Interactive Image Segmentation on Multiscale Appearances

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ABSTRACT Interactive segmentation algorithms based on graph cuts can extract the foreground successfully from a simple scene. However, they are ineffective for complex-scene images. To improve the segmentation performance, we propose an interactive segmentation algorithm which combines the segmentation and the multiscale smoothing into a unified model. This model consists of the segmentation and the smoothing. The segmentation relies on the multiscale appearances which depend on the smoothing. In the smoothing part, the total variation is used to preserve geometric shape of the foreground, and captures different scale edges and appearances for segmentation. Combining the multiscale edges and appearances, we propose a novel Gibbs energy functional for segmentation. The exact global minima of the energy can be found by jointing the image smoothing and the optimization of segmentation. In this algorithm, the smoothing motivates that the foreground could be detected easily from a proper scale. Experimental results on the BSD300 dataset and Weizmann horse’s database indicate that, compared to the existing interactive segmentation algorithms, the proposed algorithm provides competitive performance in terms of segmentation accuracy.

INDEX TERMS Interactive image segmentation, Multiscale appearance, Multiscale edge, Graph cut

I. INTRODUCTION

Image segmentation is to separate an image into meaningful and non-overlapping sub-regions [1]. Existing segmentation methods, inspired by the Wertheimer gestalt theory, have achieved an extraordinary success and have become popular in a wide range of applications, such as MR image processing [2], object tracking [3], pattern recognition [4] and so on.

With the additional user guidance, the interactive image segmentation can extract a user-specified foreground from a simpler scene. The ultimate goal is to minimize the user interaction and to maximize the quality of the segmentation. In the segmentation procession, it is very common to exploit appearance models to distinguish better the foreground from the background. An appearance model is a statistical model for the color, texture, etc. of the pixels of an image. The mainstream appearance models are often represented by the histogram [5, 6] or the Gaussian mixture models (GMMs) [7-9]. The former is an explicit representation for intensity/color distributions of the pixels of an image; however, it fully relies on a user to define the intensity/color distributions for foreground and background. It does not exploit the distributions given by the unlabeled data, to learn the appearance model. The latter (GMMs) is a parametric representation. It assumes that both the foreground and the background are represented well by compact distributions. Comparing to the histogram, the GMMs improves segmentation performance with fewer user inputs [10]. However, the representation accuracy of the existing models is low for the inhomogeneous regions in real images [9], e.g., the texture region, as the intensity/color distributions of the inhomogeneous region pixels are wide.

The existing segmentation algorithms based on graph cuts [5-9] consider the feature extraction and the segmentation process respectively. In other words, image feature extraction is independent of image segmentation. We think that feature extraction should facilitate the process of segmentation, so the foreground can be easily detected from the extracted features of an image. Therefore in this paper we propose an interactive image segmentation model based on multiscale appearances. In this model, the multiscale appearances are obtained by the total variation [11], to preserve the edges and...
smooth the inhomogeneous sub-regions in an image. The multiscale appearances facilitate to improve the accuracy of the appearance representation for segmentation because the color distributions become more compact as the scale increasing. Further, they are favor to improve segmentation accuracy because of the edge-preserving. Combining multiscale edges and multiscale appearances, we build a novel Gibbs energy functional for image segmentation. Joint the optimization of the segmentation and the multiscale smoothing, the exact global minima of the energy can be found from a proper scale appearance. Experimental results indicate that, compared to the existing interactive segmentation algorithms, the proposed algorithm provides comparable performance in terms of segmentation accuracy.

In Section 2, we review and discuss the related interactive image segmentation methods based on the graph cut or machine learning. In Section 3, we construct a novel “Gibbs” energy for image segmentation using the multiscale appearances of an image. The global minima of the proposed energy can be obtained using the minimum cut/maximum flow algorithm. Finally, the experimental results and conclusion are given in section 4 and section 5, respectively.

