Active Learning for Interactive Segmentation with Expected Confidence Change

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Abstract. Using human prior information to perform interactive segmentation plays a significant role in figure/ground segmentation. In this paper, we propose an active learning based approach to smartly guide the user to interact on crucial regions and can quickly achieve accurate segmentation results. To select the crucial regions from unlabeled candidates, we propose a new criterion, i.e. selecting the ones which maximize the expected confidence change (ECC) over all unlabeled regions. Given an image represented by oversegmented regions, our active learning based approach iterates following three steps: 1) selecting crucial unlabeled regions with maximal ECC; 2) refine the selected regions; 3) updating appearance models based on the refined regions and performing image segmentation. Specifically, a constrained random walks algorithm is employed for segmentation, since it can efficiently produce confidence for computing ECC during active learning. Compared to the conventional interactive segmentation methods, the experimental results demonstrate our method can largely reduce the interaction efforts while maintaining high figure/ground segmentation accuracy.

1 Introduction

Interactive image segmentation is an active research area in recent decades [1–5]. From the perspective of computer vision, the task is to segment an interesting object from background with user's annotation [1-5]. A good interactive segmentation approach should fulfill three criteria: 1) user friendly interface; 2) accurate segmentation results; 3) smart guidance for the user.

For the first criterion, some previous methods often allow the user to iteratively specify some visual hints in different manners, such as drawing a box containing the object [4, 6], scribbling on the object and background regions [7, 8] and initializing contour points of the interesting object[1, 9]. Among all the methods, the interaction of scribbling [3] is very popular for it requires less accurate input from the user. The method allows a user coarsely mark some object regions rather than finely tracing near object contours. For the second criterion, lots of segmentation approaches, such as active contours [1], graph cut [3–5, 10], have been proposed to pursue high segmentation accuracy. Grady [10] presents a random walk segmentation algorithm, which takes user scribbles as input and can quickly produce segmentation results and the corresponding confidence.
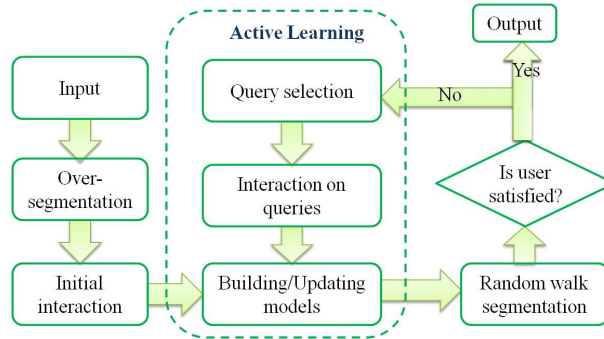
Fig. 1. Flowchart of active learning based interactive segmentation.

Although many interactive segmentation systems have been built, the major efforts often focus on the first two criteria. It is still an open issue how to smartly guide the user interaction. The challenge is how to determine which unlabeled regions should be automatically recommended for interaction. For example, a user intends to segment an object with different color components. Experienced users may know it is crucial to supply scribbles on typical regions covering different color components, while the novices do not know that.

In order to effectively guide the user, we propose an active learning based approach for interactive segmentation. The approach actively selects crucial regions based on a new criterion, which targets to cause maximal expected confidence change (ECC) after revealing the labels of selected regions. Figure 1 shows the flowchart of the proposed approach. Given an image, oversegmentation [11] is firstly performed and some initial interactions are provided by the user. Then we build appearance models (e.g. building Gaussian Mixture Models [4] of RGB values) for foreground and background and run a constrained random walks algorithm for segmentation. The active learning starts if current segmentation result is not perfect and the learning process consists of three steps: 1) selecting crucial regions with maximal ECC; 2) asking the user to answer the labels of queried regions; 3) updating appearance models by adding the queried regions to the labeled sets. After the active learning, the segmentation can re-execute based on the updated models. The procedure of active learning and segmentation will be iteratively performed, until a segmented result is satisfying.

