspond to HSV components of pixel i. The color homogeneity criterion in equation (7) can be expressed as:

$$\delta_{Color}(i, j) = \| F_{Color}(i) - F_{Color}(j) \| \quad (9)$$

which is the Euclidean distance of color features between pixel i and its neighboring region j.

The 8-dimension texture feature $F_{Texture}$ is derived from the mean and standard deviation of the filtered image by Gabor filters at 4 orientations by steps of 45 degrees. It is reduced to 4 dimensions by Principal Component Analysis (PCA). Following shows the texture homogeneity criterion:

$$\delta_{Texture}(i, j) = \| F_{Texture}(i) - F_{Texture}(j) \| \quad (10)$$

Here both the color and texture features are normalized.

3.4. Performance Evaluations

Different from the previous work, our method improves segmentation and symmetry simultaneously by symmetry integration. Therefore, both segmentation and symmetry evaluations are required as shown in the following:

$$SEG_K = \frac{1}{M * N}(1 + \log(\sqrt{R}))\sum_{i=1}^{R}[\frac{e_{SEG}^2(i)}{1 + \log(A_i)}] \quad (11)$$

$$SYM_K = \frac{1}{N_R}\sum_{i=1}^{R} e_{SYM}^2(i, i') \quad (12)$$

For segmentation evaluation of equation (11), M*N is the size of image, and R is the number of segments. The term $e_{SEG}^2(i)$ is the inter-region contrast of region *i*:

$$e_{SEG}^2(i) = \frac{\sum_{j=1}^{N_i} \| F_{Color}(j) - \bar{F}_{Color}(R_i) \|}{N_i} \quad (13)$$

$\| F_{Color}(j) - \bar{F}_{Color}(R_i) \|$ is the pixel contrast in the region, which is the Euclidean distance of color features between pixel *j* and its region R_i. N_i is the number of pixels in region i. The term $(1 + \log(\sqrt{R}))$ is a punishment for over-segmentation, and $(1 + \log(A_i))$ is a punishment for small segments, and A_i is the area of region *i*. For symmetry evaluation of equation (12), $e_{SYM}^2(i, i')$ is the difference of region properties between region *i* and its symmetric counterpart *i'* by the symmetry axis. The region difference is denoted by the sum of their mean color and orientation difference. The smaller $e_{SYM}^2(i, i')$ means more symmetric the region *i* is to its symmetric counter part *i'*. Smaller value of evaluation indicates better performance. For convenience purpose, both evaluations are adjusted so that larger is the better in experiments.

3.5. Multi-objective Optimization

The purpose of the optimization (see Fig 1) is to get a segmentation result L(x) with both its segmentation and symmetry performances optimized, that can be formulated as a multi-objective optimization problem. We use Non-dominated Sorting Genetic Algorithm (NSGA-II), a multi-objective optimization approach used in [12] to conduct the search for optimum combination of parameters, by means of non-dominated sorting of a combined parent and offspring population, which prevent both the local optima and lack of robustness. The optimized results from different segmentation methods are shown in Fig. 3.

3.6. Symmetry Integration Algorithm

The system is summarized as the following algorithm:

Global Symmetry Detection
1. Symmetry pairs extracted from SIFT interesting points;
2. Compute symmetry affinity by Curvature of GVF;

Symmetry-integrated Region Growing Segmentation
3. Seeds determination by interesting points;
4. Compute multiple aggregation criteria for region growing: color criterion by HSV basis, texture criterion by Gabor filters, and symmetry criterion by symmetry affinity. Combine them as a single aggregation criterion, with its threshold AGC (see Section 4.1);
5. Run region growing;
6. Use HSV color basis to compute region merging criterion, with its threshold MGC (see Section 4.1);
7. Run region merging and finish the segmentation;

Segmentation Optimization
8. Segmentation and symmetry performance evaluations;
9. Multi-objective optimization by NSGA-II, in parameter space of AGC and MGC, is run by the following rule:
   If segmentation and symmetry performances from 8 are *acceptable* (see Section 4.1), optimization is ended;
   If *not acceptable*, search different parameter setting of AGC and MGC, and jump to 4.