II. PREVIOUS WORK
The interactive image segmentation, which uses a small amount of user interaction, allows a user to extract the object of interest form an image. Among the existing interactive segmentation methods, the Magic Wand [12] and the Intelligent Scissors [13] are the simplest segmentation techniques. The former computes a set of pixels, which are connected to the user-specified “seed” point(s), where all pixels in the set deviate from the seed point(s) by values within a given tolerance. Because the color distributions among the foreground and background pixels have a considerable overlap, a satisfactory segmentation cannot be achieved by the method. The latter allows a user to choose a “minimum cost contour” by roughly tracing the object’s boundaries with the mouse moving. However, it is not effective for objects with a long boundary.

Combining edges and appearance models, Boykov and Jolly formulated a generative Markov random field model for the binary image segmentation [5]. Given some user constraints in the form of the foreground and background brushes, the appearance models of the foreground and background are explicitly represented as the histogram of the use-specified regions, respectively. The optimal solution of the segmentation energy could be obtained by the minimum cut/maximum flow algorithm [14]. While segmentation algorithms [5, 6] on this appearance model often give good results in practices, their segmentation performance relies on distributions of a user-labeled pixels. They cannot exploit the information given by the unlabeled data, to learn appearance models on the foreground and background. Grab Cut [7] formulated an appearance model by parametric representation, e.g., GMMs, which made use of the unlabeled data to learn parameters of the appearance models. The GMMs implicitly assume that both the foreground and background were represented well by compact distributions. However, as the intensity/color distributions of the inhomogeneous regions were wide, the Grab cut cannot achieve satisfactory segmentation results for an image with the inhomogeneous regions, e.g., textured regions. The Super Cut [9], which introduced a clustering strategy at super-pixel level, to guarantee that slightly inhomogeneous regions are classified into the same class, improved the accuracy of the appearance models for textured regions. Another problem with the existing algorithms was that the number of Gaussians in each GMM had a significant effect on the image segmentation. The improved Grab Cut [8], which used CLUSTER algorithm to analyze the foreground and background regions prior to segmentation and estimate the optimal number of Gaussians needed in each GMM in order to best model each region, removed the negative effects of an unsuitable number of Gaussians in the GMMs.

These existing appearances models for segmentation, e.g. the histogram or the GMMs, were formulated by analyzing data. They cannot produce a correct result for the real images, as these appearances models cannot approximate the inhomogeneous sub-regions in an image accurately. Li and Feng [15] proposed an image segmentation model combined multiscale decomposition and image segmentation. In the model, the multiscale features facilitated the segmentation, as the foreground can be easily detected from a proper scale. The multiscale decomposition was able to remove the negative effects of the region inhomogeneity on segmentation. However, the segmentation performance is poor for real images, since it only considers the edge features in an image. Convolution networks (CNNs) [16] can automatically extract the multiscale features by the deep learning method. Compared to the traditional methods, these methods based on the CNNs could achieve superior performances [17]. However, since they require the large data sets for learning the parameters of the CNNs to implement a specific task such as the face detection [18], handwritten numeral recognition [19] and traffic congestion identification [20], they cannot effectively extract the user specified object without training data.

III. PROPOSED SEGMENTATION MODEL
Given an initial boundary box \( T^0 \) by a user, an image \( u_0 : \Omega \rightarrow (u_p, u_c, u_b) \) with \( N \) pixels is divided into a background \( T^0_p \), a foreground \( T^0_f \) (\( T^0_p \) is an empty set in this step), and a mixture region \( T^0_m \) where there are foreground and part of background. Combining image edges and appearance models (GMMs), a Gibbs energy functional for segmentation is formulated as [7]:

\[
E(x, \omega, u_0) = U(x, \omega, u_0) + V(x, u_0)
\]  

(1)

The segmentation result is expressed as an array of variables \( x = (x_1, \cdots, x_n) \) at each pixel, \( x_n \in \{0,1\} \).
assigns to each pixel a unique GMM component either from
the background or the foreground model. Parameter \( \omega \)
represents the background or the foreground used. The data term \( U(\bullet) \), given the appearance
models, evaluates the fit of the label \( x \) to the image \( u_0 \). The
smoothness term \( V(\bullet) \) comprises the “boundary” properties
of an image. It should be interpreted as a penalty for the
discontinuity between the adjacent pixels.

