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RESEARCH ARTICLE

SEGMENTATION OF HUMAN FROM PHOTO IMAGES BASED ON MCTD AND COLOR OR CONTRAST MODIFICATIONS

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ABSTRACT

Color distribution of digital images and segmentation in photo images is a challenging and important problem that finds numerous applications ranging from album making and photo classification to image retrieval. Previous works on human segmentation usually demand a time-consuming training phase for complex shape-matching processes. In this paper, we propose a straightforward framework to automatically recover human bodies from color photos and contrast equalization, midway histogram, color enhancement, and color transfer. Employing a coarse-to-fine strategy, we first detect a coarse torso (CT) using the multi cue CT detection algorithm and then extract the accurate region of the upper body. Then, an iterative multiple oblique histogram algorithm is presented to accurately recover the lower body based on human kinematics. The approach relies on the key observation that artefacts correspond to spatial irregularity of the so-called transportation map, defined as the difference between the original and the corrected image.

INTRODUCTION

Recent trends in the development of digital cameras, more and more intelligent processing of photos is increasingly demanded, such as photo classification and image retrieval. Automatic segmenting of a person becomes more crucial, so that pose analysis (e.g., running) is available and high-level applications on human (e.g., gait recognition (Liu and Sarkar 2006; Li *et al.*, 2008)) can be performed. Image segmentation is still an open problem, and many new segmentation approaches are proposed (e.g., (Tao *et al.*, 2007; Wang *et al.*, 2010; Tarabalka *et al.*, 2010; Gao *et al.*, 2011)). However, human segmentation in static images from cluttered background is paid less attention. Precious works find the homogeneous regions and then identify those corresponding to a single object according to their feature properties, such as smoothness and continuity of bounding contours. For human segmentation, there are multiple regions of body parts, such as head, torso, and legs in the image, as a result of large appearance variation. Without additional constraints, it is not clear whether these regions can be grouped into humanlike segmentation. Some top–down cues such as shape are applied to learn the properties to guide segmentation (Winn and Jojic 5005; Kohli *et al.*, 2008; Gould *et al.*, 2009). The main challenge of these algorithms is to account for large variability of shape and appearance of a given object class. Consequently, the results may not accurately delineate contours in the context of human segmentation. Furthermore, it is rather challenging to learn person shapes that encompass large variation of arbitrary pose. Much success has only been demonstrated in the context of object segmentation with limited pose and shape variation (e.g., pedestrian). Cour and Shi (2007) grouped the over segmentation results from bottom–up methods into homogeneous regions to achieve best matching against templates. However, it is difficult to extend this approach to human segmentation as it needs to handle high-dimensional pose state and train a large number of shape templates. Although the pictorial structure method (Felzenszwalb and Huttenlocher 2005) can be applied with bottom–up visual cues to infer human pose and, in turn, used for segmentation, it is still a challenge to estimate accurate pose. Consequently, any successful extension of conventional algorithms to segment human usually employs the training-test scheme or model hypothesis on person pose.

Contrast changes to digital images are one of the most elementary tools for image enhancement. Such changes may be obtained by applying a prescribed function to the gray values of images, as in contrast stretching or Gamma correction, or by prescribing the histogram of the resulting image, as in histogram equalization or specification from an example image (Bovik 2005). Such operations are characterized by the way they affect the histogram of an image and may be seen as modifications of their gray-level distribution. Actually, a nice theoretical framework enabling to merge the gray level and

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color cases is the one of optimal transportation, also known as the Monge–Kantorovich problem (Villani 2003), as we will briefly recall in this paper. When the resulting color histogram is prescribed by a target image, one speaks of *color transfer*. Unfortunately, it is impossible to build a set of model hypothesis covering all pose variations for matching. In this paper, we propose a robust framework to recover human body from photo images via integrating top–down body information and low-level visual cues into Graph Cuts framework. As shown in Fig. 1, we divide whole-body extraction into two subtasks, i.e., upper-body and lower-body segmentations. We constrain our researches on those human poses with frontal/side faces, which are common in photos. The main problem of Graph Cuts is to assign a binary label to each pixel. A common approach (Boykov and Jolly 2001) that is utilized in our scheme is to construct the foreground and background graphs containing the likelihood term of each node being foreground/background and the piecewise smoothness term indicating the pixels in the same region having the same labels. The transportation map is filtered by averaging pixel values using weights that are computed on the original image, therefore adapting to the geometry of this initial image.