2   Related work

2.1   Interactive segmentation

As an earlier study, active contour approaches [1] ask the user to outline an object contour and evolve the contour to true boundaries. However, the algorithm tends to get local optimum. The intelligent scissors [2] also explore boundary properties, which calculates the shortest path between the input points with Dijkstra's algorithm. Nevertheless, it needs too many user-labeled points along the

boundaries. Recent studies mainly focus on region-based approaches [3–5, 10], among which the graph cut based methods are very popular [3–5]. They formulate the segmentation problem as a minimization of an energy function defined on a graph and the solution can be obtained by max-flow/min-cut algorithm [12]. As an extension, GrabCut [4] requires an input bounding box containing the object and can achieve perfect performance by iteratively adding other interaction hints. Moreover, the LazySnapping [5] utilizes both of region scribbles and boundary points. In spite of many advantages, the graph cut algorithm suffers from "short cut" problem and cannot estimate the confidence of segmentation.

In our method, a constrained random walks algorithm, which is an improved version of [10], is explored to perform segmentation. It is suited to our method, since it can fast produce segmentation results and provide the confidence of each node being foreground.

2.2 Active learning

Active learning attracts growing interest in machine learning [13, 14] and Settles provides a comprehensive survey in [15]. There have been many proposed criteria for query selection such as uncertainty sampling and expected error reduction [13]. The uncertainty sampling generally considers only the local uncertainty of the label based on current information, while the expected error reduction criterion take into account the global impact on unlabeled instances.

There are relatively few works about active learning approaches in computer vision [16–20]. To the best of our knowledge, the most related work is the iCoSeg algorithm [18], which concentrates on reducing the user efforts when labeling a group of topically related images. However, the algorithm employs the uncertainty criterion to recommend informative regions, which is quite different from ours. The disadvantage of uncertainty based approaches is that the selected regions may have very little effects on other unlabeled regions. On the contrary, the maximal ECC criterion always selects the regions which are expected to have the greatest influence on all unlabeled ones.

3   Proposed approach

3.1 Overview

We briefly describe the proposed approach. Given an image in Figure 2(a) and the user inputs in Figure 2(b), the foreground/background appearance models are learned based on the labeled regions. Then a constrained random walks algorithm (Section 4) is employed to produce the initial segmentation in Figure 2(c). The active learning starts if the user is not satisfied with current result. It consists of three steps: 1) actively selecting crucial regions (shown red in Figure 2(d)) based on the proposed ECC criterion; 2) asking the user for the labels of selected regions; 3) re-learning appearance models by adding the queried regions into the labeled sets. If the user is not satisfied, the active learning and segmentation will be iteratively performed.
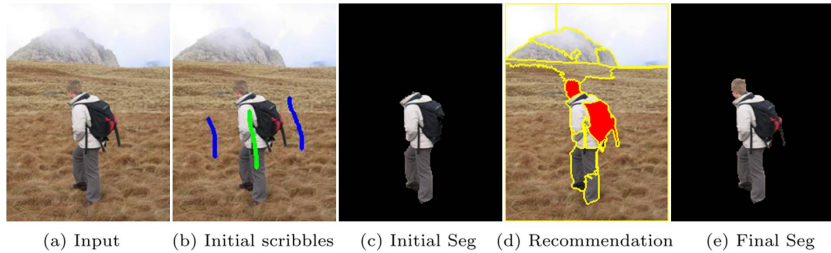
(a) Input   (b) Initial scribbles   (c) Initial Seg   (d) Recommendation   (e) Final Seg

Fig. 2. A real example using our active learning based approach. Green and Blue scribbles in (b) are initial inputs for foreground and background. (c) shows initial segmentation result. Red regions in (d) are selected for query and the yellow boundaries are produced by the oversegmentation algorithm in [11]. (e) is the final result.

Note that we employ a constrained random walks segmentation algorithm in [10]. Therefore, when the label of any region is revealed, it affects other unlabeled regions in two aspects: 1) the labeled region is added to seed sets and then propagate its information locally by a random walker; 2) it updates color models which are priors in random walks segmentation. Moreover, the image in Figure 2(d) are oversegmented by the mean shift algorithm [11], which is driven by the point density in feature space.

3.2   Formulation

We denote an image $\boldsymbol{X}$ as m non-overlapped regions. Formally, $\boldsymbol{X} = \bigcup_{i=1}^{m} X_i$ and $X_i \cap X_j = \emptyset$ when $i \neq j$. Each region is denoted as $X_i = \{x_k^{(i)} | k = 1, \ldots, n_i\}$, where n_i is the number of the pixels belonging to the ith region and $\sum_{i=1}^{m} n_i = n$ is the total number in the image $\boldsymbol{X}$. The corresponding label for i^{th} region is a binary variable, $Y_i \in \{0, 1\}$, where 0 corresponds to background and 1 corresponds to foreground.