A. MULTISCALE SMOOTHING
The segmentation performance obtained by minimizing the
Gibbs energy in (1) relies on the boundaries and the
appearance differences between the foreground and the
background. For the simper images with the stronger edges and
high contrast between the foreground and the
background, the foreground could be extracted successfully.
In practice, it was ineffective for the complex-scene images,
since the weak edge in an image weaken the boundary
information, and textures reduce the appearance discrimination among region. To remove negative effects of
the texture and preserve boundaries of the foreground, we
decompose an image into a series of multiscale smoothing
images by the total variation [11], which is formulated as the
following minimization problem:

\[
E(u) = \frac{\lambda}{2} \int_{\Omega} (u - u_0)^2 d\Omega + \int_{\Omega} |\nabla u|^2 d\Omega
\]  

(2)

Where \( u \) is a smoothing image, \( \lambda \) is regularization constant
that is tradeoff between the edge-preserved and the
inhomogeneous region smoothed. This minimization
problem in (2) admits a unique solution characterized by the Euler-Lagrange equation:

\[
\lambda(u - u_0) - \text{div}\left(\frac{\nabla u}{|\nabla u|}\right) = 0
\]  

(3)

The simple finite difference scheme and the lagged
diffusivity fixed-point iteration algorithm are used to
discretely calculate (3). Let \( p \) be a member of the four
adjacent pixel set on the pixel \( p_0 \), \( u^{k-1}(p_0) \) can be updated by:

\[
u^k(p_0) = \frac{\lambda u_0(p_0) + \sum_{p \in \Lambda} \sigma(p) u^{k-1}(p)}{\lambda + \sum_{p \in \Lambda} \sigma(p)}
\]  

(4)

Where \( \sigma(p) \) is the weight coefficient of the pixel \( p : 

\[
\sigma(p) = \left| \nabla u^{k-1}(p) \right|^{-1}
\]

(5)

A series of smoothing images can be described as:

\[
u_0 = u^0 \rightarrow u^1 \rightarrow u^2 \rightarrow \cdots \rightarrow u^{k-1} \rightarrow u^k \rightarrow u^l \rightarrow \cdots
\]  

(6)

At step \( k \), the presence of \( u^k \) at each step constantly
reminds the smoothing not to forget the raw image, which
contains the intrinsic singularities features, e.g. edges.
The \( u_0(p_0) \) in (4) facilitates to preserve boundaries of the
foreground. On the other hand, the smoothing image \( u^k \) depends on \( u^{k-1} \), it causes inhomogeneous regions
to be smeared step by step. The color distributions of \( u^k \) is more compact than that of the \( u^{k-1} \), which facilitates
the estimation of the appearance models and improves the
accuracy of parameters \( \omega \) in the appearance models. As the
number of the iterations increases, the color distributions of
the smoothing image pixels become more compact,
meanwhile, the edges are preserved.

B. APPEARANCE MODELS FOR SEGMENTATION
Given \( T^k \) which is the boundary of the foreground by
segmenting the smoothing image \( u^{k-1} \), the smoothing
image \( u^k \) is divided into a background \( T^k_B \), foreground
\( T^k_F \) ( \( T^k_B \) is an empty set in this step), and a mixture
region \( T^k_M \) that contains the foreground and the remnant
background. The background and mixture region are
modelled by GMMs, respectively. Each GMM is taken to be a
full-covariance Gaussian mixture with \( K \) components (in
this paper, \( K = 5 \)). The m-th component of the GMM is defined as:

\[
G(\mu(m), \Sigma(m), y) = \frac{1}{\sqrt{(2\pi)^K \sqrt{\det(\Sigma(m))}}} \exp\left[-\frac{(y - \mu(m))^T \Sigma^{-1}(m)(y - \mu(m))}{2}\right]
\]

