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SlimCuts: GraphCuts for High Resolution Images Using Graph Reduction

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Problem statement:

Segmentation by discrete energy minimization [1,2]

$$E(x) = \sum_{i \in \mathcal{V}} \varphi_i(x_i) + \sum_{(i,j) \in \mathcal{E}} \varphi_{i,j}(x_i, x_j)$$

Unary function: negative log likelihood of a GMM [3]

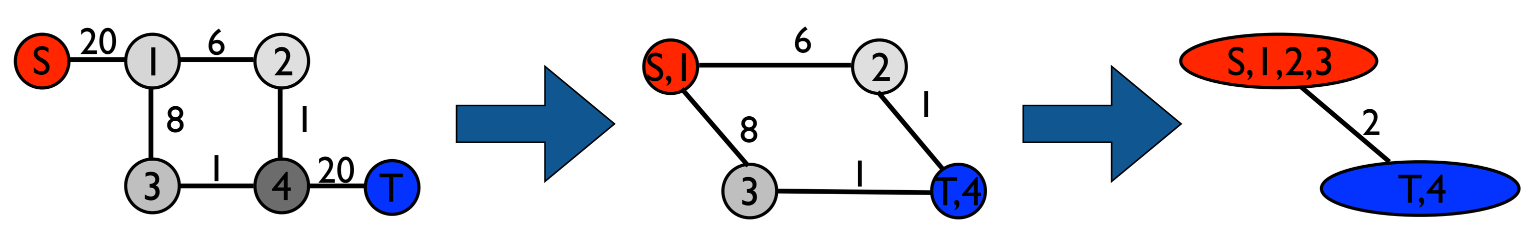
Pairwise function: contrast sensitive Ising model [3]

- ➡ solution: maximum flow algorithm
- ➡ fast for low scale benchmark images
- ➡ not applicable for large scale images

Many works on how to approximate large scale problems: parallel implementations, GPU processing, convex optimization, multi-scale approaches

Contribution:

Construction of a Slim Graph by edge contraction



- ➡ original graph is reduced to a Slim Graph
- ➡ grouping of variables with the same label in the minimum energy state

Definition:
An edge *e* connected to A is called *simple edge,* if its weight is larger then the sum of all edges adjacent to *A*.