Give the user scribbles, the image will be divided into a labeled region set $\mathcal{L}$ and an unlabeled set $\mathcal{U}$. We can learn GMM color models θ for foreground and background and perform random walks segmentation to produce initial labeling $\hat{\boldsymbol{Y}}$ and confidence map $\boldsymbol{C}$. Each unlabeled region X_u will receive an estimated label $\hat{Y}_u$ and its confidence $C(\hat{Y}_u | X_u, \theta)$. Specifically, we define $C(\hat{Y}_u | X_u, \theta)$ as a signed confidence. Let P_u be the probability of the region X_u being foreground, which is obtained by averaging over all pixels in X_u, then the label confidence is

$$C(\hat{Y}_u | X_u, \theta) = \begin{cases} P_u, & \text{if } \hat{Y}_u = 1, \\ -P_u, & \text{if } \hat{Y}_u = 0. \end{cases}, (0 \leq P_u \leq 1) \tag{1}$$

Expected Confidence Change ($\boldsymbol{ECC}$) If the user is not satisfied with the segmentation result, the active learning algorithm will start with query selection. Assume an region $X_q \in \mathcal{U}$ is selected for query, the GMM models θ will update to be $\theta_{+(X_q, Y_q)}$, which refers to the new model re-trained after adding the queried (X_q, Y_q) to $\mathcal{L}$. The random walks algorithm will also re-execute based on the

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Algorithm 1 Calculating ECC for each unlabeled region X_q

Input:

   An image $\boldsymbol{X}$, an unlabeled region X_q, the region set $\mathcal{L}$ and $\mathcal{U}$, current GMM models θ, current segmentation $\hat{\boldsymbol{Y}}$ and the confidence map $\boldsymbol{C}$.

Output:

   Estimated ECC.

Procedure:

 1: **for** each possible label $Y \in \{0, 1\}$ **do**
 2:    Retrain the GMM models based on $\mathcal{L} \cup \{(X_q, Y)\}$, denoted as $\theta_{+(X_q, Y)}$;
 3:    Run random walks segmentation to obtain new labeling $\hat{Y}'$ and the corresponding confidence $\boldsymbol{C}'$;
 4: **end for**
 5: Calculate the ECC according to Equ. (4).

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new GMM models and produce new labeling $\boldsymbol{Y}'$ and new confidence map $\boldsymbol{C}'$. For all unlabeled regions, the average Confidence Change (CC) by adding the pair of (X_q, Y_q) will be

$$\Delta C_{+(X_q, Y_q)} = \frac{1}{|\mathcal{U}|} \sum_{X_u \in \mathcal{U}} \left| C'(\hat{Y}_u'|X_u, \theta_{+(X_q, Y_q)}) - C(\hat{Y}_u|X_u, \theta) \right|. \qquad (2)$$

Since we do not know the real label of X_q, we can only estimate the expected confidence change through two possible labels $\{0, 1\}$:

$$ECC(X_q) = \sum_{Y \in \{0,1\}} P(X_q|Y, \theta) \cdot \Delta C_{+(X_q, Y)} , \qquad (3)$$

where $P(X_q|Y, \theta)$ refers to the likelihood of X_q fitting to label Y, given the GMM models θ. For clarity, we describe the computation of ECC in Alg. 1.

Weighted ECC In order to make the query selection more effective and efficient, we further explore a weighted variation of ECC. The weighted ECC takes into account both of region size and the distance from each candidate unlabeled region to the seed ones. For each candidate region X_q,

$$ECC_w(X_q) = w_q \cdot ECC(X_q), \qquad (4)$$

with $$w_q = w_{size(q)} + \lambda \cdot w_{dist(q)}. \qquad (5)$$

Here the first term $w_{size(q)} = n_q/n$ favors larger regions and the second term is related to the distance between the candidate region and the labeled regions. The factor λ is empirically set to 1. Distance-based term is defined as

$$w_{dist(q)} \propto (-D_{q,\mathcal{F}} + D_{q,\mathcal{B}})/(D_{q,\mathcal{F}} + D_{q,\mathcal{B}}), \qquad (6)$$

where $D_{q,\mathcal{F}}$ and $D_{q,\mathcal{B}}$ is the normalized distance between 0 and 1. It measures the average spatial distance between the centroid of X_q and each user-labeled region. The factor w_q is scaled to $[0, 1]$ by Min-max normalization.

