GrabCut+D

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  - Third: Robust Depth Based Seeding

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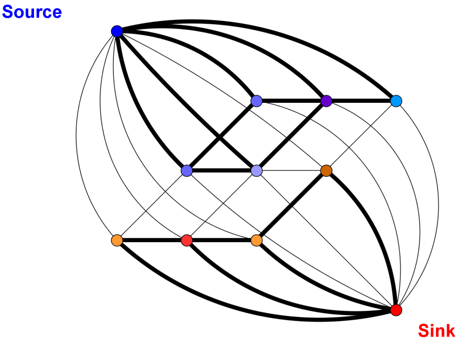

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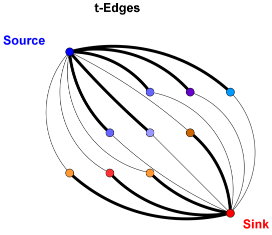

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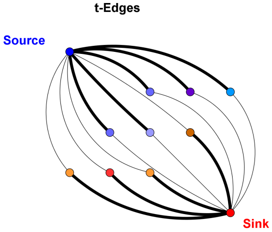

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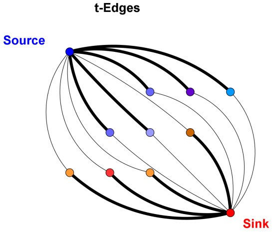

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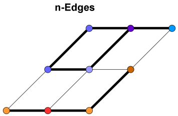

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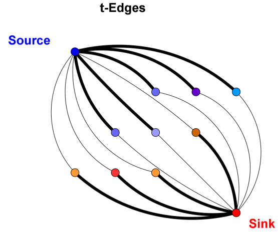

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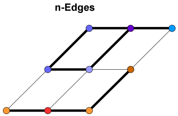

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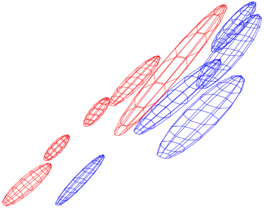

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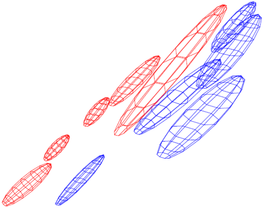

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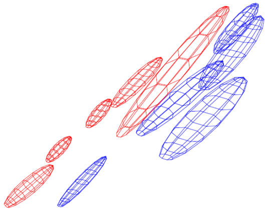

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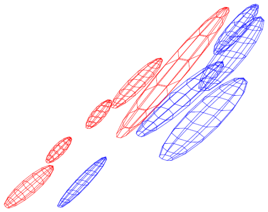

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Initial Selection

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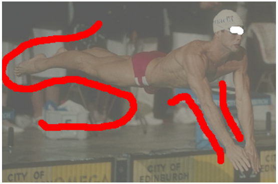
Further Interaction



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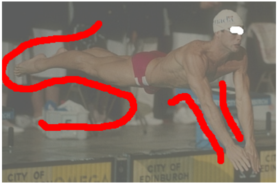

Final Result

First Approach: Region Growing

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Main Idea: Extract an object from an image implementing a priority search algorithm to identify its connected-depth component.Then, apply GrabCut in the contour of the component to improve the result.

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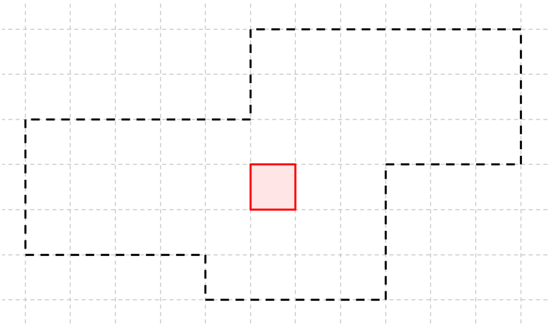

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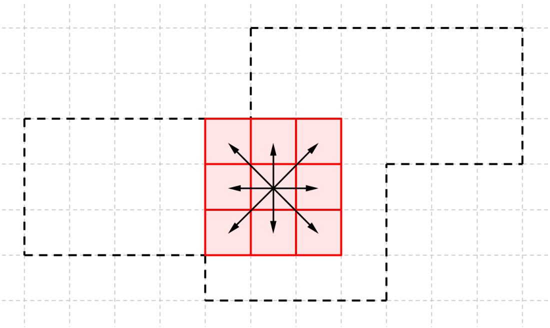

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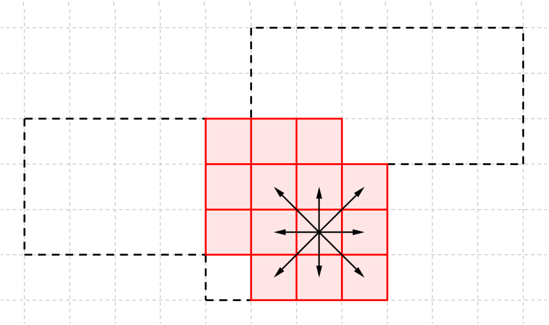