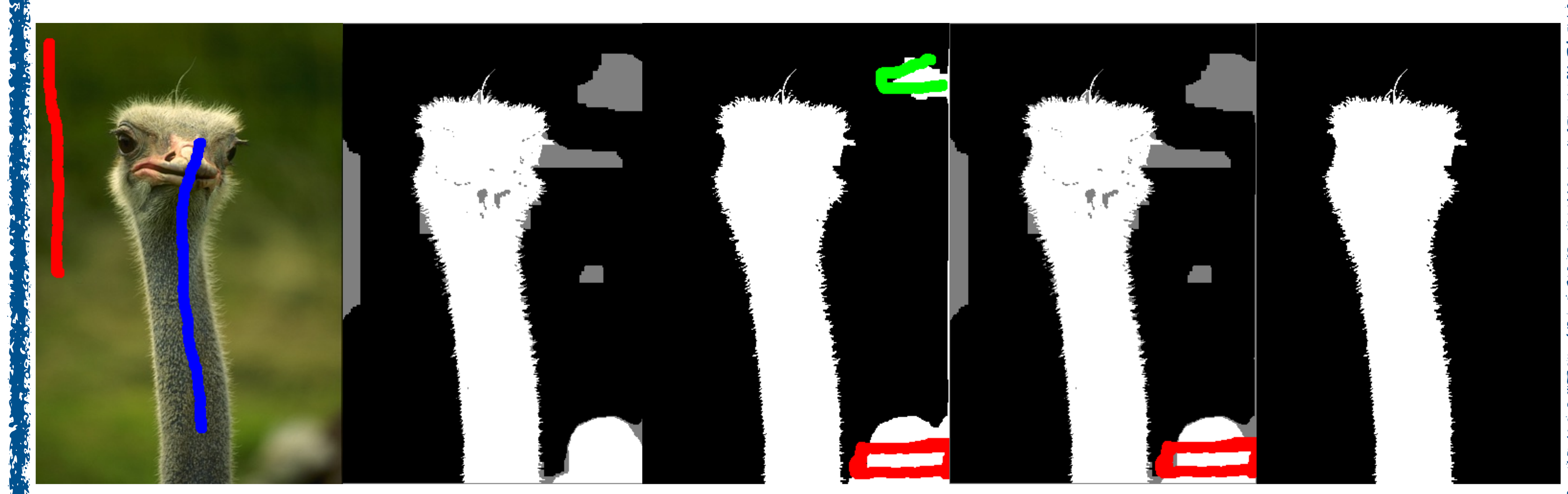
Contract only *simple edges:*

- ➡ efficient to find and to contract
- ➡ maximum flow preserved
- ➡ exact solution recovered (no approximation)
- ➡ user interaction simplified

Reduce the original Graph by contraction of simple edges:

large scale problem → find simple edges → graph reduction → energy mini-mization → solution recovery

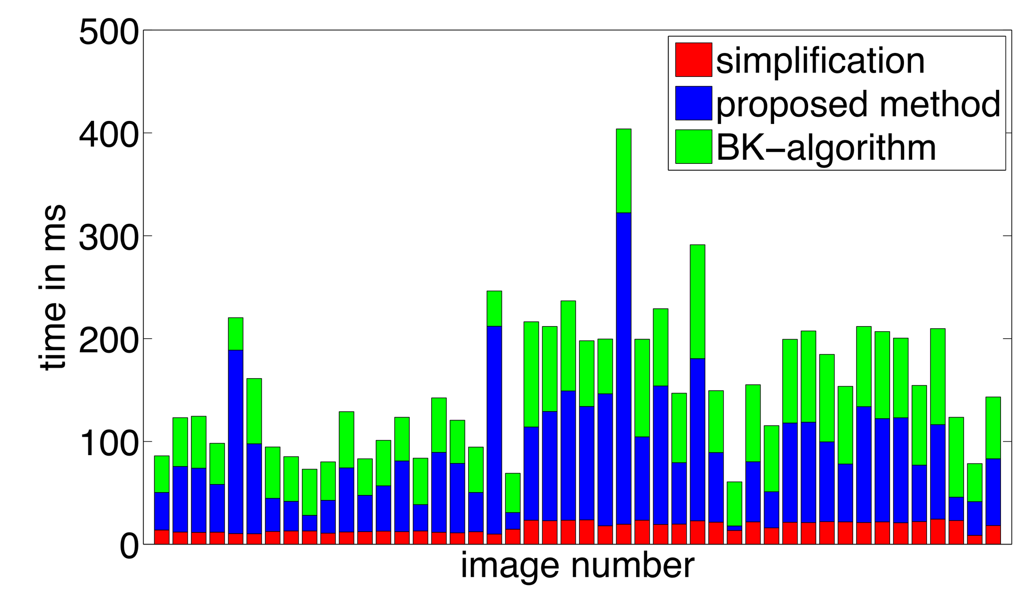
Simplified User Interaction:



(a) (b) (c) (d) (e)

