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Modified GrabCut for human face segmentation

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GrabCut;
3D human model fitting

Abstract GrabCut is a segmentation technique for 2D still color images, which is mainly based on an iterative energy minimization. The energy function of the GrabCut optimization algorithm is based mainly on a probabilistic model for pixel color distribution. Therefore, GrabCut may introduce unacceptable results in the cases of low contrast between foreground and background colors. In this manner, this paper presents a modified GrabCut technique for the segmentation of human faces from images of full humans. The modified technique introduces a new face location model for the energy minimization function of the GrabCut, in addition to the existing color one. This location model considers the distance distribution of the pixels from the silhouette boundary of a fitted head, of a 3D morphable model, to the image. The experimental results of the modified GrabCut have demonstrated better segmentation robustness and accuracy compared to the original GrabCut for human face segmentation.

1. Introduction

Several applications in computer vision such as object recognition, scene analysis, automatic traffic control systems and medical imaging require image segmentation as a pre-processing step. Image segmentation is simply the process of separating an image into foreground and background parts. Many techniques have been developed for the efficient extraction of a foreground object in a complex environment whose background cannot be trivially subtracted. Usually segmentation uses information encapsulated in the digital image to compute the best segmentation. This might be color information that is used to create histograms, or information about the pixels that indicate edges, boundaries or texture information [1].

The GrabCut technique developed by Rother et al. [2] is considered as one of the state-of-the-art unsupervised semi-automatic methodologies for image segmentation. It is a powerful extension of the graph cut technique [3] for segmentation of color images. GrabCut has been applied to different segmentation problems such as human body segmentation [4–6], video segmentation [7] and semantic segmentation [8]. Hu [4] developed an automatic extraction of human body from color images; however the process goes through many steps and iterations. His technique dynamically updates a tri-map contour using the iterated GrabCut technique. The tri-map is initialized from the results of detected faces from a scanning detector to the whole target image. The research is constrained

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to human poses with frontal side faces. Hernandez et al. [5] proposed a full-automatic Spatio-Temporal GrabCut human segmentation methodology in video sequences. The process benefits from the combination of tracking and segmentation. GrabCut algorithm is initialized using a set of seeds defined by face detection and a skin color model. Gulshan et al. [6] utilize the local color model based GrabCut to automatically segment humans from cluttered images. They use trained linear classifiers to learn segmentation masks from sparsely coded local HOG descriptors. They obtain crude segmentation of the human which is then can be refined using GrabCut local color model.

Corrigan et al. [7] extended GrabCut for video object segmentation. They extended the Gaussian Mixture Model (GMM) of GrabCut algorithm so that the color space is complemented with the derivative in time of pixel intensities in order to include temporal information in the segmentation optimization process. This led the segmentation process to be more robust. Göring et al. [8] integrate GrabCut into a semantic segmentation framework by labeling objects in a given image.

The specific problem of human face segmentation [9–13] is an essential pre-processing step needed in many applications, such as face identification, face tracking, video surveillance and security control systems. The effectiveness and robustness of these applications depend mainly on the correctness of the segmentation. The various factors associated with face segmentation are Intensity, Pose, Structural components, Image rotation, Facial expression, Poor quality, Occlusion and Illumination [11].

Different approaches [9,10,13] have been presented to solve the problem of face segmentation. These techniques introduced face position detection methods as an initialization step for the face segmentation process, especially for the images of full humans. The face detection methods introduced by [9,13] are based on a skin color model, which exhibit good behavior only in controlled environments and generates bad results in the cases of low contrast between the face and the background. The method of [9] enabled the detection and segmentation of multiple faces in a single image. However, it had a restriction to the faces with rotation larger than 45 vertical or horizontal degrees, and their results are considerably influenced in the cases of high or low illumination.

Lee et al. [10] applied the GrabCut technique for the problem of face segmentation. They tackled the problem of automatic segmentation of both human face and hair regions in images. Their probabilistic model for face position detection depends mainly on an offline training process that uses a set of manually labeled ground truth face images to train the parameters of the location, face and hair color GMM's (Gaussian Mixture Models) of the GrabCut. Their segmentation algorithm is fully automatic without any need of human intervention.