Algorithm 2 Procedure of active learning based interactive segmentation

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Input:

  An image $\boldsymbol{X}$, the labeled regions $\mathcal{L}$ and the unlabeled $\mathcal{U}$, GMM models θ, current segmentation result $\hat{\boldsymbol{Y}}$ and confidence map $\boldsymbol{C}$. Maximal iteration number T.

Output:

  The estimated label vector $\hat{\boldsymbol{Y}}'$.

Procedure:

 1: Initialize $t = 0$;
 2: **while** the user is not satisfied and $t < T$ **do**
 3:    **for** each query candidate $X_q \in \mathcal{U}$ **do**
 4:       Calculate weighted ECC of X_q according to Alg. 2;
 5:    **end for**
 6:    Select query regions according to Equ. (7);
 7:    Query the labels of regions $\{X_Q\}$ and receive answer $\{Y_Q\}$;
 8:    Update labeled set $\mathcal{L} = \mathcal{L} \cup \{(X_Q, Y_Q)\}$ and unlabeled set $\mathcal{U} = \mathcal{U} \backslash \{X_Q\}$;
 9:    Retrain GMM models $\theta' = \theta_{+\{(X_Q, Y_Q)\}}$ and predicet new labeling $\hat{\boldsymbol{Y}}'$ with random walks.
10: **end while**

Note we are apt to select regions which are close to user-labeled foreground and far from background regions. The intuition behind this setting is that regions near to the labeled foreground is also very possibly near to boundaries which will provide crucial classification cues. On the other hand, regions far away from the labeled background may contain color components, which are different from those of current background seeds. Therefore it can make the models more accurate to add such regions to $\mathcal{L}$.

3.3   Query selection

In brief, our basic idea for active learning is to greedily select queries from unlabeled regions to maximize the expected confidence change (ECC) over all unlabeled ones. Thus the region with largest ECC will be recommended first:

$$X_Q = \operatorname*{argmax}_{X_q \in \mathcal{U}} ECC(X_q). \tag{7}$$

The proposed active learning algorithm is described in Alg. 2.

Batch-mode active learning In the active learning based approach, if we query the recommended regions in serial, i.e, one at a time, it will cost lots of time to achieve satisfactory segmentation. Therefore, we employ the batch-mode, which actively queries a group of regions at a time for learning, to accelerate the process. Although there are several works on how to select the optimal set for batch query [16, 21], we adopt a strategy with medium complexity, but is sufficiently effective for our approach. Specifically, we firstly choose a group of k unlabeled regions with the largest ECC to ensure the recommended ones are informative. Then we randomly sample N_q from these k candidates to ensure the

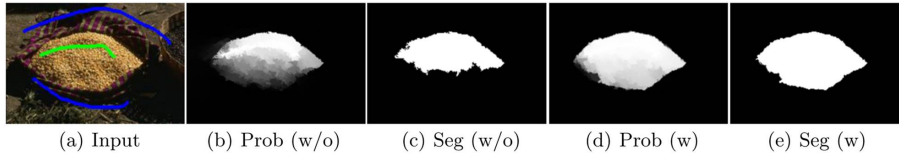| (a) Input | (b) Prob (w/o) | (c) Seg (w/o) | (d) Prob (w) | (e) Seg (w) |

Fig. 3. The effect of the prior term on the probability map (Prob) and segmentation results (Seg). Green and blue scribbles are for foreground and background. 'w' denotes 'with prior' and 'w/o' denotes 'without prior'.

recommended regions are diverse. In our implementation, $k = 8$ and $2 \leq N_q \leq 5$. For batch mode active learning, we denote the queried region sets as $\{X_Q\}$.

4 Constrained random walks for segmentation

Random walks (RW) algorithm is employed for two reasons: 1) it can be efficiently computed; 2) it can provide the segmentation confidence, i.e. the probability of each pixel belonging to foreground. We briefly review the RW algorithm.