(7)

Each pixel in an image is assigned a unique GMM component, one component from either the foreground or the
background model, according to \( x^k = 0 \) or 1. This means that
the appearance model parameter \( \omega^j \) comprise the variables

\[
\omega^j = \{\pi^j_F(m), \mu^j_F(m), \Sigma^j_F(m), \pi^j_B(m), \mu^j_B(m), \Sigma^j_B(m), m = 1 \sim 5\}
\]

(8)

Here, \( \mu(m) \) and \( \Sigma(m) \) are the mean vector and
covariance matrix, respectively, of the m-th component,
and \( \pi(m) \) is a mixture weighting coefficient.
The data term \( U(\bullet) \) in the Gibbs energy functional (1),
given the model \( \omega^j \), is defined for all pixels in \( T^k_M \) as:

\[
U(x^k, \omega^k, u^k) = -\sum_{i \in T^k_M} \sum_{m=1}^{5} \log \pi^k_F(m)G(\mu^k_F(m), \Sigma^k_F(m), u^k(i))
\]

(9)

The smoothness term \( V(\bullet) \) measures the similarity
between pairs of pixels in the color space. It is defined as a
penalty weight which is high with the low gradient and low
with the high gradient. The similarity between pixel \( u^k(i) \) and \( u^k(j) \) is captured the following form:
\[ V(x^k, u^k) = \sum_{j \in \Lambda_i} \gamma \left[ x^k_i \neq x^k_j \right] \exp(-\beta (u^k(i) - u^k(j))^2) \] (10)

Where \( [\phi] \) denotes the indicator function taking values 0, 1 for a predicate \( \phi \). And \( \Lambda_i \) is the set of pairs of neighboring pixels, the factor \( \text{dis}(\bullet) \) is the Euclidean distance of neighboring pixels. \( \gamma \) is a constant. As shown in [7], it is far more effective to set \( \gamma > 0 \), as this relaxes the tendency to smoothness in regions of high contrast. In this paper, \( \gamma \) is set as 50 which is same as that of the Grab cut [5]. To ensure the exponential term in (10) could switch appropriately between high and low contrast, the constant \( \beta \) is chosen to be:

\[ \beta = 0.5 \langle (u^k(i) - u^k(j))^2 \rangle^{-1} \] (11)

Here \( \langle \bullet \rangle \) denotes the expectation over an image sample.
C. SEGMENTATION MODEL FOR MULTISCALE APPEARANCES

The multiscale smoothing images capture different scale features for segmentation, such as the multiscale edges and multiscale appearances. These features facilitate the process of segmentation, as the foreground can be detected easily from a proper scale. By combining the multiscale edges and appearance models of an image, the Gibbs energy functional for binary segmentation can be formulated as an estimation of a global minimum

$$x^* = \arg \min_k \left\{ \min \left\{ \min \left\{ E(x^k, o^k, u^k) \right\} \right\} \right\}$$ (12)

The exact global minima can be found by alternating the segmentation part and the multiscale smoothing part. For segmentation of the given-scale smoothing image $u^k$, the procedure for the minimization of (12) alternates between two operations: 1) Given the parameters $o^k$ of appearance models, the segmentation $x^k$ can be found by using a standard minimum cut/maximum flow algorithm [20]. 2) Given the segmentation $x^k$, the unknown model $o^k$ is inferred using the EM-style procedure for GMM fitting. Owing to the presence of the partial background in the mixture region, the foreground extraction is performed iteratively. After the first iteration, some background pixels in the mixture region will be classified correctly, and the parameters of the appearance models will be updated in the next iteration. In each step, the total energy of segmentation is guaranteed not to increase. The method can be run until a local minimum is found.