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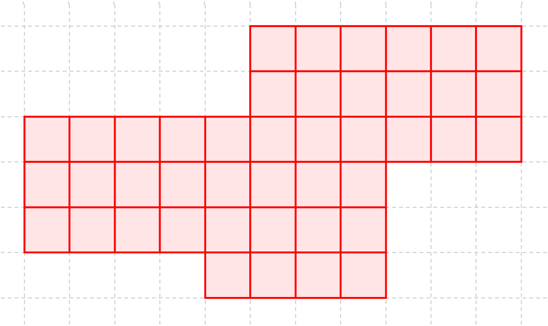

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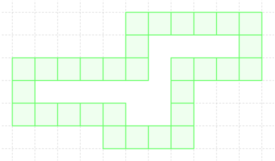

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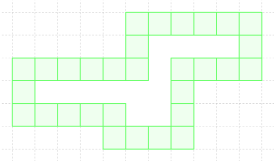

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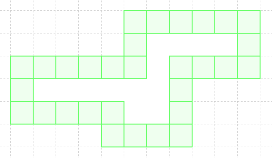

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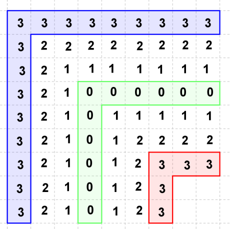

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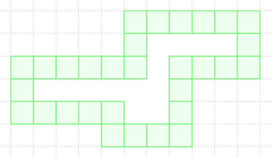

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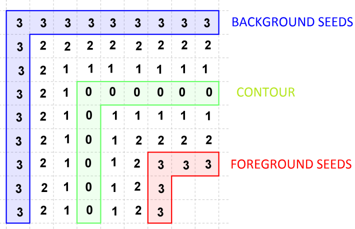

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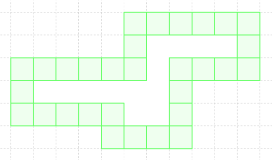

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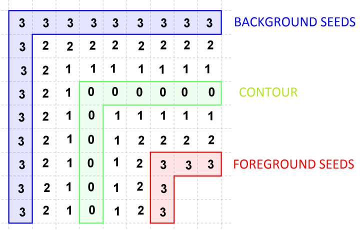

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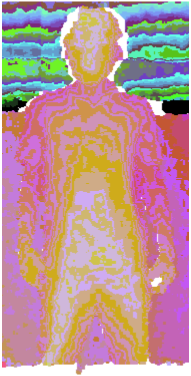
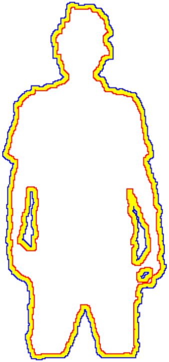
Depth



Graph



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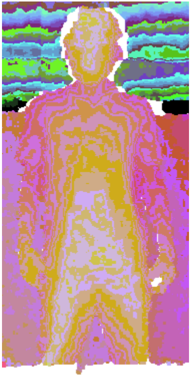

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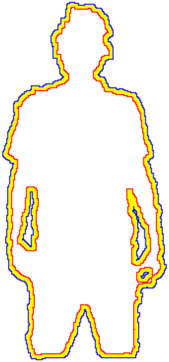

Result

Depth data must be improved!

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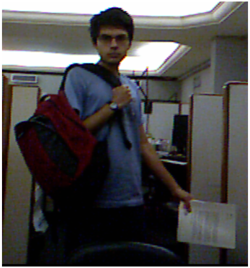

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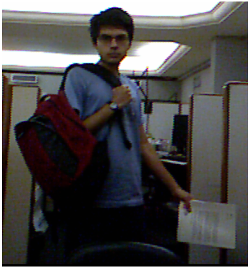

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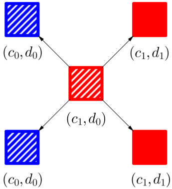

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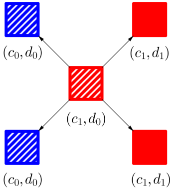

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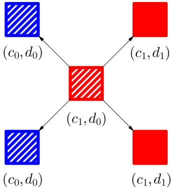

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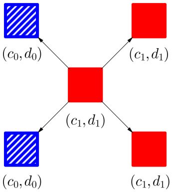

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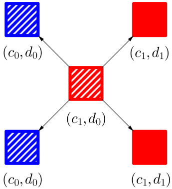

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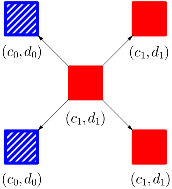

Result of Color Based Depth Filter

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Filter

Previous Result

New Result

Detail

Remarks First Approach

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- Cons:
  1. Vulnerable to depth noise.
  2. No useful in the case of object-background adjacency.

Second Approach: Probabilistic Model

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Main Idea: Extend the energy function model implemented in GrabCut to include the depth data in analogous way to colour. Construct Gaussian Mixture Models associated to FG and BG depth and use them to define the seeding.

