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Posture Recognition of Standing Human Bodies in Static Images

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Abstract

Recognition of human bodies in images is a challenging task that can facilitate numerous applications, like scene understanding and activity recognition. In order to cope with the highly dimensional pose space, scene complexity, and various human appearances, the majority of existing works require computationally complex training and template matching processes. We propose a bottom-up methodology for automatic extraction of human bodies from single images, in the case of almost upright poses in cluttered environments. The position, dimensions, and color of the face are used for the localization of the human body, construction of the models for the upper and lower body according to anthropometric constraints, and estimation of the skin color. Different levels of segmentation granularity are combined to extract the pose with highest potential. The segments that belong to the human body arise through the joint estimation of the foreground and background during the body part search phases, which alleviates the need for exact shape matching.

Introduction:

Extraction of the human body in unconstrained still images is challenging due to several factors, including shading, image noise, occlusions, background clutter, the high degree of human body deformability, and the unrestricted positions due to in and out of the image plane rotations. Knowledge about the human body region can benefit various tasks, such as determination of the human layout, recognition of actions from static images and sign language recognition. Human body segmentation and silhouette extraction have been a common practice when videos are available in controlled environments, where background information is available, and motion can aid the segmentation through background subtraction. In static images, however, there are no such cues, and the problem of silhouette extraction is much more challenging, especially when we are considering complex cases. Moreover, methodologies that are able to work at a frame level can also work for sequences of frames, and facilitate existing methods for action recognition based on silhouette features and body skeletonization.

The major contributions of this study address upright and not occluded poses.

1) We propose a novel framework for automatic segmentation of human bodies in single images.

2) We combine information gathered from different levels of image segmentation, which allows efficient and robust computations upon groups of pixels that are perceptually correlated.

3) Soft anthropometric constraints permeate the whole process and uncover body regions.

4) Without making any assumptions about the fore ground and background, except for the assumptions that sleeves are of similar color to the torso region, and the lower part of the pants is similar to the upper part of the pants, we structure our searching and extraction algorithm based on the premise that colors in body regions appear strongly

RELATED WORK

We classify approaches for human body segmentation into the following categories. The first includes

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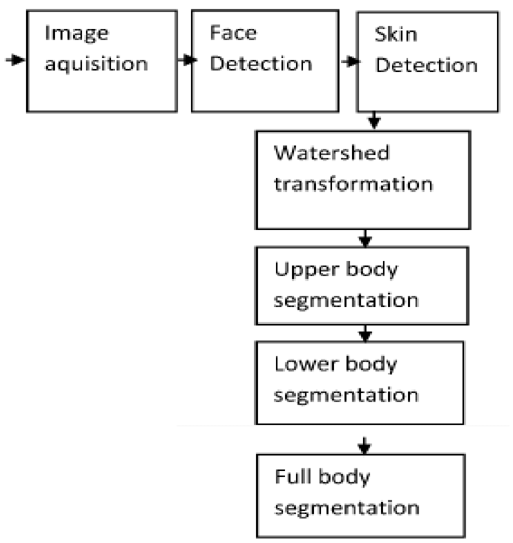
interactive methods ([10]–[14]) that expect user input in order to discriminate the foreground and background. Interactive segmentation methods are useful for generic applications, and have the potential to produce very accurate results in complex cases. However, since they rely on low-level cues and do not employ object-specific knowledge, they often require user input to guide their process, and are inappropriate for many real-world problems, where automation is necessary. In general, this category differs from the other two, which are automatic and often task specific.

The second category includes top-down approaches, which are based upon a priori knowledge, and use the image content to further refine an initial model. Top-down approaches have been proposed ([15]–[17]) as solutions to the problem of segmenting human bodies from static images. The main characteristic of these approaches is that they require high-level knowledge about the foreground, which in the case of humans is their pose. One method for object recognition and pose estimation is the pictorial structures (PS) model and its variations ([3], [18]–[20]). In general, human body segmentation approaches based on PS models can deal with various poses, but they rely on high-level models that might fail in complex scenarios, restricting the success of the end results. Besides, high-level inference is time consuming and, thus, these methods usually are computationally expensive.