The process of segmentation for an image is shown as the Fig.1. The multiscale appearances are favor to the estimation of parameters on each GMM, because the color distributions of the smoothing image become more compact with the scale of smoothing increasing, shown as the Fig.1a. For segmentation of the smoothing image $u^k$ ($k > 0$), the initial bounding box is set as the segmented foreground boundary of $u^{k-1}$. Since this initial bounding box is adjacent to the boundaries of the foreground, there are little of background pixels in the mixture region. In the process of the segmentation, the parameters of each GMM change slightly. The computer cost of segmentation becomes lower gradually with the number of smoothing increasing, shown in the Fig.1b. In this paper, we stop it after three iterations.

For the multiscale smoothing, a series of different-scale smoothing images are obtained using the fixed-point iteration algorithm mentioned in Section III. A. As the number of iterations increases gradually, the appearances of the smoothing image become coarser, while the color distributions become more compact. It is favor to improve segmentation performance. However, there may be pseudo overlapping between the foreground and background without smoothness constraint. The pseudo overlapping leads to poor segmentation results. To avoid this phenomenon, we construct an image smoothness termination condition by using the foregrounds extracted from the adjacent-scale smoothing images, which is defined as follows:

$$\frac{\text{card}(T^k_T \cap T^{k-1}_T)}{\text{card}(T^k_T \cup T^{k-1}_T)} \leq \frac{\text{card}(T^{k-1}_T \cap T^{k-2}_T)}{\text{card}(T^{k-1}_T \cup T^{k-2}_T)}$$ (13)

The pseudocode for this algorithm is shown as following:

**Require:** $T^0_M$ and $T^0_B$ using bounding box $T^0$.
1: Set $T^0_T = \phi$
2: Initialize $T^0_T = \phi$. $x_n^0 = 0$ for $n \in T^0_M$ and $x_n^0 = 1$ for $n \in T^0_B$.
3: Compute the smoothing image $u^k$ using the formula (4).
4: $T^k_T = \phi$.
5: Analyze the border information using the formula (2) for $u^k$.
6: Estimate the number of sub-regions in the $u^k$.
7: Estimate initial $o^k$ using EM.
8: $N:=1$
9: Repeat
9: $\quad$ Update $x^k$ given current $o^k$ using graph cut.
10: $\quad$ Update $o^k$ given current $x^k$ using EM.
11: Until
12: $\quad$ $N:=N+1$
13: If the (13) is not fulfilled,
14: $\quad$ Update $T^{k+1} = \{T^{k+1}_M, T^{k+1}_B, T^{k+1}_F\}$ and go to step 3
15: Else,
16: $\quad$ Output the foreground $T^*_F$.

IV. EXPERIMENTAL RESULTS

The experiments of this study were conducted using VC 6.0 on a PC with Intel-Core i5 CPU @ 3.40 GHz and 4 GB of RAM without any particular code optimization. We used two widely evaluation metrics: the intersection over union (IOU) metric [21] and the F-measure. The former was estimated by the following:

$$\text{IOU} = \frac{F(s) \cap F(g)}{F(s) \cup F(g)}$$ (14)

Where $F(s)$ and $F(g)$ denote the segmented foreground and the ground truth, respectively. The latter is also used for the evaluations and computed by the following:

$$\text{F-measure} = \frac{2 \times \text{precision} \times \text{recall}}{\text{precision} + \text{recall}}$$ (15)

Where

$$\text{precision} = \frac{F(s) \cap F(g)}{F(g)} \text{, recall} = \frac{F(s) \cap F(g)}{F(s)}$$ (16)
This segmentation method combines the multiscale edges and appearances information of an image. In the segmentation procession, the edge-preserved and the region-smoothed rely on the regularization constant $\lambda$ in (2). Thus, in one extreme, when $\lambda = 0$, then the global minima of (2) is $|\nabla u| = 0$, that is, the pixel values of the smoothing image are constant everywhere, and the edges and regional appearance differences are eliminated. Conversely, when $\lambda \to \infty$, then $u \approx u_e$. The $\lambda$ lies somewhere between these two extremes. A 512×321-pixel butterfly image is smoothed with different $\lambda$, and the results of segmentation are shown as Fig.2. If $\lambda \to 0$, then edges are blurred, which causes the poor segmentation accuracy, as shown in Fig.2.c. If $\lambda \to \infty$, then the remaining inhomogeneity leads to under-segmentation, the partial pixels of the background are mistaken divided into the foreground, as shown in Fig.2.e.

