A Saliency-Guided Method for Automatic Photo Refocusing

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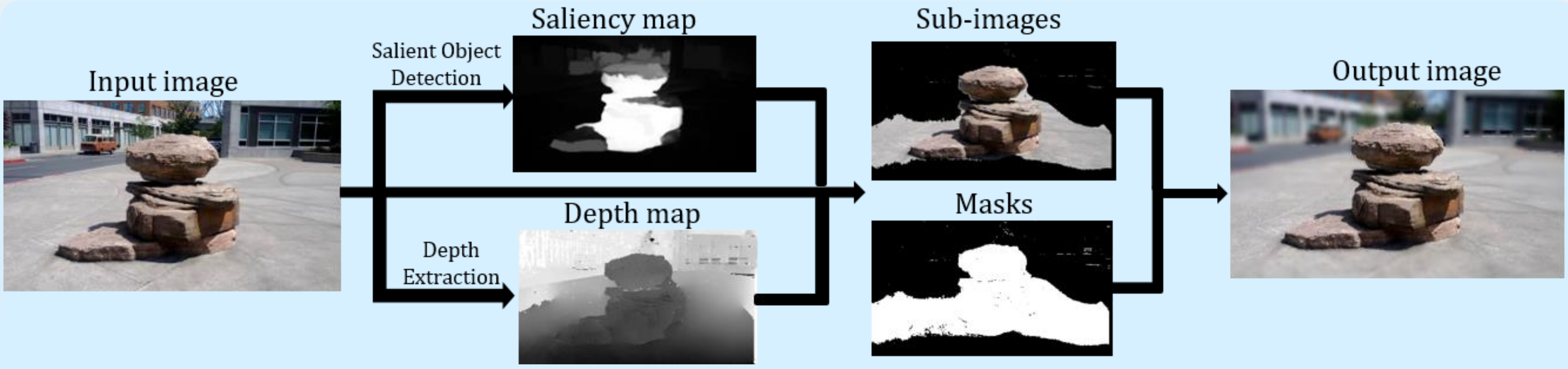
Introduction

With the prevalence of smart phones and pocket cameras, photo refocusing has become a basic editing and processing method for its power in interesting object emphasis and photo beautification. We present a simple but effective method to perform image refocusing automatically and rapidly. The key of our method lies in the utilization of the characteristics of human visual systems. By leveraging current saliency detection methods, we locate the region of interest for a given photo rapidly. Then we calculate its depth map according to the frames captured before shooting. The original image is softly segmented into layers and blurred with different confusion sizes according to the depth map. At last, the blurred layers are softly combined into a refocused photo. Experimental results demonstrate our method performs outstandingly both in automatic photo refocusing and computational complexity.

Proposed approach



For an input image, we first calculate the corresponding depth map[1] and saliency map[2]. Then the image is segmented into layers and blurred with different confusion based on the two maps. Finally the output image is generated by combining the blurred layers and will refocus on salient objects.

Key idea 1:

We introduce adaptive segmentation and blurring. The thresholds are chosen based on the gray distribution of depth map:

$$\forall D' \in [D_i - \sigma, D_i + \sigma], \mathcal{F}(D') \geq \mathcal{F}(D_i)$$

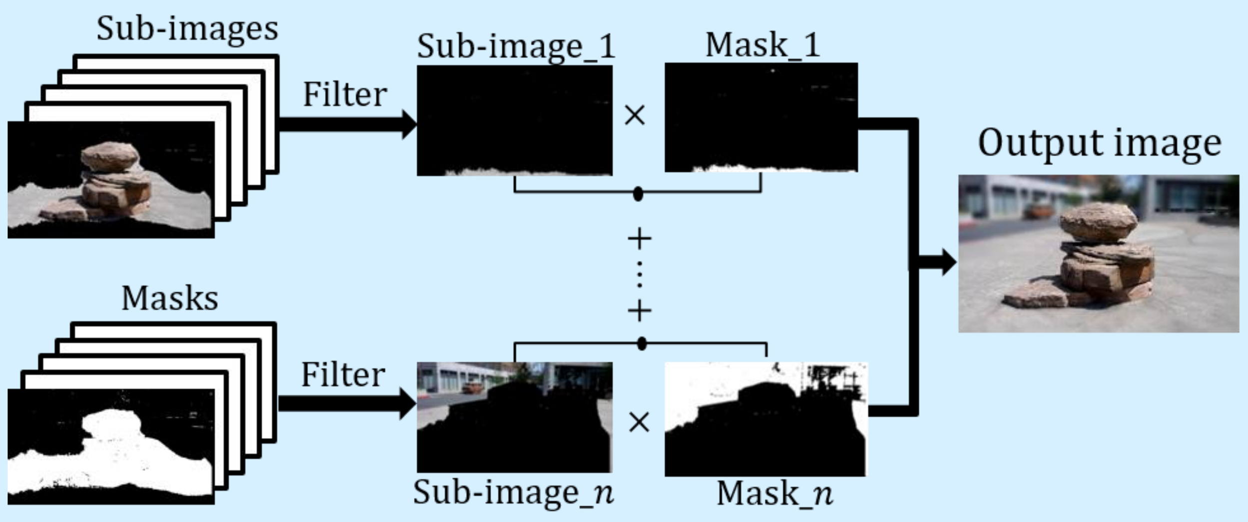
where $\mathcal{F}$ is the frequency of gray value D_i. Therefore the thresholds are local minimums which ensure that the blurring degree for one object is the same as much as possible. The input image is segmented into sub-images according to the thresholds, each sub-image is performed a segment-level blurring.