4.1 Preliminaries

Following the framework in [10], we formulate the segmentation problem on a graph $G = (V, E)$, with nodes $x \in V$ and edges $e \in E \subseteq V \times V$ with $n = |V|$. An edge, spanning two nodes x_i and x_j, is denoted by e_{ij}. A weighted graph specifies a value w_{ij} to each edge e_{ij} called a weight. Given an image $\boldsymbol{X}$, each node represents a pixel and the nodes are locally connected via an 8-connected lattice. Given the user input, the nodes are partitioned into two sets, $\mathcal{L}$ and $\mathcal{U}$. The labeled set $\mathcal{L}$ consists of $\mathcal{L}^{\mathcal{F}}$ and $\mathcal{L}^{\mathcal{B}}$, which are foreground and background seeds. Let p_i denote the probability of a walker starting from x_i to reach a first foreground seed. Then producing a segmentation $\boldsymbol{Y}$ is to find a solution to

$$min \sum_{e_{ij} \in E} w_{ij}(p_i - p_j)^2, \tag{8}$$

$$\text{s.t.} \qquad p_i = 1, \text{ if } x_i \in \mathcal{L}^{\mathcal{F}}; \;\; p_i = 0, \text{ if } x_i \in \mathcal{L}^{\mathcal{B}}.$$

One can analytically and quickly determine the solution [10]. Finally, each node x_i is assigned a label $\hat{y}_i = 1$ if $p_i \geqslant 0.5$ or $\hat{y}_i = 0$ if $p_i < 0.5$. Denote the probability of each region X_u belonging to foreground as P_u, which is the average probability of each pixel in X_u belonging to the foreground. Then the region label $\hat{Y}_u$ will be $\hat{Y}_u = 1$ if $P_u \geqslant 0.5$ or $\hat{Y}_u = 0$ if $P_u < 0.5$.

4.2 Edge weights

Generally, each edge weight is associated with the neighborhood distance [22]:

$$w_{ij} = exp\left(-(\beta\|\boldsymbol{I}_i - \boldsymbol{I}_j\|^2 + \|h_i - h_j\|^2)\right), \tag{9}$$

(a) Input   (b) Initial scribbles (c) Initial result (d) Recommendation (e) Final result
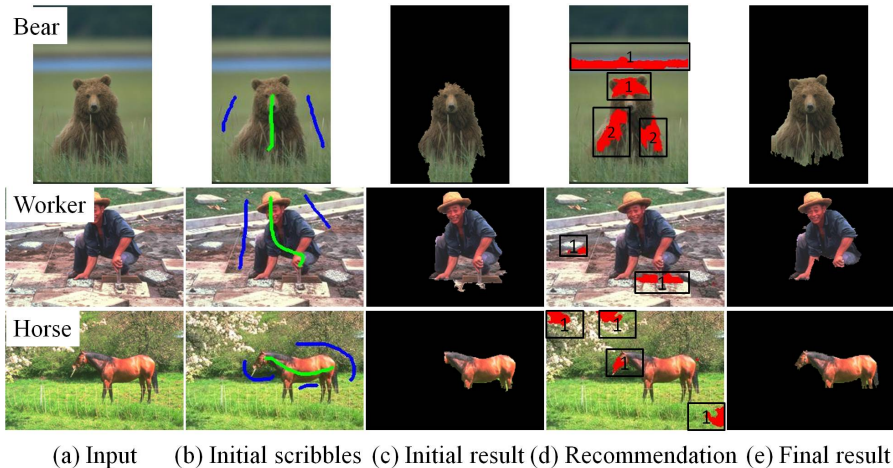
Fig. 4. Example results of the proposed approach. The number '1' and '2' labeled in (d) means the red regions are queried in the 1st and 2nd iteration of active learning.

where $\boldsymbol{I}_i$ denotes the color vector and h_i denotes the spatial position of pixel i. β is a scaling factor. However, under such configurations, the probability of each node reaching foreground or background are quite sensitive to the seed positions. To deal with this problem, we integrate the prior models into the weight. Similar to [23], we define

$$w_{ij}^{new} = exp\big(-(\beta d_{ij}^2 + \|h_i - h_j\|^2)\big), \tag{10}$$

where

$$d_{ij}^2 = \|\boldsymbol{I}_i - \boldsymbol{I}_j\|^2 + \alpha \left(P_i^{\mathcal{F}} - P_j^{\mathcal{F}}\right)^2. \tag{11}$$

Here $P_i^{\mathcal{F}}$ is the normalized probability of the node x_i belonging foreground:

$$P_i^{\mathcal{F}} = \big(-\log P(x_i|\mathcal{B})\big) / \big(-\log P(x_i|\mathcal{F}) - \log P(x_i|\mathcal{B})\big), \tag{12}$$

where $P(x_i|\mathcal{F})$ and $P(x_i|\mathcal{B})$ are the likelihoods of each node fitting to the foreground and background GMMs. The weight $\alpha \in [0, 1]$ is defined as:

$$\alpha = \frac{1}{n} \sum_{i=1}^{n} \left| \frac{\log P(x_i|\mathcal{F}) - \log P(x_i|\mathcal{B})}{\log P(x_i|\mathcal{F}) + \log P(x_i|\mathcal{B})} \right|. \tag{13}$$

Note the second term in Equ. (11) plays a dominant role, when foreground and background colors are well separable. Figure 3 compares the probability maps and results calculated by random walks algorithms with and without priors.