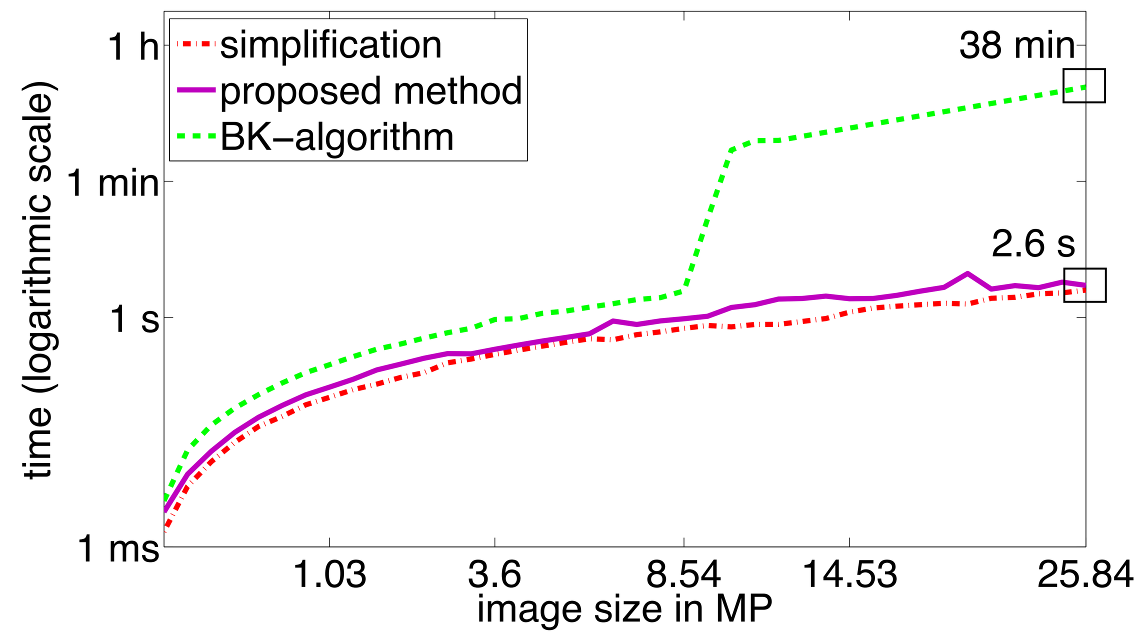
(a) original image; (b) label map defined by the Slim Graph; (c) resulting segmentation and additional user strokes; (d) label map with one additional user stroke; (e) final segmentation

Quantitative results:



46 small scale images (up to 640x480 pixels):

- ➡ average speedup of 1.4 compared to BK-algorithm [1]



High quality image (up to 25.84 MP):

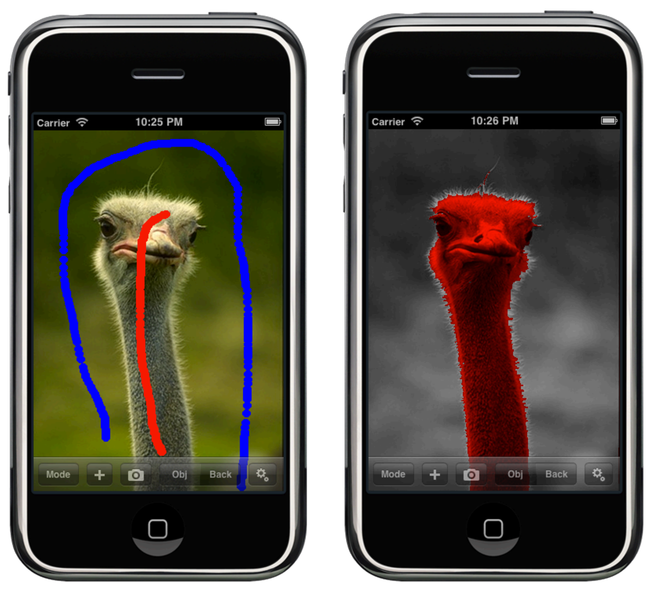
- ➡ speedup of two for an image size of 8.54 MP
- ➡ speedup of ~800 for larger images, because the BK-algorithm exceeded the physical memory (4GB)

Weak vs. strong unary terms and different trimaps (lasso, strokes and user scribbles):

- ➡ significant speedup for strong unary terms
- ➡ small speedup for weak unary terms and poor trimaps

Resource-limited systems:

- ➡ average speedup of 1.3



Conclusion:

- ➡ efficient method for graph simplification
- ➡ proofed that maximum flow is not changed
- ➡ speedup of 1.4 for small scale problems
- ➡ speedup of 800 for large scale problems
- ➡ visualization can be used to guide the user

References:

[1] Boykov, Y., Kolmogorov, V.: An experimental comparison of min-cut/max-flow algorithms for energy minimization in vision, TPAMI 2004

[2] Boykov, Y., Jolly, M.: Interactive graph cuts for optimal boundary & region segmentation of objects in nd images, ICCV 2001

[3] Rother, C., Kolmogorov, V., Blake, A.: Grabcut: Interactive foreground extraction using iterated graph cuts, SIGGRAPH 2004

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