Involving depth data in Energy Function

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$$\begin{aligned} V(x, z, d) = & \gamma_C \Big(\sum_{(p,q \in N)} dis(p,q)^{-1} \exp\{-\beta_C ||z_p - z_q||^2\}[x_p \neq x_q] \Big) + \\ & \gamma_D \Big(\sum_{(p,q \in N)} dis(p,q)^{-1} \exp\{-\beta_D ||d_p - d_q||^2\}[x_p \neq x_q] \Big) \end{aligned}$$

Involving depth data in Energy Function

- Depth model ω_D is constructed from Gaussian Mixtures.

$$E(x, \omega_C, \omega_D, z, d) = U(x, \omega_C, \omega_D, z, d) + V(x, z, d)$$

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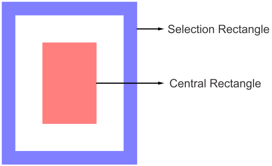

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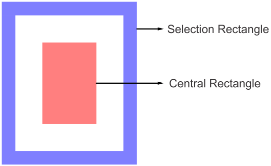

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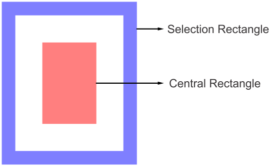

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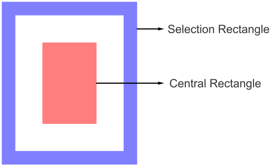

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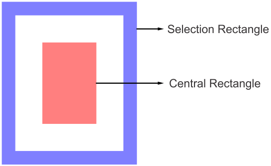

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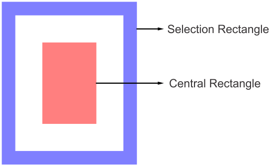

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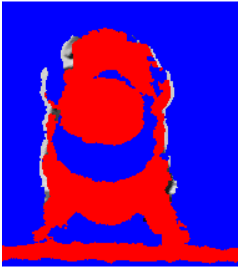

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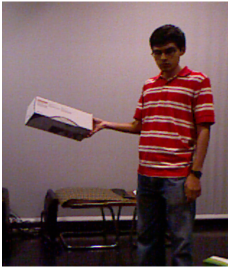

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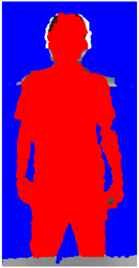

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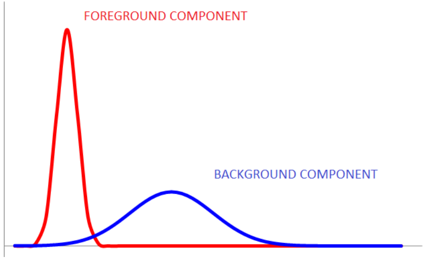

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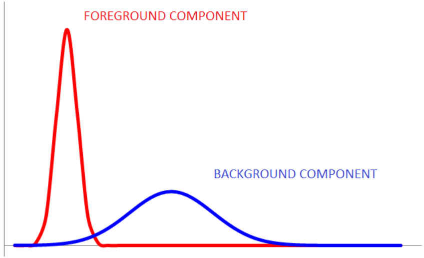

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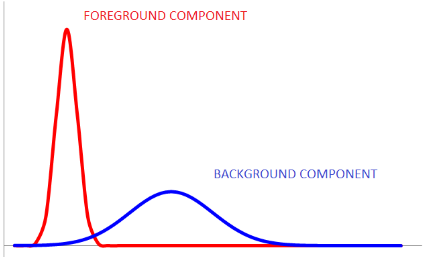

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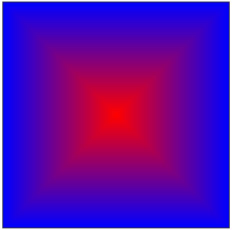

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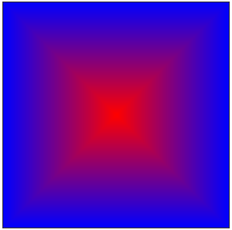

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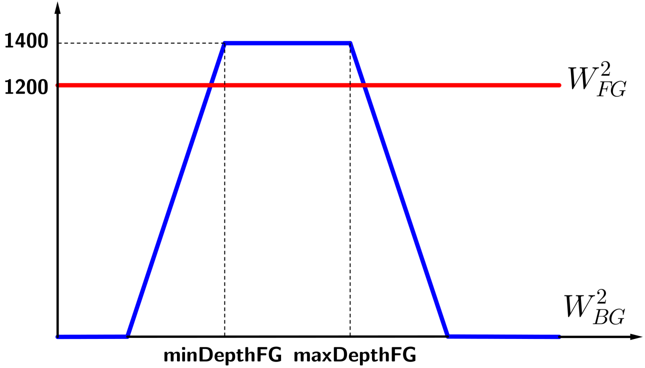
8. For all p set $W^2_{FG}(p) = 1200$.
9. Set W^2_{BG} a stepwise linear function that separates between close pixels and far pixels respect to FG clusters.