This paper focuses mainly on the problem of face segmentation from images of entire humans. It presents a similar framework to Lee et al. [10], through which it presents a new probabilistic model for face position detection as part of the GrabCut segmentation [2]. This face position detection model is applied through a semi-automatic way, however it avoids the computational overhead of the offline training process used in [10]. The proposed technique also aims at providing a more robust and accurate solution for face segmentation in difficult environments. Such environments are like those of low color contrast between background and foreground [9,13], and those of faces with restricted face orientation angles [9].

The fundamental contribution of this paper is modifying the energy function of the GrabCut optimization model. Modification includes adding a new shape prior term in addition to the original color model. This location term considers the pixels' distance to the boundary of the localized human face in the image. The proposed technique eliminates the need to user intervention after segmentation, and provides more robust and accurate segmentation than the results of the original GrabCut [2].

The remainder of this paper is organized as follows; Section 2 illustrates more details about the original technique of the GrabCut. The main contribution of the paper is described in Section 3. Results and discussions are presented in Section 4 with visually qualitative and quantitative evaluations.

2. Background

Image segmentation is simply the process of separating an image into foreground and background parts. Graph cut technique [3] was considered as an effective way for segmentation of monochrome images, which is based on the Min-Cut/Max-Flow algorithm [14]. GrabCut [2] extended the graph cut algorithm to segment color images. It uses GMMs to learn color distributions of the foreground and background by giving each pixel a probability to belong to a cluster of other pixels. The user intervention in the GrabCut is allowed by specifying only the background pixels by drawing a rectangle around the desired foreground object. The GrabCut technique can be explained as follows: Given a color image I, let us consider the array $z = (z_1, \ldots, z_n, \ldots, z_N)$ of N pixels where $z_i = (\mathrm{R}_i, \mathrm{G}_i, \mathrm{B}_i)$, $i \in [1, \ldots, N]$ in the RGB space. The segmentation is defined as an array $\alpha = (\alpha_1, \alpha_N)$, $\alpha_i \in \{0, 1\}$, assigning a label to each pixel of the image, indicating if it belongs to the background or the foreground. A tri-map T is defined by the user, in a semi-automatic way, which consists of three regions: TB, TF and TU, each one containing initial background, foreground, and uncertain pixels, respectively. Pixels belonging to TB and TF are considered as background and foreground respectively, whereas those belonging to TU are labeled by the algorithm.

A full covariance GMM of K components is defined for background pixels ($\alpha_i = 0$), and another one for foreground pixels ($\alpha_j = 1$), parameterized as follows:

$$\theta = \{\pi(\alpha, k), \mu(\alpha, k), \quad \Sigma(\alpha, k), \alpha \epsilon \{0, 1\}, k = 1 \cdots \mathrm{k}\} \tag{1}$$

where π represents the weights, μ represents the means of the GMM's and Σ the covariance matrices of the model. We also consider the array $k = \{k_1, \ldots, k_i, \ldots, k_N\}$, $k_i \in \{1, \ldots, K\}$, $i \in [1, \ldots, N]$ which is considered to indicate the component of the background or foreground GMM (according to α_i) the pixel z_i belongs to. The energy function for the segmentation is then

$$E(\alpha, k, \theta, z) = U(\alpha, k, \theta, z) + V(\alpha, z) \tag{2}$$

which consists of a data term U and a smoothness term V. The data term U computes the likelihood of a pixel to belong to some label. It is based on $p(\cdot)$; the Gaussian probability distributions of the GMM and $\pi(\cdot)$, which are the mixture weighting coefficients:

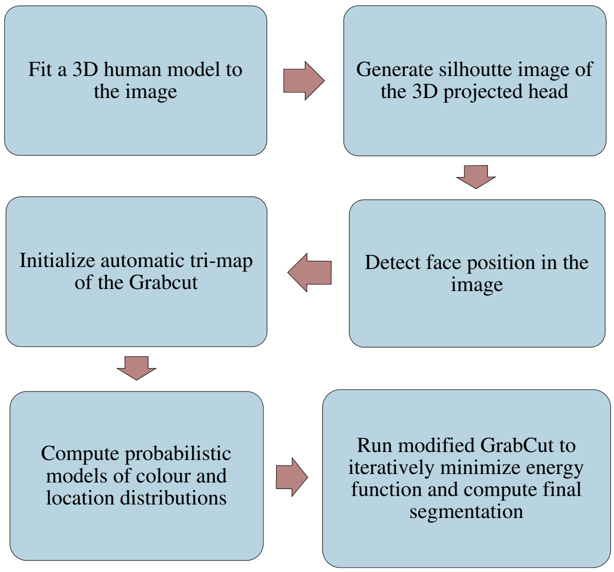

Figure 1 The framework of the modified GrabCut technique.