4. Experimental Results and Discussions

In this section, the performance of our method, named Symmetry-integrated Region Growing, is compared with four segmentation approaches: color & texture region growing, gray-scale region growing, meanshift and watershed. Our method provides superior segmentation performance meanwhile the symmetry is highly preserved.

4.1. Datasets and Parameters

The proposed method is applied to images demonstrating a wide range of region properties, as illustrated in Fig 3. The parameter space for segmentation and symmetry optimization is composed of 2 thresholds, with respect to multiple aggregation criteria (AGC) threshold and region merging criterion (MGC) threshold, which build a 2D parameter space as in Fig 4(b). The multi-objective optimization stops if both the performances of segmentation and symmetry are *acceptable* as follows:

a. Both segmentation and symmetry performances are better than pre-set thresholds (set by 0.62 and 0.70, respectively);

b. The combination of the two performances reaches its global optimum value in NSGA-II.

The optimization stops if both conditions are met, otherwise it will continue by searching the different combination of parameters recursively.

4.2. Symmetry-constrained Region Growing

The results of symmetry-based region growing are presented in Fig 2. Fig 2 (a) shows the original image for a symmetric butterfly body with complex non-symmetric background, and Fig 2(b)-(d) show the symmetry axis, the segmentation result, and the ground-truth segmentation respectively. Fig 2(e) shows the curve of relationship between symmetry and segmentation performances. Each point in the curve is obtained by running segmentation by a parameter setting within the parameter space, and getting evaluations of segmentation and symmetry, both of which can be improved simultaneously as indicated by the curve. Fig 2(f) shows the receiver operating characteristic (ROC) plot, which indicates the classification accuracy of the result in Fig 2(c) compared to the ground-truth segmentation in Fig 2(d). The plot is derived from statistical results by running segmentation in wide range of parameter space.

4.3. Segmentation Improvement by Symmetry

We get a decent segmentation improvement using symmetry constraints when compared to other segmentation methods without exploiting symmetry. All the results in Fig 3(a)-(d) are optimized results by NSGA-II. We infer from Fig 3 that the most complete and complex symmetric objects are segmented by our proposed method as shown in results in (a), as compared to (b)-(d), which have segmentation defects in symmetric regions. Once regions indicate symmetric property, they are more likely to be aggregated by symmetry constraint. As an example, for the result (a) of image (4) in Fig 3, our approach can segment the whole symmetric face shape, regardless of its noise and holes, while other results fail to accomplish so. The percentage data in Table 1 represents the segmentation improvement compared to the result of the method in the next row, with highest performance from symmetry-integrated method. Fig 4(a) shows the curves between symmetry and segmentation performances for five segmentation methods. The squared points marked as 'a'-'e' are the multi-objective optimization results by NSGA-II. A comparison among five curves

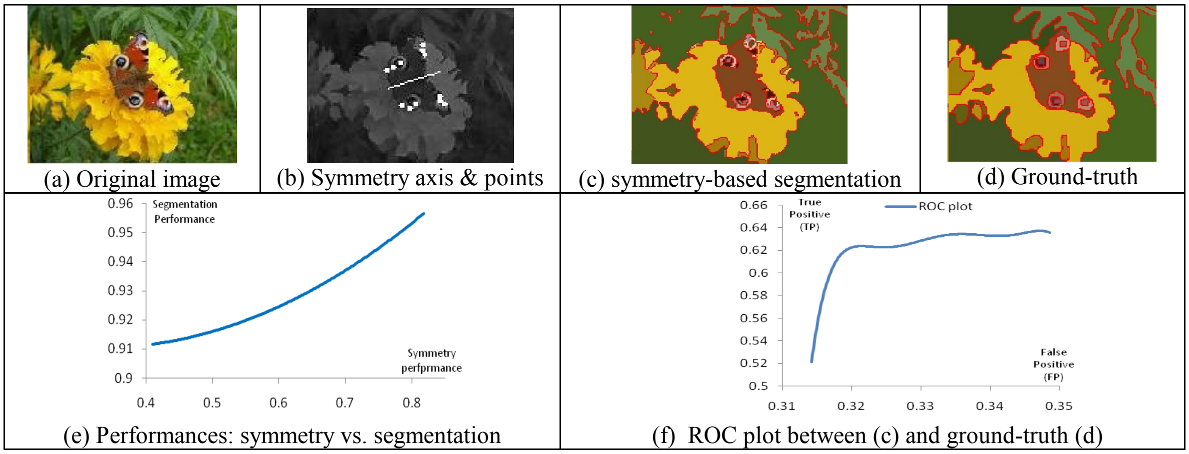


Fig. 2. Symmetry-constrained segmentation results and analysis.