5   Experimental results

We evaluate the proposed method in two aspects. Firstly, we evaluate how many efforts can be reduced by using our active learning based approach, compared
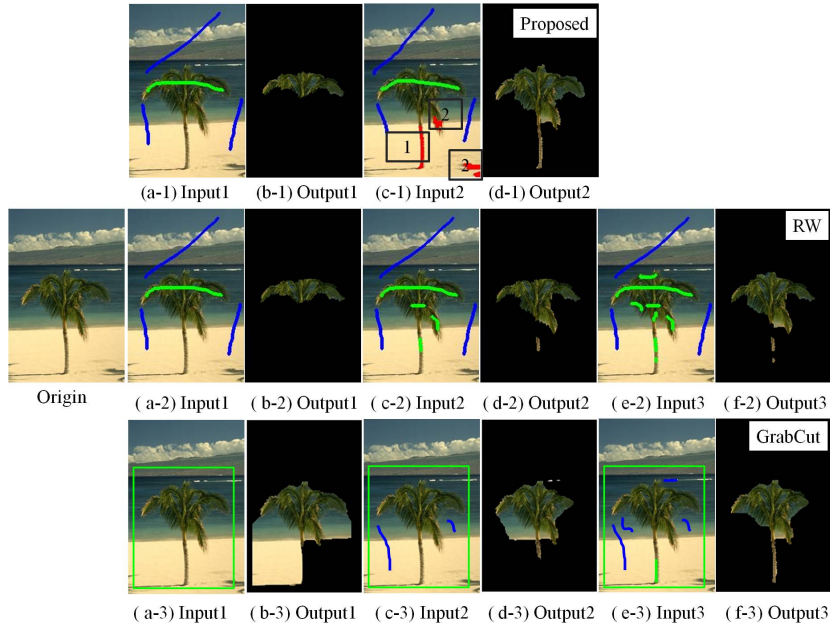
Fig. 5. Comparing user efforts of three algorithms. For our method, (c) in top row paints the recommended regions red, where the labeled number means the iteration number. For GrabCut, the green bounding box is the user input.

with conventional segmentation algorithms. Secondly, we validate the superiority of ECC for query selectioncompared with another typical criterion, i.e. uncertainty sampling [15]. For comparison, we select 20 representative challenging images from the GrabCut [4] and BSD database [24]. Among these images, foreground objects contain complex shapes or appearances in which color distributions of foreground and background are very similar. We manually label the ground truth and pixel-based accuracy is adopted to evaluate segmentation performance.

5.1   Interaction effort reduction test

Figure 4 gives some qualitative results of the proposed approach. In Figure 4(d), the river regions in the 'bear' image, the regions near the left leg in the 'worker' image and some regions of horse head in the 'horse' image are selected for query. These selected regions are usually near the boundaries or have different appearance distribution from the scribbled ones. Therefore, querying such informative regions can largely reduce the user input to achieve perfect results.

  Figure 5 shows an example to qualitatively compare the user efforts of three methods: the proposed method, random walks (RW) [10] and GrabCut [4]. Note that the parameter β in Equ. (10) is set to 300. The figure shows that random walks algorithm needs the user to successively add lots of scribbles to achieve perfect results and a few details are still missed (e.g. tree trunk regions). Likewise, GrabCut requires the user to draw a bounding box and finely give more
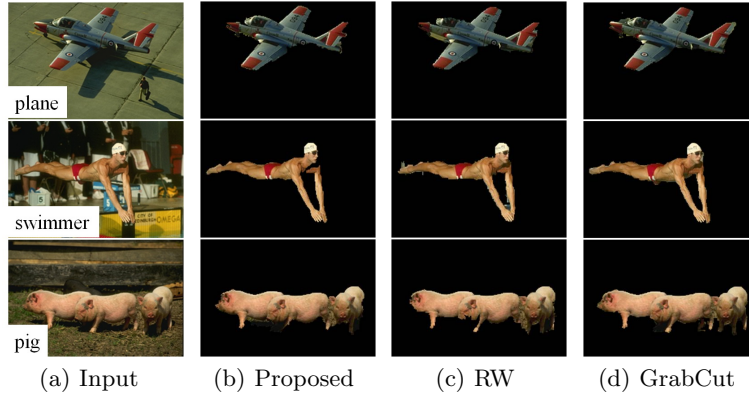
(a) Input   (b) Proposed   (c) RW   (d) GrabCut