$$U(\alpha, k, \theta, z) = \Sigma_i - \log p(z_i|\alpha_i k_i, \theta) - \log \pi(\alpha_i, k_i) \tag{3}$$

The smoothness term V is a regularizing prior term that assumes that segmented regions should be coherent in terms of the color, considering the neighborhood C around each pixel. With this energy minimization scheme and given the initial tri-map T, the final segmentation is performed using the minimum cut algorithm of the graph cut [3].

3. Modified GrabCut

The main problem with the original GrabCut technique, for image segmentation, is that it produces unacceptable segmentation results, especially in the cases of camouflage, where the color of foreground and background is not clearly separated. This is mainly due to the probabilistic model, of the pixel color distribution, which represents the core component of the energy function of the GrabCut optimization algorithm. Consequently, extra user refinements are applied; using touch-up tools to enhance the segmentation results. The proposed human face segmentation technique tries to solve the aforesaid drawback by extending the data term of the GrabCut energy function, Eq. (3). This extension includes adding a new shape prior term representing the face location model as described in Section 3.3. The outline of the proposed technique is shown in Fig. 1.

The proposed human face segmentation technique starts with pose fitting of a 3D morphable human model to an image of a full human. This allows for automatic detection of the face position in the image, in addition to automatic initialization of the GrabCut GMM color and location models without any

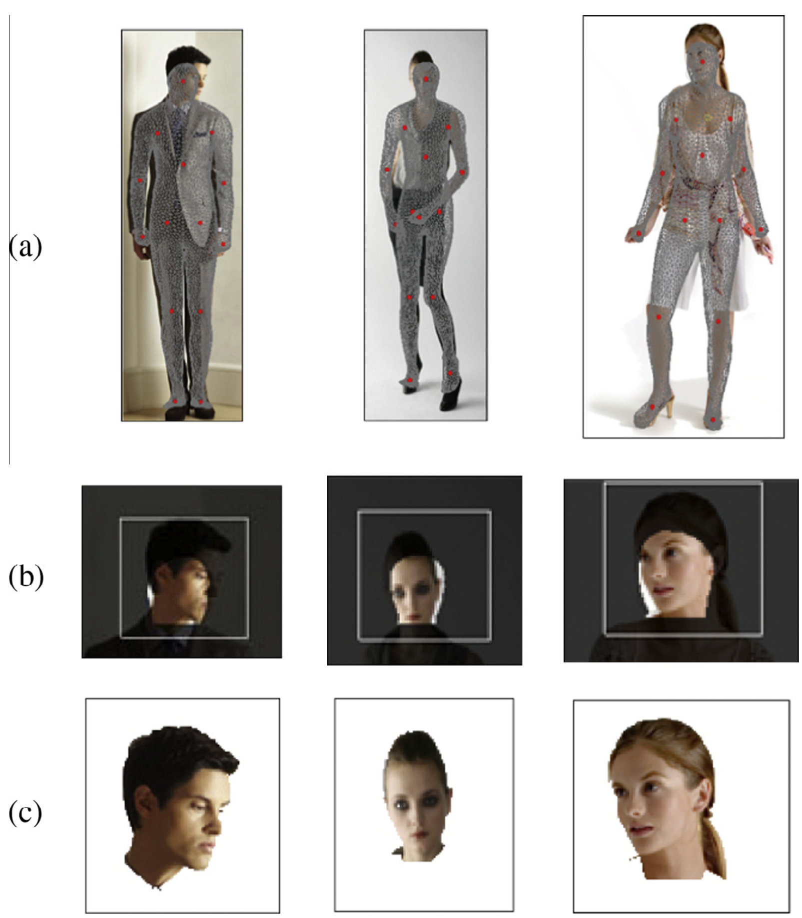

Figure 2 Sample results for different stages of the modified GrabCut: (a) human pose fitting, (b) projected head silhouette and initialization of the modified GrabCut, and (c) the segmented head.