With the different $\lambda$, the scores of segmentation (precision, recall, and F-measure) and computation cost are listed in Table I. In this work, $\lambda$ was obtained as 0.01 by optimizing performance against ground truth over 200 images.

To evaluate the segmentation performance, experiments were conducted to compare the proposed method with the comparable existing methods such as the segmentation models based on multiscale and graph cut. The multiscale image segmentation model [15] consisted of two parts: the segmentation part and the multiscale decomposition part. The segmentation part was performed by the level-set method based on edge, while the multiscale decomposition part preserved the geometric shape of the foreground using the total variation. These methods combining the appearance models and edges extracted the user-specified foreground using the graph cut, such as the Grab cut [7], improved Grab cut [8], and Super cut [9] methods. The works in [8] and [9] extended the Grab cut for the GMM optimization and super-pixels, respectively. The tested images were obtained from the Berkeley segmentation database (BSD300) and the Weizmann horse’s database. The former included 300 images and the corresponding ground truth data. It was divided into a training set of 200 images and a test set of 100 images. The latter included 328 side-view color images of horses that were manually segmented. The segmentation metrics using the different methods are listed in Table II. From the F-measure and IOU, the proposed method was found to be superior to the other methods.

### Table I

<table>
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<th>$\lambda$</th>
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<th>0.005</th>
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<th>0.1</th>
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<td>0.985</td>
<td>0.963</td>
<td>0.932</td>
<td>0.902</td>
<td>0.881</td>
<td>0.868</td>
<td>0.859</td>
<td>0.843</td>
<td>0.812</td>
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<tr>
<td>Recall</td>
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<td>0.98</td>
<td>0.981</td>
<td>0.981</td>
<td>0.982</td>
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<tr>
<td>F-measure</td>
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<td>0.983</td>
<td>0.971</td>
<td>0.955</td>
<td>0.940</td>
<td>0.928</td>
<td>0.922</td>
<td>0.917</td>
<td>0.908</td>
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<td>19.6</td>
<td>21.5</td>
<td>28.8</td>
<td>26.9</td>
<td>23.7</td>
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<td>16.4</td>
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**FIGURE 2.** The extracted foreground with different regularization constant $\lambda$. a) the original image and initial boundary box, b) the ground truth, c-e) the smoothing image and the extracted foreground with different regularization constant: 0.001, 0.01, and 4.0.
The partial results on the images obtained from the BSD300 and the Weizmann horse’s database are shown in the Fig.3 and Fig.4, respectively. For simpler scene images, e.g., Fig.3.a, b, the Fig.4a, and b, the segmentation results using the proposed model were almost the same as that of the other models. However, the segmentation results of the proposed model were visually better for images with inhomogeneous regions and weak edges. The proposed model inserted multiscale smoothing images into the process of segmentation to facilitate foreground detection from a proper-scale smoothing image. As the smoothing scale (the number of iterations) increased gradually, the appearances of the smoothing image became coarser. One hand, it made the color distributions of the foreground and background more compact; on the other hand, it enhanced the appearance disparity between the foreground and background. The former improved the accuracy of parameters for each GMM. Compared to the Super cut [9], the proposed model provided comparable performance for images with substantial disparity between the foreground and background. The proposed model achieved better results than the Super cut [9], the proposed model provided comparable performance for images with substantial disparity between the foreground and background. The former improved the accuracy of parameters for each GMM. Compared to the Super cut [9], the proposed model provided comparable performance for images with substantial disparity between the foreground and background. The proposed model achieved better results than the Super cut [9], the proposed model provided comparable performance for images with substantial disparity between the foreground and background. The proposed model achieved better results than the Super cut [9], the proposed model provided comparable performance for images with substantial disparity between the foreground and background. The proposed model achieved better results than the Super cut [9], the proposed model provided comparable performance for images with substantial disparity between the foreground and background. The proposed model achieved better results than the Super cut [9], the proposed model provided comparable performance for images with substantial disparity between the foreground and background. The proposed model achieved better results than the Super cut [9], the proposed model provided comparable performance for images with substantial disparity between the foreground and background. The proposed model achieved better results than the Super cut [9], the proposed model provided comparable performance for images with substantial disparity between the foreground and background. The proposed model achieved better results than the Super cut [9], the proposed model provided comparable performance for images with substantial disparity between the foreground and background. The proposed model achieved better results than the Super cut [9], the proposed model provided comparable performance for images with substantial disparity between the foreground and background. The proposed model achieved better results than the Super cut [9], the proposed model provided comparable performance for images with substantial disparity between the foreground and background.
FIGURE 3. Comparison of proposed method with Grab cut, Super cut, improved Grab cut and the multi-scale image segmentation model on the partial images in the DSB300. Row 1: original images and initial bounding box, Row 2: the ground truth, Row 3: this method, Row 4: Super cut, Row 5: improved Grab Cut, Row 6: Grab cut, Row 7: the multi-scale image segmentation model.
FIGURE 4. Comparison of proposed method with Grab cut, Super cut, the improved Grab cut and the multi-scale image segmentation model on the partial images in the Weizmann horse’s database. Row 1: original images and initial bounding box, Row 2: the ground truth, Row 3: our method, Row 4: Super cut, Row 5: improved Grab Cut, Row 6: Grab cut, Row 7: the multi-scale image segmentation model.
Compared to the methods based on the graph cut, the multiscale segmentation model [15] exhibited poor performance. The main reason was that the multiscale model extracted the foreground by using the constraints of the edges, without the appearance information. The weak edges caused the curve to converge to the local minimum; thus, the positioning accuracy was poor.