BLOCK DIAGRAM OF PROPOSED WORK:



FACE DETECTION

Localization of the face region in our method is performed using OpenCV's implementation of the Viola–Jones algorithm [33] that achieves both high performance and speed. The algorithm utilizes the Adaboost method on combinations of a vast pool of Haar-like features, which essentially aim in capturing the underlying structure of a human face, regardless of skin color.Since skin probability in our methodology is learned from the face region adaptively, we prefer an algorithm that is based on structural features of the face. The Viola–Jones face detector is prone to false positive detections that can lead to unnecessary activations of our algorithm and faulty skin detections. To refine the results of the algorithm, we propose using the skin detection method presented in [34], and the face detection algorithm presented in [35]. The skin detection method is based on color constancy and a multilayer perceptron neural network trained on images collected under various illumination conditions both indoor and outdoor, and containing skin colors of different ethnic groups. The face detection method is based on facial feature detection and localization using low-level image processing techniques, image segmentation, and graph-based verification of the facial structure.

WATERSHED TRANSFORMATION

Watershed Transformation is the concept of Watersheds which is well known in topography. It was first proposed as a potential method for image

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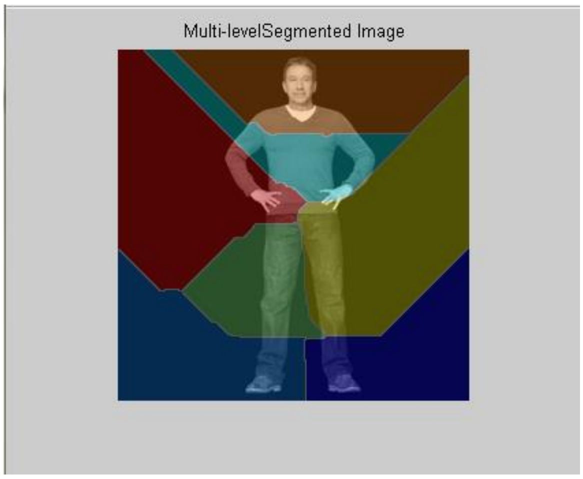
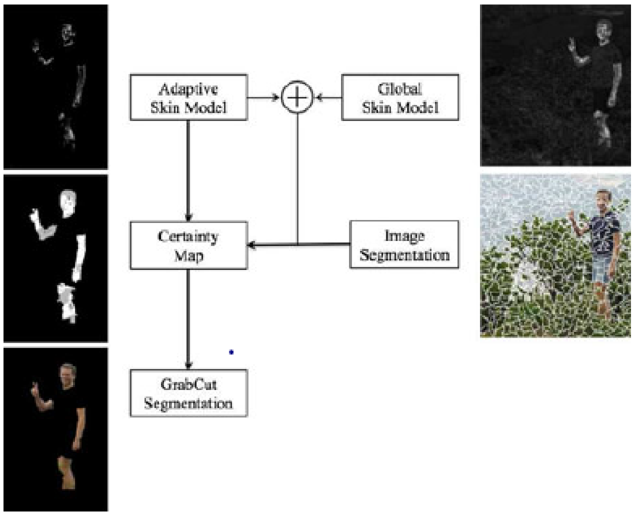
segmentation. It is a morphological based method of image segmentation. The gradient magnitude of an image is considered as a topographic surface for the watershed transformation. Watershed lines can be found by different ways. The complete division of the image through watershed transformation relies mostly on a good estimation of image gradients. The result of the watershed transform is de- graded by the background noise and produces the over-segmentation. Also, under segmentation is produced by low-contrast edges generate small magnitude gradients, causing distinct regions to be erroneously merged. There are different ways to find watershed lines. Different approaches may be employed to use the watershed principle for segmentation. Local minima of the gradient of the image may be chosen as markers, in this case an over-segmentation is produced and a second step involves region merging. Marker based watershed transformation make use of specific marker positions which have been either explicitly defined by the user or determined automatically with morphological operators or Watershed segmentation is a common technique for image segmentation.