SYSTEM DESIGN MODEL

In this paper, we propose a robust framework to recover human body from photo images via integrating top–down body information and low-level visual cues into Graph Cuts framework. As shown in Fig. 1, we divide whole-body extraction into two subtasks, i.e., upper-body and lower-body segmentations. We constrain our researches on those human poses with frontal/side faces, which are common in photos.

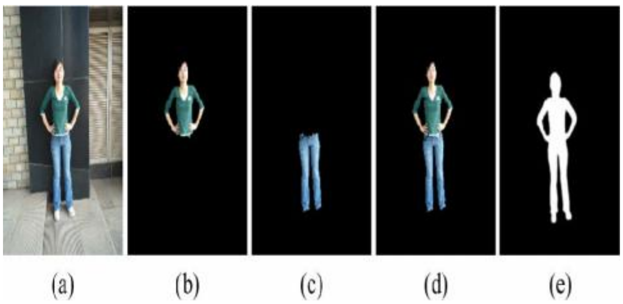

Fig. 1. Human body segmentation. (a) Input image. (b) Upper-body segmentation. (c) Lower-body segmentation. (d) Final result. (e) Ground truth

Smoothness and continuity of bounding contours. For human segmentation, there are multiple regions of body parts, such as head, torso, and legs in the image, as a result of large appearance variation. Without additional constraints, it is not clear whether these regions can be grouped into humanlike segmentation. In this paper, we propose a robust framework to recover human body from photo images via integrating top–down body information and low-level visual cues into Graph Cuts framework. As shown in Fig. 1, we divide whole-body extraction into two subtasks, i.e., upper-body and lower-body segmentations. We constrain our researches on those human poses with frontal/side faces, which are common in photos. The proposed algorithm can accurately and robustly detect part regions, thereafter accurately setting the seed points inside and outside the body regions, respectively, and achieving fine results. It will be shown that irregularities are progressively suppressed by iterating this filtering stage and that the proposed filter. To extract accurate human region and overcome shortcomings of conventional algorithms, a coarse-to-fine strategy is employed to obtain the human shape constraints, which is integrated into the Graph Cuts framework with low-level cues for final segmentation. Fig. 2 shows the flowchart of our method. We first adopt a multi-view face detector to locate the face region as *a priori*, and then, the multi-cue coarse torso detection algorithm (MCTD) is utilized to segment the upper body that adjoins to head, in which the Normalized Cuts and global probability of boundary (gPb) are effectively combined. According to human topology, the accurate lower body is segmented based on iterative multiple oblique histogram (MOH). Automatic seed point setting is very important, which is highly dependent on the accuracy of part detection. The proposed algorithm can accurately and robustly detect part regions, thereafter accurately setting the seed points inside and outside the body regions, respectively, and achieving fine results.