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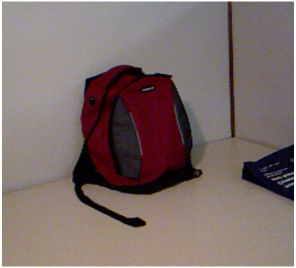

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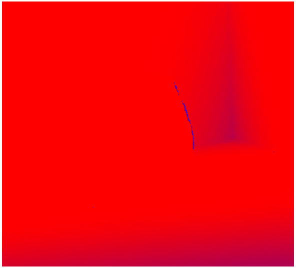


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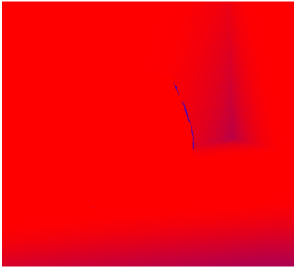

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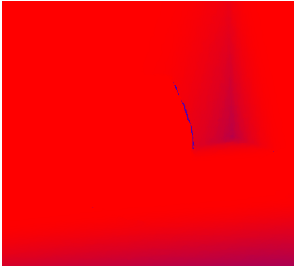

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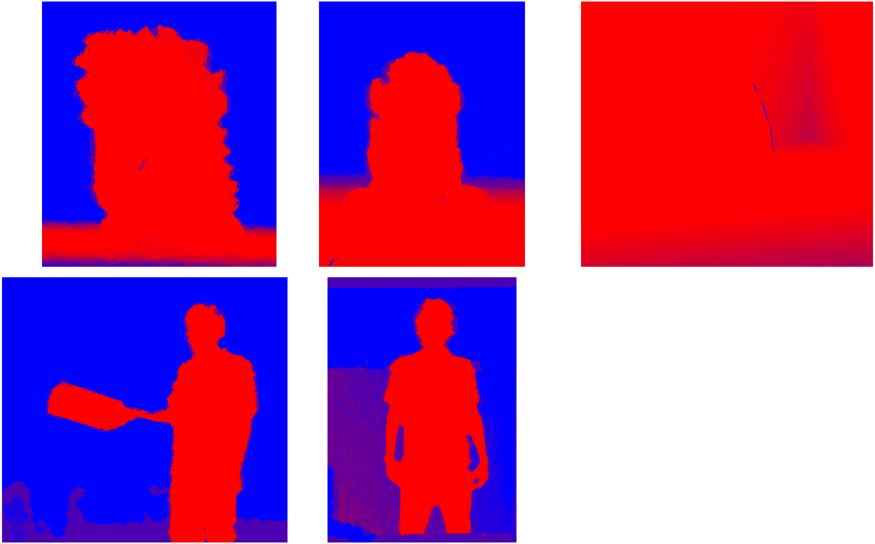

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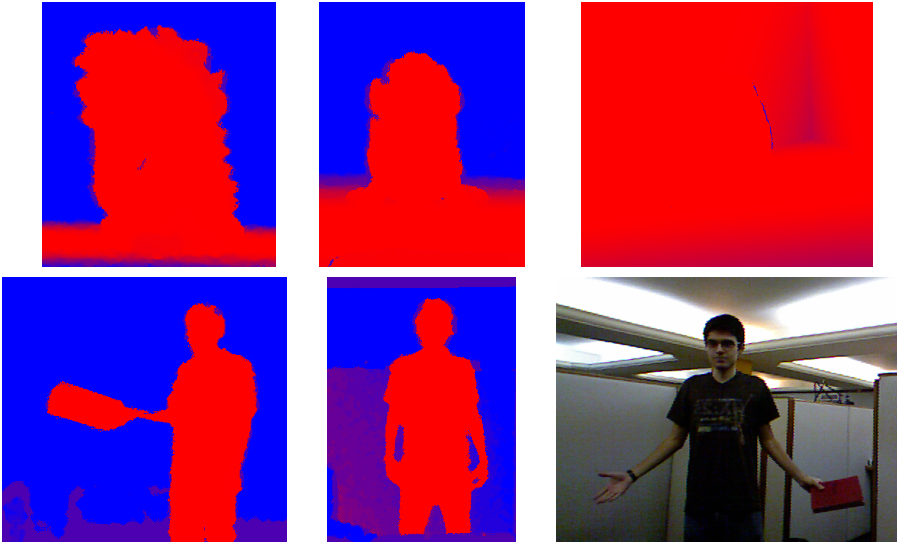

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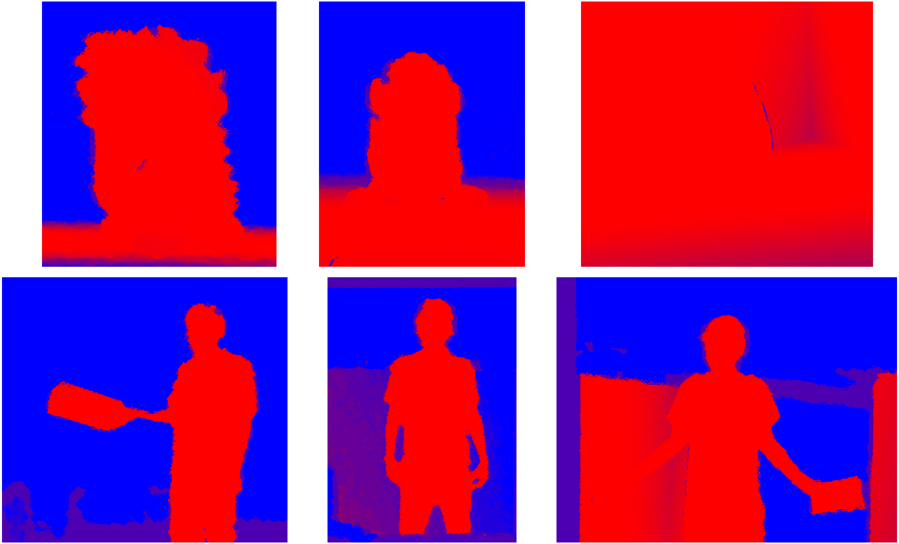