SKIN DETECTION

Among the most prominent obstacles to detecting skin regions in images and video are the skin tone variations due to illumination and ethnicity, skin-like regions and the fact that limbs often do not contain enough contextual information to discriminate them easily. In this study, we propose combining the global detection technique [39] with an appearance model created for each face, to better adapt to the corresponding human's skin color (Fig. 3). The appearance model provides strong discrimination between skin and skin-like pixels, and segmentation cues are used to create regions of uncertainty. Regions of certainty and uncertainty comprise a map that guides the Grab-Cut algorithm, which in turn outputs the final skin regions. False positives are eliminated using anthropometric constraints and body conne



Skin detection algorithm.

Fig: skin Detection Example

UPPER BODY SEGMENTATION:

In this section, we present a methodology for extraction of the whole upper human body in single images, extending [40], which dealt with the case, where the torso is almost upright and facing the camera. The only training needed is for the initial step of the process, namely the face detection and a small training set for the global skin detection process. The rest of the methodology is mostly appearance based and relies on the assumption that there is a connection

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between the human body parts. Processing using super-pixels instead of single pixels, which are acquired byan image segmentation algorithm, yield more accurate results and allow more efficient computations. The initial and most crucial step in our methodology is the detection of the face region, which guides the rest of the process. The information extracted in this step is significant. First, the color of the skin in a person's face can be used to match the rest of his or her visible skin areas,making the skin detection process adaptive to each person. Second, the location of the face provides a strong cue about the rough location of the torso. Here, we deal with cases, where the torso is below the face region, but without strong assumptions about in and out of plane rotations. Third, the size of the face region can further lead to the estimation of the size of body parts according to anthropometric constraints. Face detection here is primarily conducted using the Viola–Jones face detection algorithm for both frontal and side views. Since face detection is the cornerstone of our methodology, we refine the results of the aforementioned method using the face detectionalgorithm presented in [35].

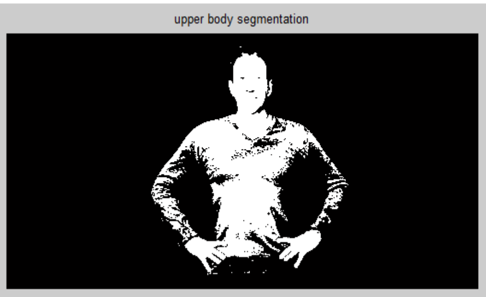

Figure: upper body segmentation

LOWER BODY EXTRACTION:

The algorithm for estimating the lower body part, inorder to achieve full body segmentation is very similar to the one for upper body extraction. The difference is the anchor points that initiate the leg searching process. In the case of upper body segmentation, it was the position of the face that aided the estimation of the upper body location. In the case of lower body segmentation, it is the upper body that aids the estimation of the lower body's position. More specifically, the general criterion we employ is that the upper parts of the legs should be underneath and near the torso region. Although the previously estimated UBR provides a solid starting point for the leg localization, different types of clothing like long coats, dresses, or color similarities between the clothes of the upper and lower body might make the torso region appear different (usuallylonger) than it should be. To better estimate the torso region,we perform a more refined torso fitting process, which does not require extensive computations, since the already estimated shape provides a very good guide.

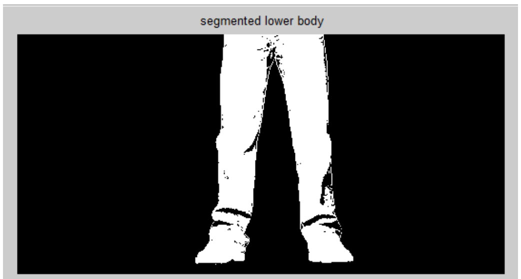

Figure: Lower body Segmentation

RESULTS:

To evaluate our algorithm, we used samples from the publicly available INRIA person dataset [41], which includes people performing everyday activities in outside environments inmostly upright position. This is a challenging dataset, since the photos are taken under various illumination conditions, in heavily cluttered environments and people appear in various types of clothing.