Key idea 2:

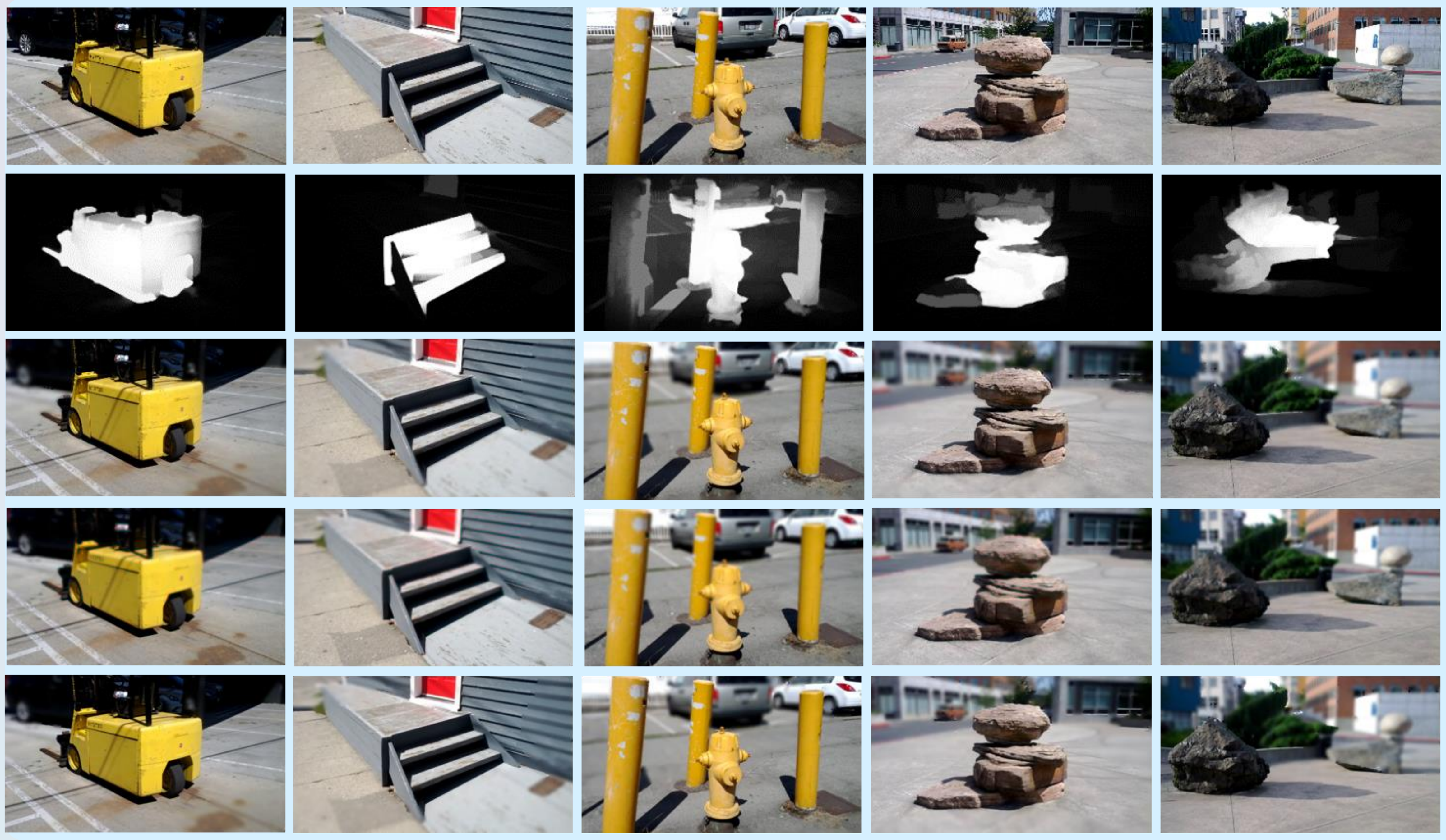
We introduce augmented re-combination. We multiply the processed sub-images with their corresponding masks and add them up to generate the output image:

$$Output\ image = \sum_{i=1}^{n} \frac{1}{\aleph_i} Sub\_image_i \times Mask_i$$

where $\aleph_i$ is the normalization coefficient. This process makes the stitching edges of the output image more smooth.



Experiments



effectiveness Evaluation:

We evaluate our method on tiny dataset[1] and compare it with the method in [3] and the more accurate algorithm which blurs pixels one by one. Compared with [3], the salient object in our method stands sharper against its background. Besides, our method works better in processing of edges between segments. Moreover, our method is automatic while [3] is not. Compared with the accurate algorithm, our method has no obvious difference with it. However, the accurate algorithm is much slower.

execution efficiency:

Our method achieves linear time complexity. to be specific, regardless of the size of blurring kernel, the time complexity of the algorithm is $O(N)$, where N is the number of pixels.

*Examples of comparison. (Top row) Input images. (Second row) Saliency maps. (Third row)Results of our method. (Forth row) Results of algorithm in [3]. (Bottom row) Results of accurate method.

Some References

[1] F. Yu and D. Gallup. 3d reconstruction from accidental motion. In *CVPR*, pages 3986–3993. IEEE, 2014.

[2] J. Zhang, S. Sclaroff, Z. Lin, X. Shen, B. Price, and R. Mˇech. Minimum barrier salient object detection at 80 fps. In *ICCV*, pages 1404–1412, 2015.

[3]. Y. Bando and T. Nishita. Towards digital refocusing from a single photograph. In *PG*, pages 363–372.IEEE, 2007.

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