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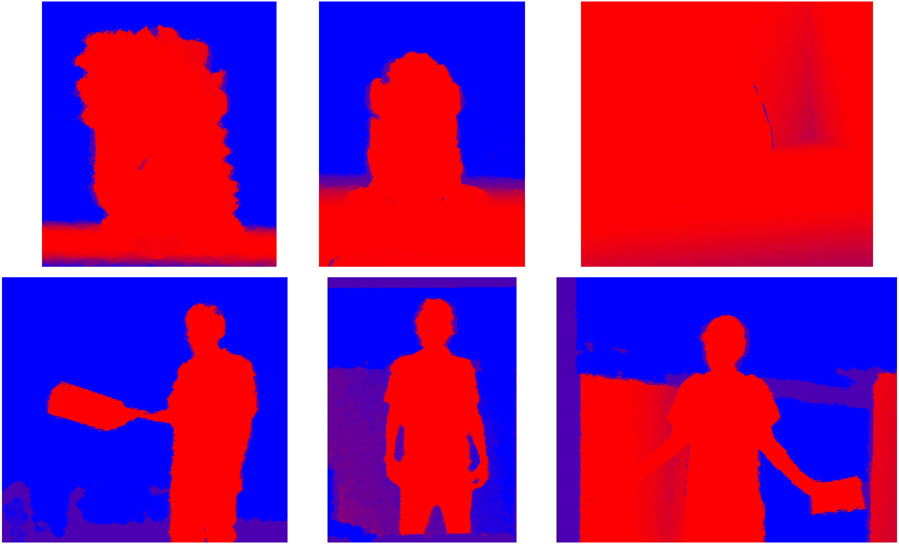

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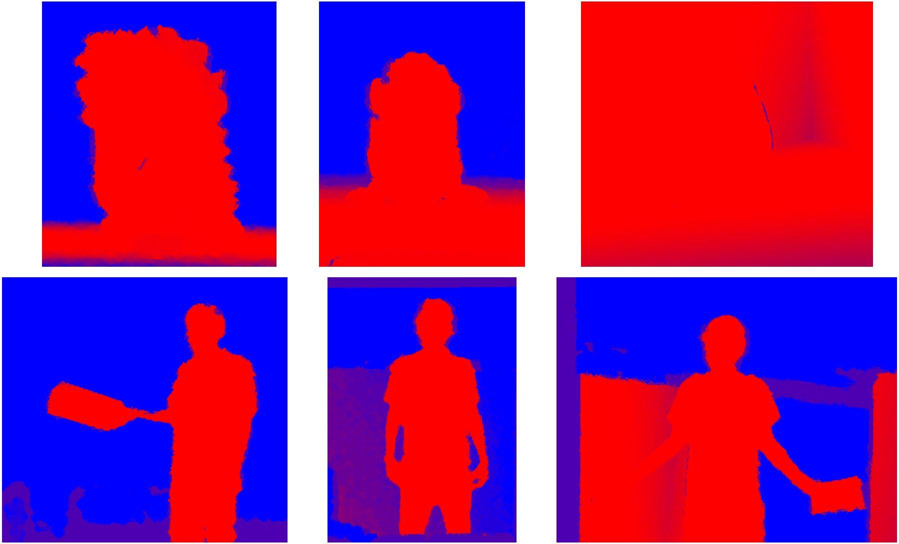

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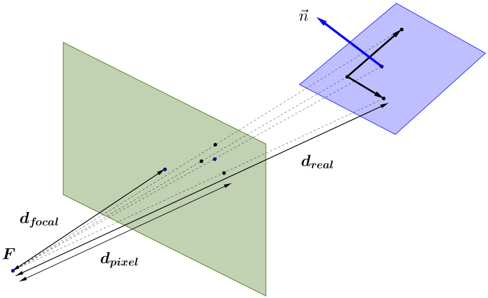

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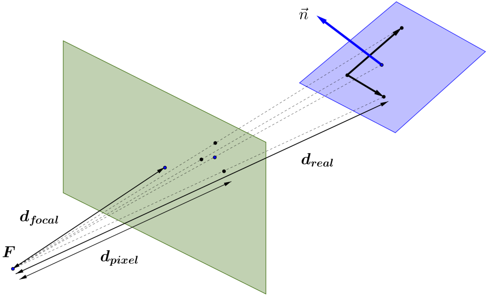