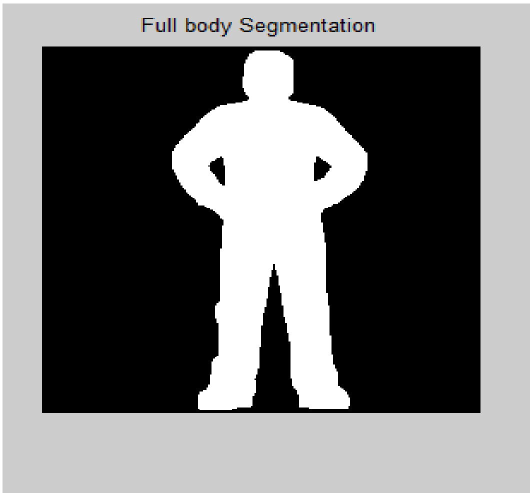

Figure: Full body Segmentation

Conclusion

The first advantage of our methodology over those tested is that it can automatically localize and segment the human body.Additionally, the final results achieve very good accuracy, evenin complex scenarios, and the small standard deviation shows that it is stable. The main advantages of our method are as follows. First, we combine cues from multiple levels of segmentation; therefore, to take into consideration different perceptual groupings from coarse to fine. Second, during our searching process, we try to find arbitrary salient regions that are comprised by segments that appear strongly inside the (hypothesized) foreground rectangles and weakly outside. By considering foreground and background conjunctively, we alleviate the need for exact mask fitting and dense searching, and we allow the masks to be large according to anthropometric constraints so that they may perform sufficient sampling in fewer steps. Third, we demonstrate how soft anthropometric constraints can guide and automate the process in many levels, from efficient mask creation and searching to the refinement of the probabilistic map that leads to the final mask for the body regions. Searching for the upper and lower body parts, as well as the similar process of torso fitting, however, still remain one of the most computationally expensive steps of the methodology.

REFERENCES

[1] M. Andriluka, S. Roth, and B. Schiele, "Pictorial structures revisited: People detection and articulated pose estimation," in Proc. IEEE Conf.Comput. Vis. Pattern Recog., 2009, pp. 1014–1021.

[2] M. Everingham, L. Van Gool, C. K.Williams, J.Winn, and A. Zisserman, "The pascal visual object classes (VOC) challenge," Int. J. Comput. Vis., vol. 88, no. 2, pp. 303–338, 2010.

[3] V. Ferrari, M. Marin-Jimenez, and A.Zisserman, "Progressive search space reduction for human pose estimation," in Proc. IEEE Conf. Comput.Vis. Pattern Recog., 2008, pp. 1–8.

[4] M. P. Kumar, A. Zisserman, and P. H. Torr, "Efficient discriminative learning of parts-based models," in Proc. IEEE 12th Int. Conf. Comput.Vis., 2009, pp. 552–559.

[5] V. Delaitre, I. Laptev, and J. Sivic, "Recognizing human actions in still images: A study of bag-of-features and part-based representations," in Proc. IEEE Brit. Mach. Vis. Conf., 2010.

[6] A. Gupta, A. Kembhavi, and L. S. Davis, "Observing human-object interactions: Using spatial and functional compatibility for recognition," IEEETrans. Pattern Anal. Mach. Intell., vol. 31, no. 10, pp. 1775–1789, Oct. 2009.

[7] B. Yao and L. Fei-Fei, "Grouplet: A structured image representation for recognizing human and object interactions," in Proc. IEEE Conf. Comput.Vis. Pattern Recog., 2010, pp. 9–16.