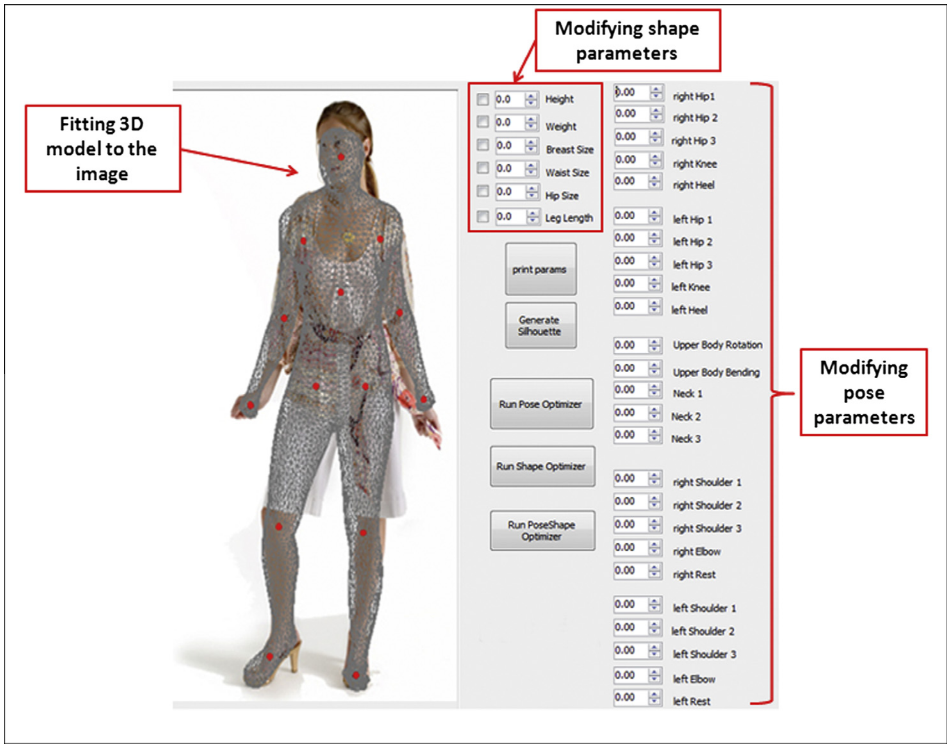

Figure 3 Snapshot of the graphical user interface for fitting the 3D human model to the image.

further user intervention (see Section 3.2). Sample results for the main stages of the modified GrabCut technique are shown in Fig. 2, while details are described in the following subsections.

3.1. Human pose fitting

The 3D morphable human model is a parametric model that allows for non-rigid pose and shape deformations. This model was learned from a publicly available database of full body laser scan of real persons and which was kindly provided by Hasler et al. [15]. This model is based on a kinematic skeleton comprising of 14 joints and a surface mesh. It allows for pose and shape variations as a variant of the SCAPE model by Anguelov et al. [16]. The fitting of the morphable model to the image, Fig. 3, is performed manually using a locally developed graphical user interface. This graphical interface is designed to allow a high degree of interactivity, through which the 3D model shape and pose parameters are easily fitted using quick up/down sliders in a process that takes less than a minute per image.

3.2. Automatic initialization of the modified GrabCut

Fitting the 3D human model to the image is an initial step to approximately define the face position in the image. This eliminates the need to the user intervention to determine the desired rectangle around the foreground object. The GrabCut starts automatically by drawing the required bounding box B, extended by a small distance ratio from the box dimensions, around the boundary of the projected head silhouette of the fitted model, Fig. 2(b). This initializes the tri-map T from the bounding box B resulted from the fitting as follows: $TU = \{z_i \in B\}$, $TB = \{z_i \notin B\}$.

3.3. Modified GrabCut energy function

The energy function of the original GrabCut, Eq. (3), will be modified by adding a new shape prior term that minimizes the distances of image pixels to the silhouette image of the projected head. The distance is computed using the Squared Euclidean Distance Transforms (SEDT). This distance transforms work by labeling each pixel of the image with its distance di to the nearest boundary pixel of the silhouette image. Squared distance between point $p = (p_1, p_2, \ldots, p_n)$ and $q = (q_1, q_2, \ldots, q_n)$ is given by:

$$d(p,q) = \sum_{i=1}^{n} (q_i - p_i)^2 \tag{4}$$

Two new GMMs for representing the location model, each consists of only one component, are introduced; one for the background pixels ($\alpha_i = 0$) and the other for the foreground pixels ($\alpha_j = 1$). These two GMMs are now parameterized as follows:

$$\theta' = \{\mu(\alpha), \sigma(\alpha), \alpha\epsilon\{0,1\}\} \tag{5}$$

where μ is the mean and σ is the standard deviation of the GMM. Eq. (3) of the original GrabCut energy function is now updated into:

$$U(\alpha, k, \theta, z, d, \theta') = \Sigma_i - \log p(z_i|\alpha_i, k_i, \theta) - \log p(d_i|\alpha_i, \theta') - \log \pi(\alpha_i, k_i) \tag{6}$$

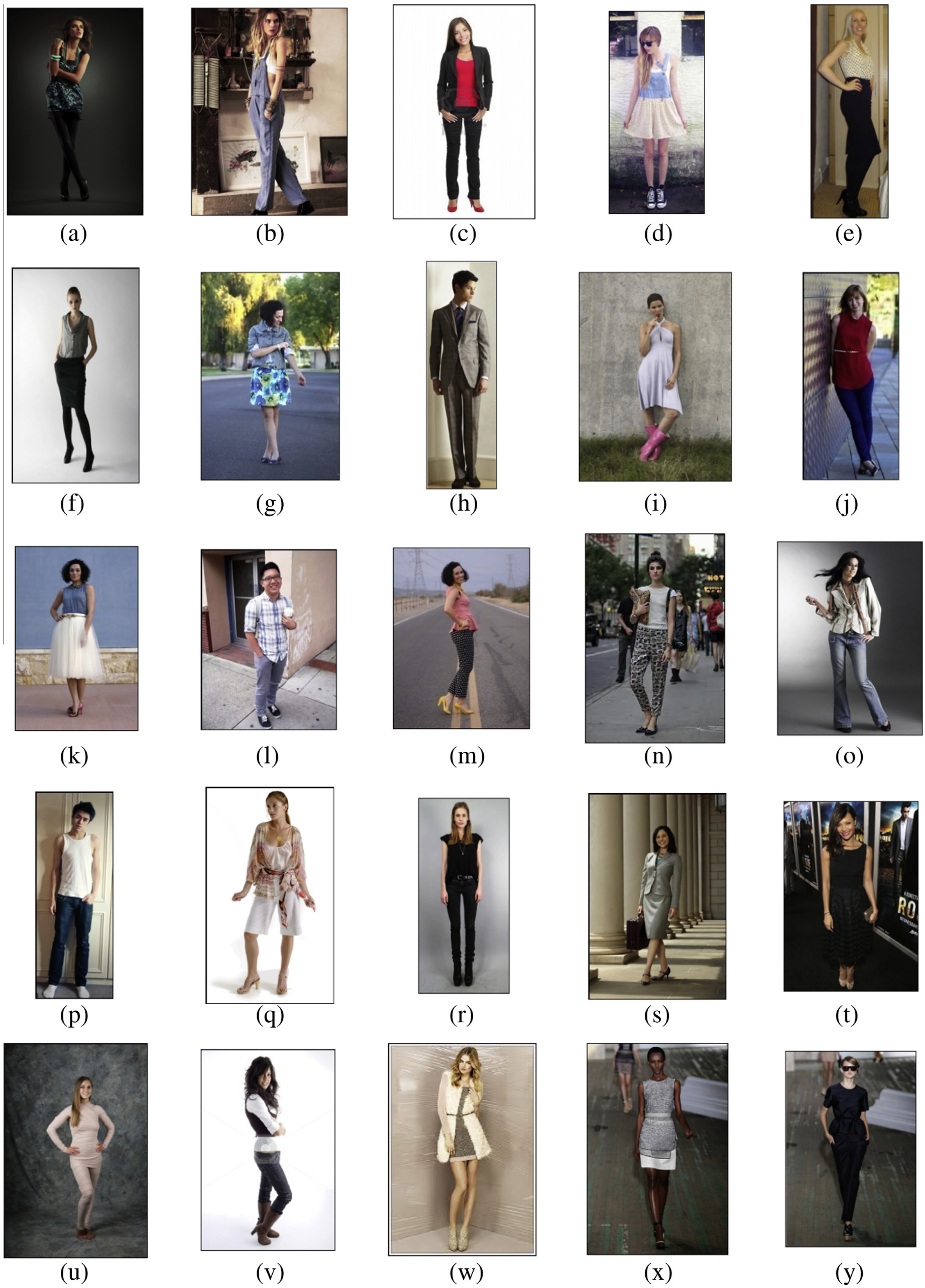

Figure 4 The dataset of full human images.