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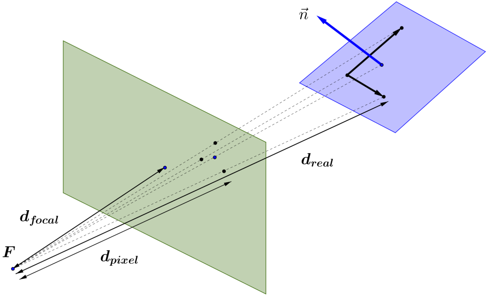

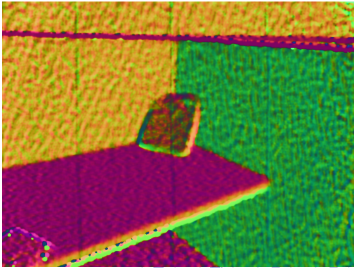

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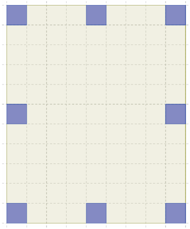

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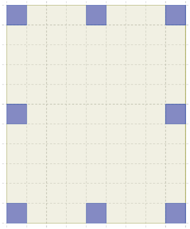

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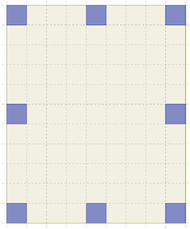

3. Fix parameters for normal tolerance e_n and color tolerance e_c.
4. Pick the first pixel of the queue p and identify the connected set of pixels around p satisfying $||n_p - n_x|| < e_n$ and $||c_p - c_x|| < e_c$. Call this set of pixels $PN(p)$, and label all these pixels as *belong Component*.

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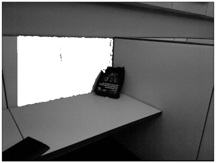

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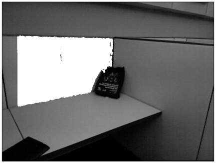

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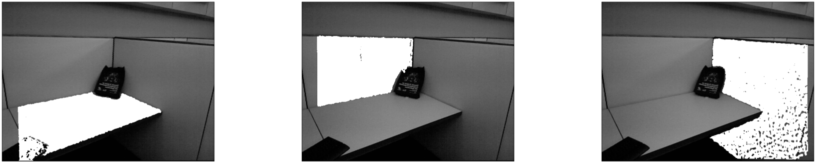

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 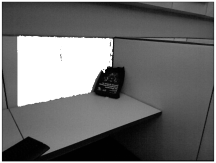 

7. Set $W^3_{BG}(p) = 0$ for all pixels p. Set $W^3_{FG}(p) = 1200 \iff p$ is *planar Pixel*.

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  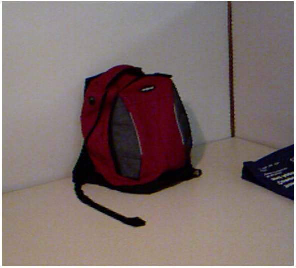

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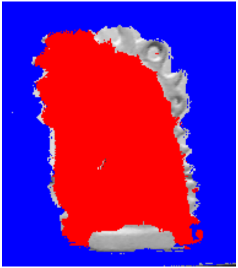

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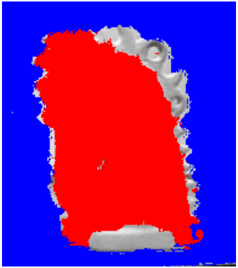

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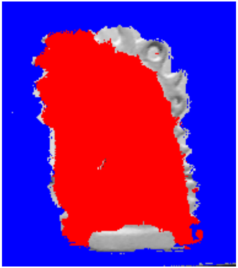

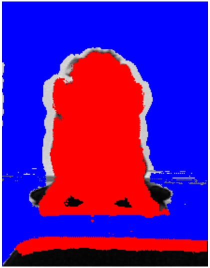

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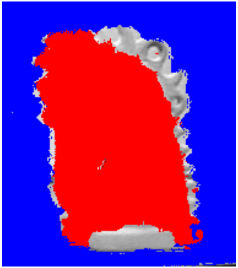 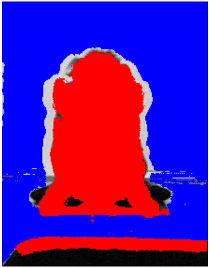 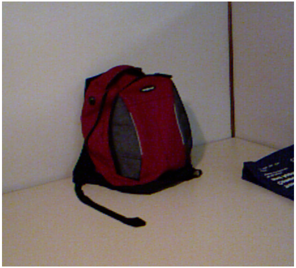

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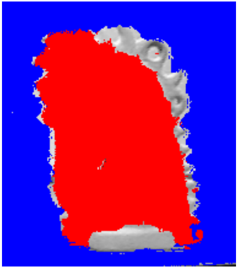