[8] P. Buehler, M. Everingham, D. P. Huttenlocher, and A. Zisserman, "Long term arm and hand tracking for continuous sign language TV broadcasts," in Proc. 19th Brit. Mach. Vis. Conf., 2008, pp. 1105–1114.

[9] A. Farhadi and D. Forsyth, "Aligning ASL for statistical translation usinga discriminative word model," in Proc. IEEE Comput. Soc. Conf. Comput.Vis. Pattern Recog., 2006, pp. 1471–1476.

[10] L. Zhao and L. S. Davis, "Iterative figure-ground discrimination," in Proc. 17th Int. Conf. Pattern Recog., 2004, pp. 67–70.

[11] L. Grady, "Random walks for image segmentation," IEEE Trans. Pattern Anal. Mach. Intell., vol. 28, no. 11, pp. 1768–1783, Nov. 2006.

[12] C. Rother,V.Kolmogorov, and A. Blake, "Grabcut: Interactive foreground extraction using iterated graph cuts," ACM Trans. Graph., vol. 23, no. 3, pp. 309–314, Aug. 2004.

ISSN No: 2348-4845
International Journal & Magazine of Engineering, Technology, Management and Research
A Peer Reviewed Open Access International Journal

[13] V. Gulshan, C. Rother, A. Criminisi, A. Blake, and A. Zisserman,“Geodesic star convexity for interactive image segmentation,” in Proc.IEEE Conf. Comput. Vis. Pattern Recog., 2010, pp. 3129–3136.

[14] Y. Y. BoykovandM.-P. Jolly, “Interactive graph cuts for optimal boundary & region segmentation of objects in ND images,” in Proc. IEEE 8th Int.Conf. Comput. Vis., 2001, pp. 105–112.

[15] M. P. Kumar, P. H. S. Ton, and A. Zisserman, “Obj cut,” in Proc. IEEE Comput.Soci. Conf. Comput. Vision Pattern Recog., 2005, pp. 18–25.

[16] S. Li,H. Lu, and L. Zhang, “Arbitrary body segmentation in static images,” Pattern Recog., vol. 45, no. 9, pp. 3402–3413, 2012.

[17] L. Huang, S. Tang, Y. Zhang, S. Lian, and S. Lin, “Robust human bodysegmentation based on part appearance and spatial constraint,” Neurocomputing,vol. 118, pp. 191–202, 2013.

[18] P. F. Felzenszwalb and D. P. Huttenlocher, “Pictorial structures for objectrecognition,” Int. J. Comput.Vis., vol. 61, no. 1, pp. 55–79, 2005.

[19] D. Ramanan, “Learning to parse images of articulated bodies,” Adv. Neur. Inf. Process. Sys., pp. 1129–1136, 2006.

[20] M. Eichner and V. Ferrari, “Better appearance models for pictorial structures,” in Proc. Brit. Mach. Vis. Conf., 2009.

[21] Y. Bo and C. C. Fowlkes, “Shape-based pedestrian parsing,” in Proc. IEEE Int. Conf. Comput. Vis. Pattern Recog., 2011, pp. 2265–2272.

[22] Z. Hu, G. Wang, X. Lin, and H. Yan, “Recovery of upper body poses in static images based on joints detection,” Pattern Recog. Lett., vol. 30, no. 5, pp. 503–512, 2009.

[23] J. Malik, S. Belongie, T. Leung, and J. Shi, “Contour and texture analysis for image segmentation,” Int. J. Comput. Vis., vol. 43, no. 1, pp. 7–27, 2001.

[24] M. Yao and H. Lu, “Human body segmentation in a static image with multiscalesuperpixels,” in Proc. 3rd Int. Conf. Awareness Sci. Technol., 2011, pp. 32–35.

[25] Y. Hu, “Human body region extraction from photos,” in Proc. Mach. Vis. Appl., 2007, pp. 473–476.

[26] Z. Lin, L. Davis, D. Doermann, and D. DeMenthon, “An interactive approach to pose-assisted and appearance-based segmentation of humans,” in Proc. IEEE 11th Int. Conf. Comput. Vis., Oct. 2007, pp. 1–8.