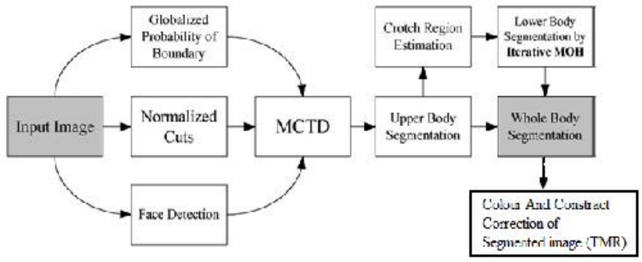

Fig. 2. Flowchart of the proposed method

UPPER-BODY SEGMENTATION

In this section, we describe the details of our scheme for segmenting upper body, which is crucial for whole-body segmentation. Given a photo image, we first use a face detection method (14) to locate the human face, which is available in most current digital cameras. In addition, then, a coarse torso (CT) as shown in Fig. 3(d) is detected by grouping Normalized Cuts segments (Fig. 3(b)). A pixelwise torso is then segmented using Graph Cuts (12). To find the torso, Mori *et al.* (23) first searched for all combinations of Normalized Cuts segments that satisfy a scale constraint and then classified these candidates with a set of cues. However, their torso results may be broken or contain background, particularly when some Normalized Cuts segments simultaneously contain background and foreground. In addition, the exhaustive search for all combinations may bring more amphibolous candidates. Hu *et al.* detected torso on dominant colors generated by using the *k*-means clustering algorithm. However, the dominant colors are not reliable in appearance variation and cluttered backgrounds.

LOWER-BODY SEGMENTATION

Lower-body segmentation is more challenging than upper body segmentation, because the poses of legs are unpredictable. Mori *et al* detected "half-limbs" as single Normalized Cuts segments and then extended half-limbs to full legs using super pixels, as well as contour cue.

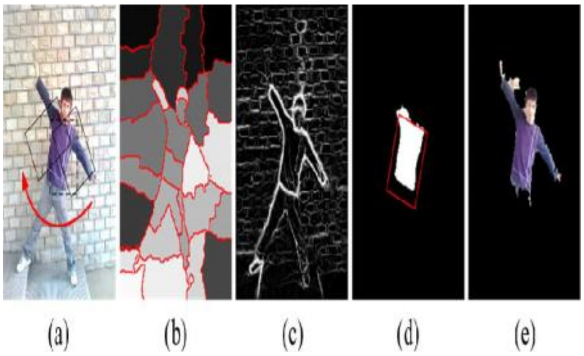

Fig. 3. Upper-body segmentation. (a) Input image with bounding-box candidates. (b) Normalized Cuts segments. (c) Result of gPb. (d) CT with the bounding box. (e) Upper-body segmentation

However, the performance of half-limb detection is not robust, as it is uncertain that all legs can be entirely split into half-limbs. In addition, the extension may fail when the Pb of legs is not salient, as shown in Fig. 3(c). In which the legs are located by finding parallelism based on Pb. We develop a coarse-to-fine scheme to segment the lower body. As shown in Fig. 5, at first, the pixels on the dominate color of the foreground seed region (c), which is estimated using the segmented upper body (b), are used to construct *t* links connecting to figure. Meanwhile, the grounds connected to t-links are set based on the segmented upper-body region, as well as the region around the lower body and between the legs if necessary (d). Then, the coarse lower body (e) can be obtained by employing the max-flow/min-cut algorithm. The final segmentation can be achieved by iterative MOH.

MOH-Based Body Segmentation

In a coarse lower body, there are still many false negatives. Here, we introduce an iterative MOH algorithm to refine the figure/ground distributions, thereby obtaining fine results. *MOH:* First, we introduce the MOH projection basis utilized to improve segmentation. The basis consists of a vector (red arrow line) with the orientation from the torso center pointing to legs' and its perpendicular. Each bin of MOH represents multiple cues of coarse segment results: accumulation, span, number of line segments, and boundary points of figure/ground on each projection line. The accumulation refers to the number of all segmented pixels that divide the projection line into multiple segments in a given bin; and the span is defined as the length of a line segment. Therefore, the shape and structure of segmentation can be effectively analyzed. In our method, MOH can obtain the missed parts and judge the integrity of the lower body, so that it is used to update Graph Cuts seeds.

Color and Contrast Modification

Here, we recall how color and contrast modifications can be applied to images and why they are likely to create visual artifacts. In this section, we investigate different applications of contrast modification to illustrate the interest of the proposed approach.