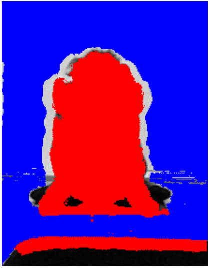

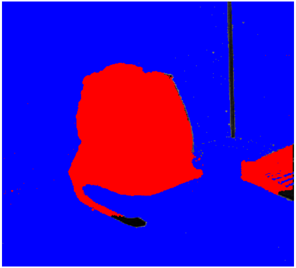

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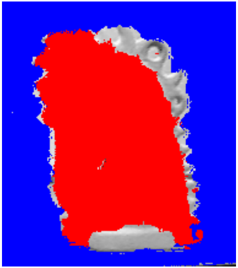
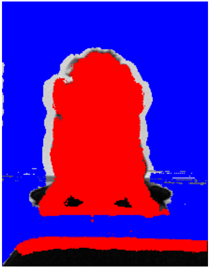
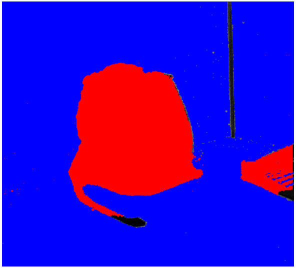


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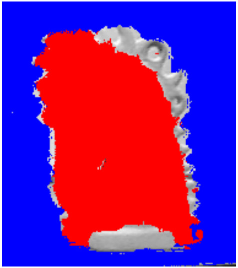

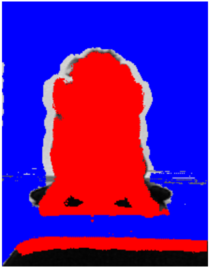

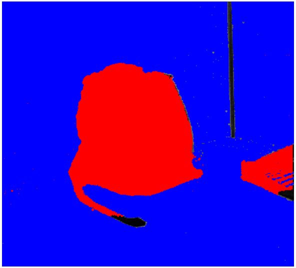

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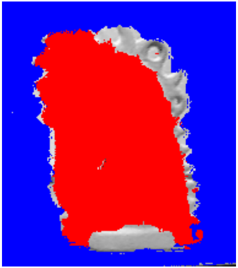
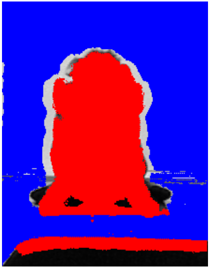
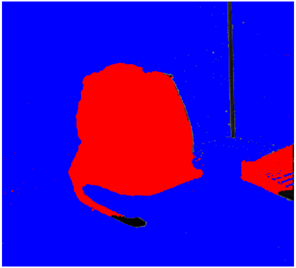

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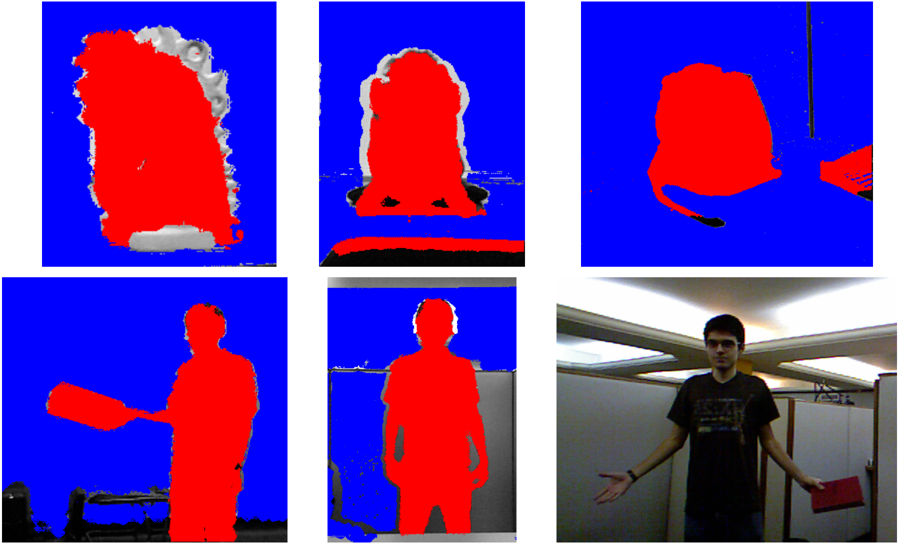

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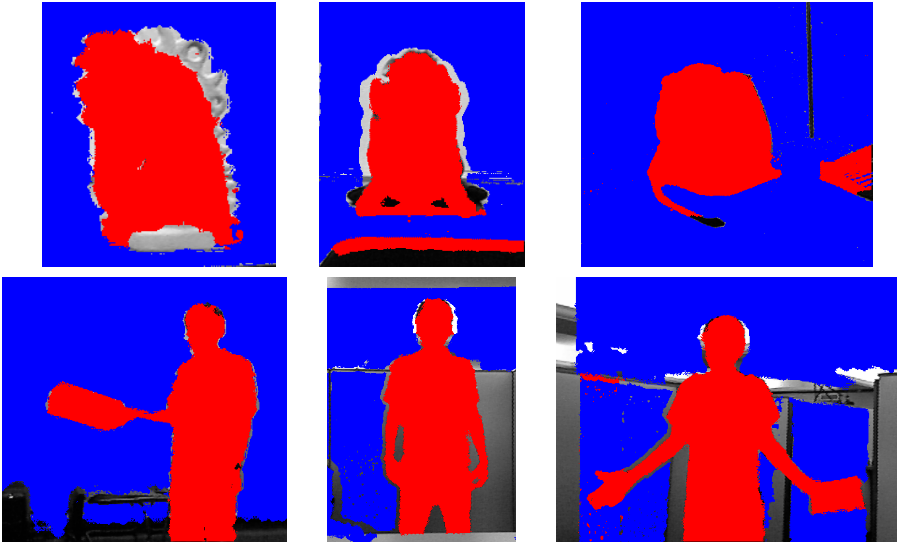