By combining the optimization for segmentation and estimation of multiscale appearances, the foreground could be detected easily from a proper-scale smoothing image. However, since this method utilized the appearance difference between the foreground and background to segment the foreground, the segmentation performance was poor for images with a wide overlap between the foreground and background appearances, such as the one in Fig.3 f. Furthermore, the smoothing term in (1) had a bias toward the shorter boundaries. The positioning accuracy was poor for a foreground with a long boundary, such as the one in Fig.3 d.

The CPU time and segmentation evaluations for the images in Fig.3 and 4 are listed in TableII. For images with significant differences between the foreground and background, the IOU and F-measures of segmentation by the methods based on the graph cut were similar. The maxima differences of the F-measure and IOU were 0.10 and 0.084, respectively. For images with substantial inhomogeneous regions, the segmentation metrics using this method were higher than those of the other methods. In this work, owing to the lack of prior scale information on the foreground, the multiscale appearances for segmentation are obtained through iterations, which led to a higher CPU time. The iteration time mainly depends on the region’s inhomogeneous degree for images, such as images with same size in Fig.3a and e. The CPU time using the proposed method is 13.53 and 24.48s, respectively. However, Grab cut [6] and Improved Grab cut [7, 8] don’t process the inhomogeneous region by iteration method. The CPU time is lower than that of the proposed method.

V. CONCLUSION

In this work, we present a segmentation algorithm based on the multiscale appearances. The multiscale appearances are obtained by the smoothing process using the total variation which preserves the geometric shape of the foreground and removes sub-region inhomogeneity in an image. On the one hand, the edge and region features extracted from the multiscale appearances facilitate to improve segmentation performance. On the other hand, the multiscale appearances are combined into the process of segmentation, which benefits the foreground extraction from a proper scale. However, the fixed number of Gaussians in each GMM for each smoothing image caused a negative effect. In addition, the weak edge could not be enhanced in the process of smoothing. It leads to poor segmentation performance for images with weak edges. To improve the segmentation performance, we plan to design a nonlinear smoothing filter to enhance the weak edges of smoothing images, and estimate the optimal number of Gaussians in each GMM by using the histogram shape analysis.

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