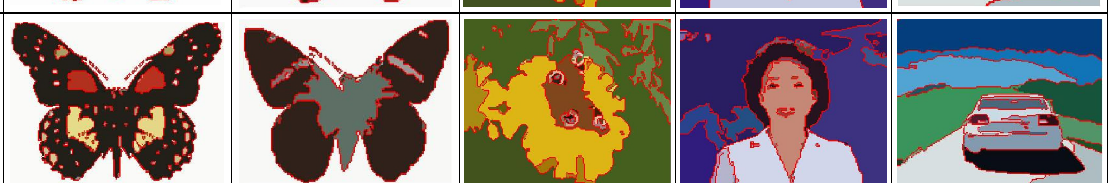
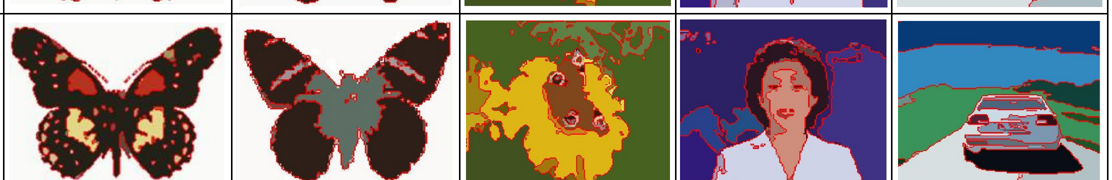
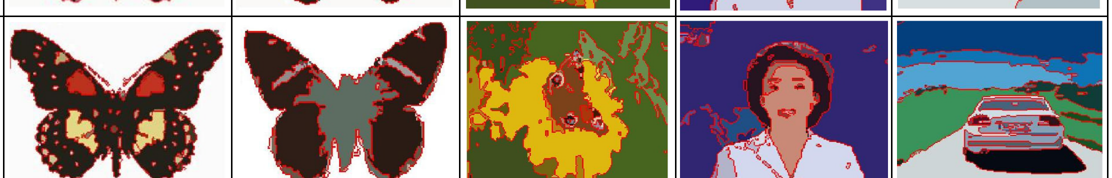
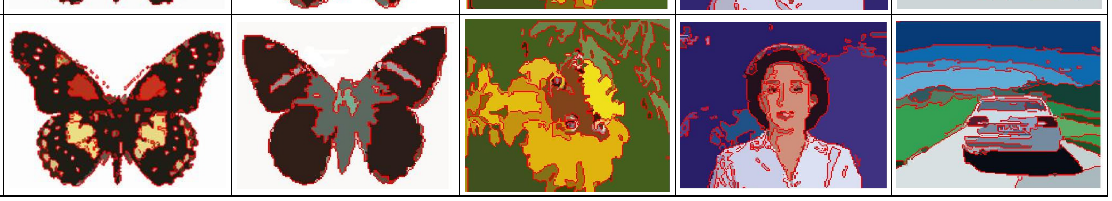
Image	(1) Butterfly 1	(2) Butterfly 2	(3) Butterfly 3	(4) human	(5) Car
Region properties	Uniform symmetric regions without background	Textured symmetric regions without background	Uniform & textured symmetric regions with background	Uniform & textured symmetric regions with background	Uniform symmetric regions with background
Original					
Ground-Truth					
(a)Symmetry –based Color & Texture Region Growing					
(b) Color & Texture Region Growing					
(c) Meanshift					
(d) Gray-scale Region Growing					

Fig. 3 Sample segmentation results: sample images (1)-(5) with results (a)-(d) from 4 segmentation methods.

indicates that the symmetry-integrated segmentation of curve 'a' achieves the best performances. Moreover, Fig 4(a) indicates that the performance improvement of curve 'a' compared to curve 'b' comes only from symmetry integration, that both curves 'a' and 'b' use the same color-texture region growing approach, but the method of curve 'a' integrates symmetry as a new constraint. Fig 4 (b) shows the clusters of both segmentation and symmetry performances on the 2D parameter space, where parameter 1 means the region aggregation criterion (AGC) threshold, and parameters 2 indicates the region merging criterion (MGC) threshold. The results indicate that by applying symmetry constraints, both segmentation and symmetry are improved in most part of the parameter space.