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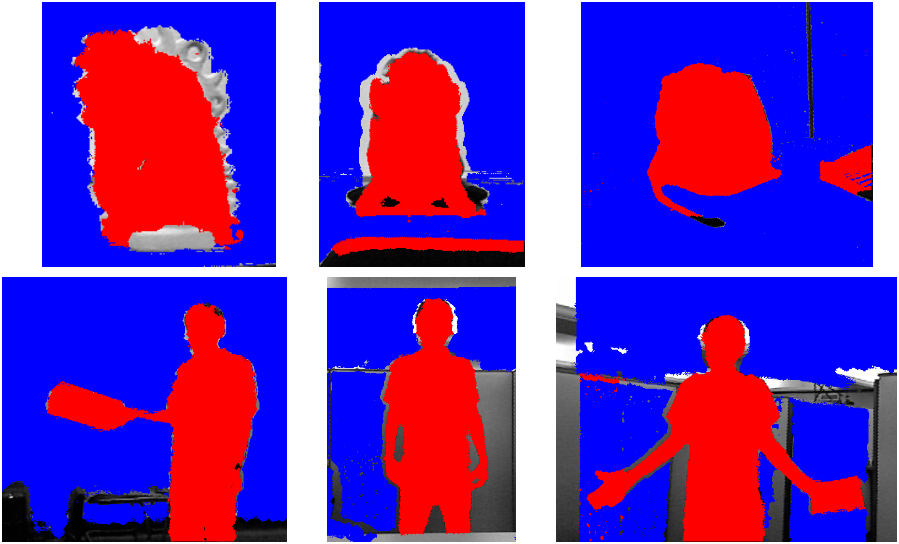

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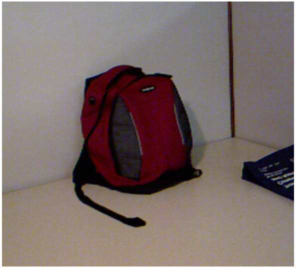

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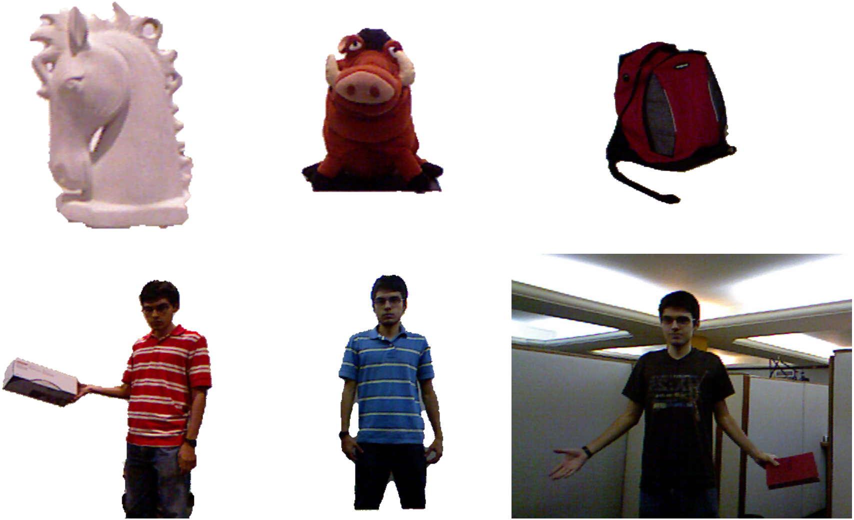

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- Third Approach improves the seeding using planar subtraction and gets good results in general cases. It still requires calibration.

Further Research: Video Object Extraction

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Why not include depth data and optical flow data in the energy function?...

Thanks to Djalma, Francisco, Leandro, Lucas, and professor Luiz, for suggestions and support!.

Y. Boykov and M-P. Jolly. *Interactive graph cuts for optimal boundary and region segmentation of objects in N-D images*. Proc. IEEE Int. Conf. on Computer Vision, 2001.

C. Rother, V. Kolmogorov, and A. Blake. *Grabcut interactive foreground extraction using iterative graph cuts*. Proc. ACM Siggraph, 2004.

Y. Boykov and V. Kolmogrov. *An experimental comparison of min-cut/max-flow algorithms for energy minimization in vision*. IEEE Trans. on Pattern Analysis and Machine Intelligence, volume 26, pages 11241137, 2004.

C. Rother, V. Kolmogorov, Y. Boykov, and A. Blake. *Interactive Foreground Extraction using graph cut*. Microsoft Technical Report:MSR-TR-2011-46.