The new data term of the energy function computes the likelihood that each pixel in the image belongs to foreground or background based on both color and distance distributions.

4. Results and discussion

The modified GrabCut technique was experimentally tested using a dataset collected from publically available images, shown in Fig. 4. These images were selected to include different human poses, head orientations and different color contrast between human face and background. The current implementation performs only the hard segmentation part of the original GrabCut technique [2].

Visual comparisons for the segmentation results of sample images from the dataset, Fig. 4, are shown in Fig. 5. These sample images were selected to cover different head orientations and color contrast between foreground and background. Comparison was performed between the modified GrabCut and original GrabCut [2]. It can be observed that the results of the modified GrabCut are more accurate, compared to the results obtained by the original GrabCut, where some parts of the segmentation are mistakenly excluded (highlighted with red marks in the close up view images on the right). Exclusions occur mainly at the parts adjacent to the face border, Fig. 5(iii and iv), where low contrast exists between foreground and background colors, while others occur internally in the face region as showed in all sample images.

Table 1 shows quantitative comparisons between both techniques for selected sample images from the dataset presented in Fig. 4. The segmented ground truth data for the whole dataset are manually generated using standard image processing tools.[1] The silhouette images for the segmentation results of the ground truth, and both techniques (original and modified GrabCut) are also generated for all images. Two measures; the percentage error and the percentage overlap score; are computed for and compared between both techniques. The percentage error is calculated as the fraction of pixels with wrong segmentation divided by the total number of pixels in the image. Comparisons show that the modified GrabCut technique exhibits better accuracy compared to the original GrabCut. The mean percentage error rate is 0.19 ± 0.06% for the modified GrabCut compared to 0.29 ± 0.15% for the original GrabCut technique.

Between any two binary segmentations y_1 and y_2, an overlap score is given by $y_1 \cap y_2 / y_1 \cup y_2$, while the standard-error, in the segmentation process, is computed as the standard-deviation divided by the square root of the data set size. The modified GrabCut exhibits average overlap score of 90.97% and standard-error of 1.35% compared to 85.97% and 3.53% for the original GrabCut. Fig. 6 shows graph plots of the experimental results for better visual comparisons.

Table 2 demonstrates a proof of how the minimization function of the modified GrabCut techniques outperforms the original one in terms of minimizing the error and improving the segmentation accuracy. The table presents the results of one sample image, Fig. 4(f), which exhibits bad segmentation results using original GrabCut technique. It shows the error

[1] Adobe Photoshop™.