[27] P. Kohli, J. Rihan, M. Bray, and P. Torr, “ Simultaneous segmentation and pose estimation of humans using dynamic graph cuts,” Int. J. Comput. Vis., vol. 79, no. 3, pp. 285–298, 2008.

[28] G. Mori, X. Ren, A. A. Efros, and J. Malik, “Recovering human body configurations: Combining segmentation and recognition,” in Proc. IEEEComput. Soc. Conf. Comput. Vis. Pattern Recog., 2004, pp. II-326–II-333.

[29] S. Li, H.-C. Lu, X. Ruan, and Y.-W.Chen, “ Human body segmentation based on deformable models and two-scale superpixel,” Pattern Anal.Appl., vol. 15, no. 4, pp. 399–413, 2012.

[30] H. Lu, G. Fang, X. Shao, and X. Li, “Segmenting human from photo images based on a coarse-to-fine scheme,” IEEE Trans. Syst., Man, Cybern.B, Cybern., vol. 42, no. 3, pp. 889–899, Jun. 2012.

[31] S. Li, H. Lu, and X. Shao, “Human body segmentation via data-driven graph cut,” IEEE Trans. Cybern., vol. 44, no. 11, pp. 2099–2108, Nov. 2014.

[32] I. Rauschert and R. T. Collins, “A generative model for simultaneous estimation of human body shape and pixel-level segmentation,” in Proc. Eur. Conf. Comput. Vis., 2012, pp. 704–717.

[33] P. Viola and M. Jones, “Rapid object detection using a boosted cascade of simple features,” in Proc. IEEE Comput. Soc. Conf. Comput. Vis. PatternRecog., 2001, pp. I-511–I-518.

[34] P. Kakumanu, S. Makrogiannis, R. Bryll, S. Panchanathan, and N. Bourbakis, “Image chromatic adaptation using ANNs for skin color adaptation,”inProc. 16th IEEE Int. Conf. Tools Artif.Intell. Conf., 2004, pp. 478–485.

[35] A. Tsitsoulis and N. Bourbakis, “A methodology for detecting faces from different views,” in Proc. IEEE 24th Int. Conf. Tools Artif.Intell.,2012, pp. 238–245.

[36] A. Tsitsoulis and N. Bourbakis, “An LG-graph-based early evaluation of segmented images,” Meas. Sci. Technol., vol. 23, no. 11;

[37] H. Zhang, J. E. Fritts, and S. A. Goldman, “Image segmentation evaluation:A survey of unsupervised methods,” Comput. Vis. Image Understanding, vol. 110, no. 2, pp. 260–280, 2008.

[38] M.-Y. Liu, O. Tuzel, S. Ramalingam, and R. Chellappa, “Entropy rate superpixelsegmentation,” in Proc. IEEE Conf. Comput. Vis. Pattern Recog., 2011, pp. 2097–2104.

[39] C. O. Conaire, N. E. O’Connor, and A. F. Smeaton, “Detector adaptation by maximizing agreement between independent data sources,” in Proc.IEEE Conf. Comput. Vis. Pattern Recog., 2007, pp. 1–6.

[40] M. C. Shin, K. I. Chang, and L. V. Tsap, “Does color space transformationmake any difference on skin detection?” in Proc. IEEE 6thWorkshop Appl.Comput. Vis., 2002, pp. 275–279.

[41] N. Dalal and B. Triggs, “Histograms of oriented gradients for human detection,” in Proc. IEEE Comput. Vision Pattern Recog.,Comput. Soc.Conf., Jun. 2005, pp. 886–893.

[42] I. EndresandD.Hoiem, “Category independent object proposals,” in Proc. Eur. Conf. Comput. Vis., 2010, pp. 575–588.

[43] H. Jiang, “Human pose estimation using consistent max covering,” IEEE Trans. Pattern Anal. Mach. Intell., vol. 33, no. 9, pp. 1911–1918, Sep.2011.