Table.1. Symmetry/**segmentation evaluation (segmentation performance improvement)**, compared to the method of next row.

	(1) Butterfly 1	(2) Butterfly 2	(3) Butterfly 3	(4) human	(5) Car
(a) Symmetry–based RG	0.852 / **0.874 (7.5%)**	0.782 / **0.986 (6.6%)**	0.616 / **0.954 (3.6%)**	0.668/ **0.79(6.4%)**	0.607 / **0.738 (4.8%)**
(b) Color & Texture RG	0.849 / **0.813 (2.1%)**	0.779 / **0.925 (4.0%)**	0.609 / **0.921(26.3%)**	0.666 / **0.739 (16.1%)**	0.613 / **0.705 (12.5%)**
(c) Meanshift	0.857 / **0.796 (7.7%)**	0.784 / **0.889 (11.3%)**	0.550 / **0.729(19.5%)**	0.660 / **0.636 (7.9%)**	0.589 / **0.620 (9.6%)**
(d) Regular RG	0.831 / **0.739(10.8%)**	0.781 / **0.799 (12.4%)**	0.534 / **0.610(16.2%)**	0.667 / **0.590 (3.2%)**	0.574 / **0.566 (8.5%)**
(e) Watershed	0.834 / **0.667**	0.761 / **0.711**	0.523 / **0.525**	0.633 / **0.574**	0.584 / **0.522**

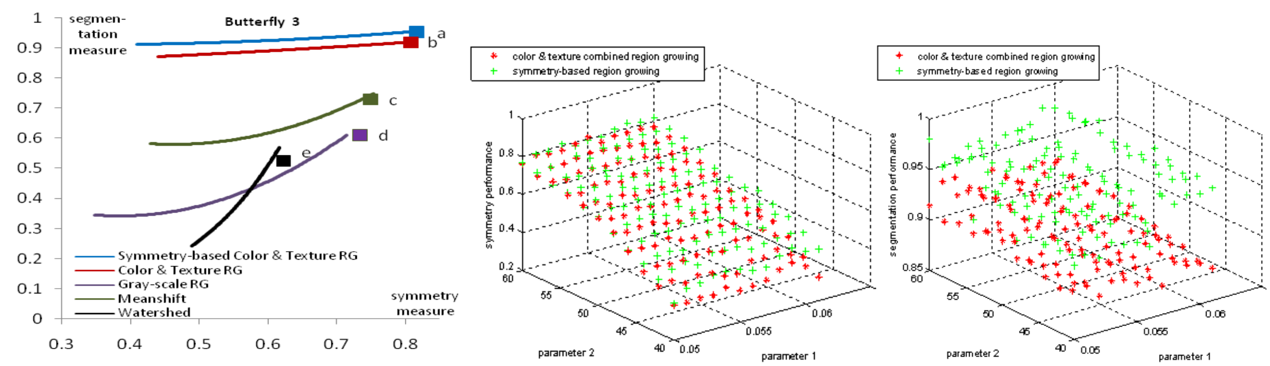


Fig 4. (a) Symmetry and segmentation performance curves for image 'butterfly 3'.

(b) segmentation and symmetry performances of image 'butterfly 3' in large parameter space.

5. Conclusions

In this paper, a new symmetry integrated region-based segmentation scheme is proposed for natural image segmentation. We perform experiments on a wide variety of images. The qualitative and quantitative experimental results indicate that with the symmetry constraints enforced by symmetry affinity, both the symmetry and segmentation are improved, with better performance compared to several other well known region-based segmentation methods.

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