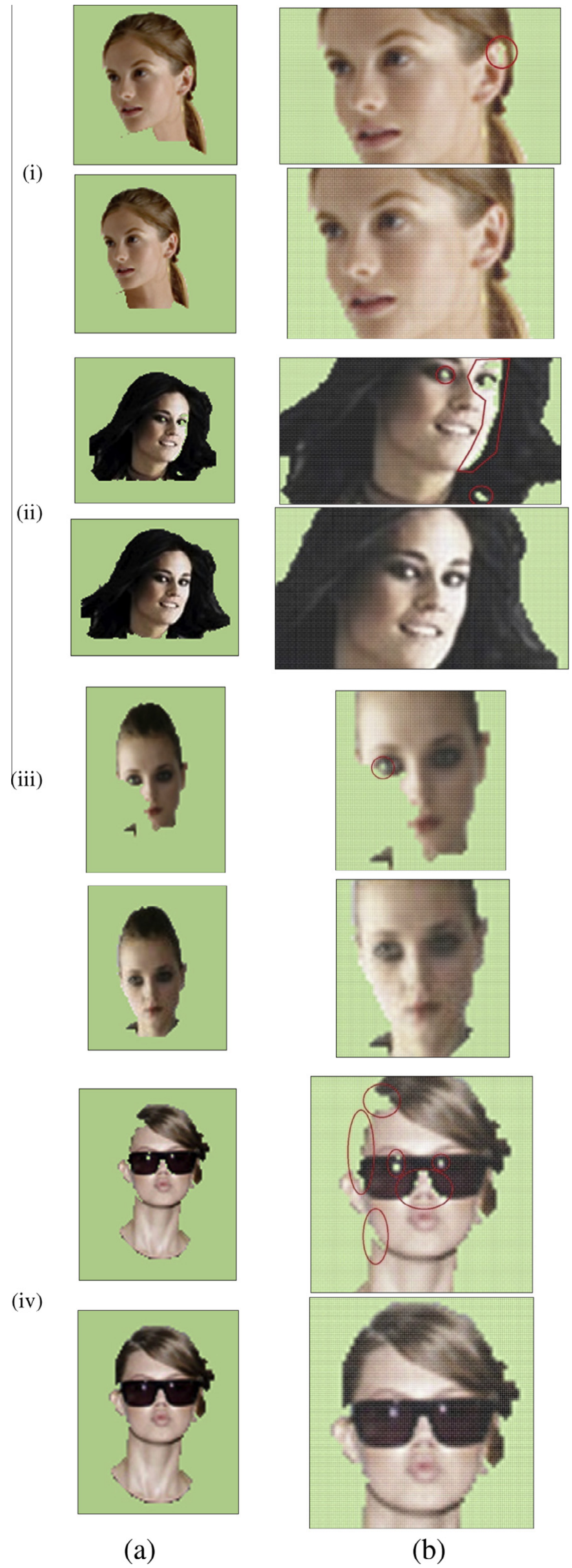

Figure 5 Visual comparison for the segmentation results of original GrabCut (the first row of each image) and modified GrabCut (in the second row). (a) The segmentation results. (b) The close up view on the right shows parts of exclusion highlighted with red marks.

Table 1 Experimental segmentation results of sample images.

Image	Error % in the original GrabCut (%)	Error % in the modified GrabCut (%)	Overlap score % in the original GrabCut (%)	Overlap score % in the modified GrabCut (%)
Fig. 4(f)	0.41	0.21	70	85
Fig. 4(h)	0.17	0.17	92	93
Fig. 4(o)	0.54	0.30	83	90
Fig. 4(q)	0.23	0.20	90	92
Fig. 4(y)	0.14	0.13	92	93
Fig. 4(x)	0.22	0.13	89	93
Mean	0.29	0.19	85.97	90.97
SD	0.15	0.06	8.64	3.32
Standard error			3.53	1.35

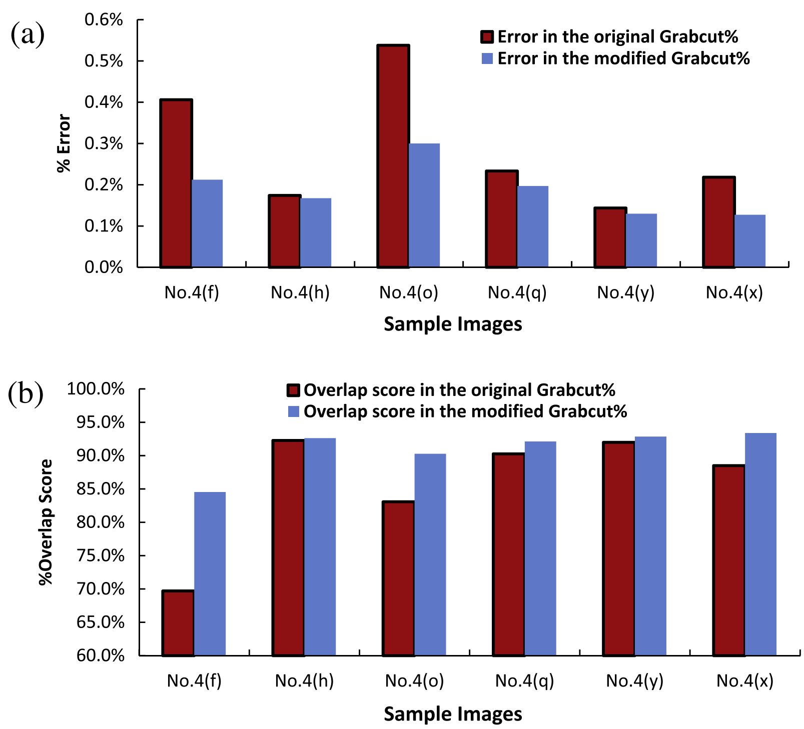

Figure 6 Plot of experimental results: (a) percentage error and (b) percentage overlap score, between original and modified GrabCut techniques of selected sample images.