Fig. 6. Final segmentation results of our method, random walks algorithm and Grab-Cut. The corresponding accuracies are reported in Table 1.

inputs on foreground and background. Compared with these two algorithms, ours significantly reduces user efforts while preserving perfect segmentation result.

We further quantitatively compare the user efforts and segmentation accuracy of the three methods. We train 5 naive users with the interactive tools and compare the user efforts for the three images in Figure 6. Table 1 illustrates the average interaction times of the 5 users, when the segmentation accuracy of each image reaching to 97%. It can be seen that the proposed method can consistently achieve satisfactory results with least interactions. Moreover, we take one of the five users as an example and gives how the accuracy increases with this user's interaction times in Table 2. Figure 6 compares the final segmentations of different methods with this users' interactions. It is observed that the proposed method reduces the user interactions on these images while maintaining high accuracy, compared with other two methods. The main reason is that our method can actively recommend informative regions, while the user may aimlessly interact on regions which are no good for accuracy improvement.

Table 1. Average interaction times from 5 naive users.

Times	plane	swimmer	pig
GrabCut	3.2	4.6	4.2
RW	4.0	3.6	4.6
Proposed	2.6	2.0	4.0

Table 2. The accuracy change with interaction times of one user (%).

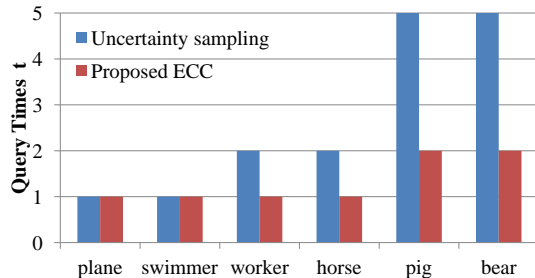| Times	plane					swimmer					pig			
	1	2	3	4	5	1	2	3	4	5	1	2	3	4
GrabCut	92.8	97.7	98.9	99.2	-	79.4	95.6	97.0	98.8	98.9	94.4	95.2	97.7	97.9
RW	96.9	96.5	98.0	98.1	98.1	96.9	98.0	98.3	98.0	98.3	95.9	95.6	96.3	96.4
Proposed	96.9	98.0	-	-	-	96.9	98.2	-	-	-	95.9	95.4	97.0	-

Fig. 7. Comparison of query times by using uncertainty sampling and the proposed ECC criterion. The smaller the value of t is, the fewer user interactions are needed.

5.2   Maximal ECC criterion test

We compare the maximal ECC criterion with another competing criterion of query selection for active learning, called uncertainty sampling. Following the general setting, we use entropy to evaluate the uncertainty:

$$X_Q = \underset{X_q \in \mathcal{U}}{\operatorname{argmax}} \sum_{Y \in \{0,1\}} \left\{ -P(X_q|Y,\theta)\log P(X_q|Y,\theta) \right\}, \tag{14}$$

in which all notations are defined as in Section 3.

For fair comparison, we use the batch-mode for both of the ECC based and uncertainty based active learning. For the images in Figure 4 and Figure 6, each method iteratively queries informative regions and perform the Alg. 2 until the accuracy of 97% is reached. Figure 7 compares the query times for each method. It tells that we can achieve a fixed accuracy with fewer queries than uncertainty sampling does. This is due to the uncertainty sampling only considers local properties without predicting the global influence on other region labels.

6   Conclusion

We focus on how to actively recommend crucial regions to reduce user inputs. The main contribution lies in two aspects. Firstly, we propose an approach which can successively recommend informative regions based on random walks. Secondly, we propose a novel criterion, maximal ECC, which aims to select regions that will change most on the expected confidence over all unlabeled ones. Experiments on a challenging dataset demonstrate that compared with conventional interactive segmentation methods, our approach can significantly reduce user efforts and help more quickly achieve satisfactory results. Future work is to extend the proposed method to other application such as training set annotation.

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