Histogram Modification

The first lines of Fig. 1 illustrate the interest of the TMR filter for several contrast enhancement techniques, namely histogram equalization (Fig. 1(b) and (g)), spatial adaptive histogram equalization, shape-preserving equalization) and histogram clipping. Notice how the artefacts described in are present in these examples, in particular the enhancement of both noise and compression artefacts. In each case, the iterated TMR filter permits to remove these artefacts while preserving contrast and restoring details. It presents several applications of the TMR filter. Observe that this filter relies on two different parameters. The most important one is, which is used to compute the weighting terms in the computation of the regularized map. The method manages to harmonize the local contrast in the sequence. However, as we can see, the flicker and film compression are so brutal that several artefacts appear on some parts of the frames. The algorithm shows how these defects are corrected by the iterated TMR filter.

SIMULATION RESULTS

We compare our body part segmentation with the part detectors. our performance is better than that of the previous method proposed . validated on our own data set. First, we find out 15.09% more half-limbs than their method, as we focus on the top–down segmentation scheme whereas Normalized Cuts usually do not segment half-limb accurately. Second, there are 12.15% more torsos we found. Because we employed MCTD to detect torsos by grouping blocks with region and boundary cues, whereas exhaustively search torso candidates and score the candidates using four low-level cues, as well as relationship between head and torso candidates.

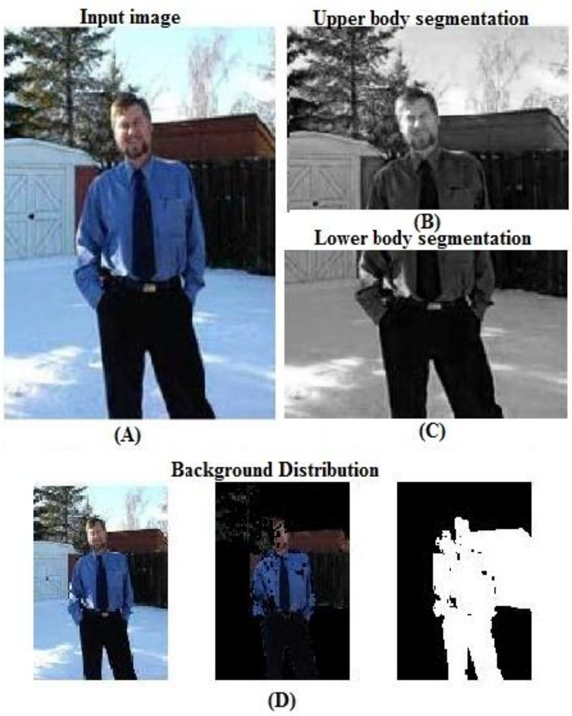

Fig 4.(a) Input Image, (b) Segmented upper body with fitted rectangle, (c)Coarse lower-body segmentation, (d) Seeds for computing background distribution

We have introduced a generic filtering procedure in order to remove the different kinds of artefacts created by radiometric or color modifications. The ability of the proposed TMR filter to deal with these artefacts while restoring the fine details of images has been demonstrated on various examples.

Fig. 5. The first row exhibits several images resulting from different contrast enhancement methods applied to the same original image, The second row shows the zoom before iterated TMR and zoom after TMR filter and The third row shows the corresponding applications of the TMR filter

Conclusion

In this paper, we has proposed an effective coarse-to-fine segmentation-based approach to automatically recover human body in static photo image, which is still one of the most challenging tasks in the computer vision field. The main contributions of this work have been drawn as follows:

1) We have proposed a straightforward segmentation-based framework for recovering human body from a static image.
2) We have presented the MCTD to detect torso.
3) We have introduced a robust iterative MOH algorithm to recover lower-body segmentation.
4) We have introduced a generic filtering procedure in order to remove the different kinds of artefacts created by radiometric or color modifications. Our proposed method is still very simple as we used a face detector to locate head position currently.

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