Table 2 Experimental results across minimization process for a sample image.

Iteration	No. of pixels changed during minimization		Error %		Overlap score %	
	Original GrabCut	Modified GrabCut	Original GrabCut (%)	Modified GrabCut (%)	Original GrabCut (%)	Modified GrabCut (%)
1	5394	5108	0.249	0.258	81.621	80.987
2	271	28	0.41	0.224	70.445	81.250
3	1	9	0.41	0.223	70.400	81.924
4	0	2	0.41	0.221	70	83.834
5		0		0.21		85

and overlap score percentages as calculated after each iteration within the minimization process of both original and modified GrabCut. The first two columns show the number of pixels that have been changed across minimization by transferring between foreground and background segments. The minimization process converges whenever there is no longer change in the

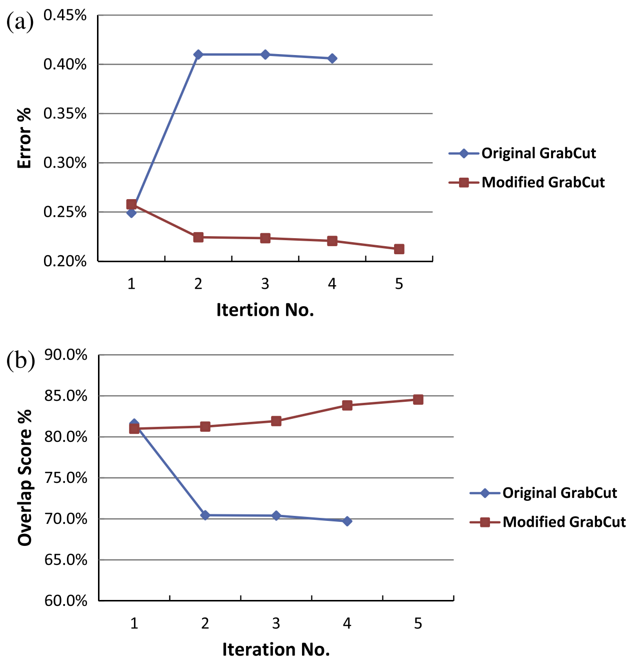

Figure 7 Plot of experimental results across the minimization process of a sample image: (a) percentage error and (b) percentage overlap score.

number of pixels. It can be noticed that although the modified technique needs one more iteration to converge, both error and overlap score percentages improve. The same results are visually compared in Fig. 7.

As shown, the modified GrabCut energy function is able to overcome one of the original GrabCut drawbacks, which occurs in the cases of camouflage. Such case occurs when the true foreground and background distributions overlap partially in the color space. This is because the minimization algorithm is no longer dependent only on the color distributions. Combining both color and location distributions into the energy function allows the segmentation to be more robust to segment different faces even when foreground and background objects are not cleanly separated. Although the segmentation process is still semi-automatic with initial manual fitting, it is able to avoid much computational overhead of the pre-processing such as the offline training process presented in [10]. In addition, the interactivity in fitting the parametric model is able to overcome the problem of human faces with different views or orientation angels. Besides, no further enhancements are required after segmentation through user touch-up (manual editing via a brush tool), as presented in the original paper of GrabCut [2].

5. Conclusions

A modified GrabCut technique is proposed by adding a new "location" term to the existing color term of the minimization energy function of the original GrabCut. The new location term considers the distance distribution of the pixels from the silhouette boundary of a fitted head, of a 3D morphable model, to the image. The results of the modified technique were tested and compared both qualitatively and quantitatively to the original GrabCut technique. The results and the comparisons proved that the modified technique is more robust and accurate than the original GrabCut technique for the segmentation of human faces from images of full humans.

In spite of being still semi-automatic, with the need for initial fitting of the 3D morphable human model to the image, the modified technique has many advantages over the original GrabCut. First, it solves the robustness problem of the original GrabCut in the cases of camouflage. Second, it directly produces face segmentation with acceptable accuracy without extra segmentation refinements. Finally, it provides an improvement toward the segmentation of the entire human body from images, which will be considered in the future work. Future work will also look forward for generalizing the modified algorithm to segment three dimensional models with proper minimization function(s).

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