FancyMc Moves
Fusion Moves for Multicut Objectives

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Abstract

Multicuts rule.

1. Introduction

The tale of the multicut

1.1. Related Work

1.1.1 Multicut

- Andres *et al*. [1]
- Kappes *et al*. [5]
- Bagon and Galun [2]
- Yarkony *et al*. [6]
- Beier *et al*. [3]

1.1.2 Fusion Moves

Move making algorithms, in particular fusion moves, have become increasingly popular for energy minimization [**?**, 4]. For many large scale computer vision applications fusion moves lead to good approximations with state of the art any time performance [4].

2. Name of My Method (Union Fusion Cut)

Global optimal solvers for multicut do not scale beyond ??? [**?**]. Good approximate solvers for planar graphs exist [3, 6] but have difficulties to find good solutions for non planar graphs [3].

2.1. Proposal Generators

2.2. Fusion Move Solver

3. Experiments

4. Conclusion

References

[1] B. Andres, J. H. Kappes, T. Beier, U. Köthe, and F. A. Hamprecht. Probabilistic image segmentation with closedness constraints. In *ICCV*, pages 2611–2618. IEEE, 2011. 1

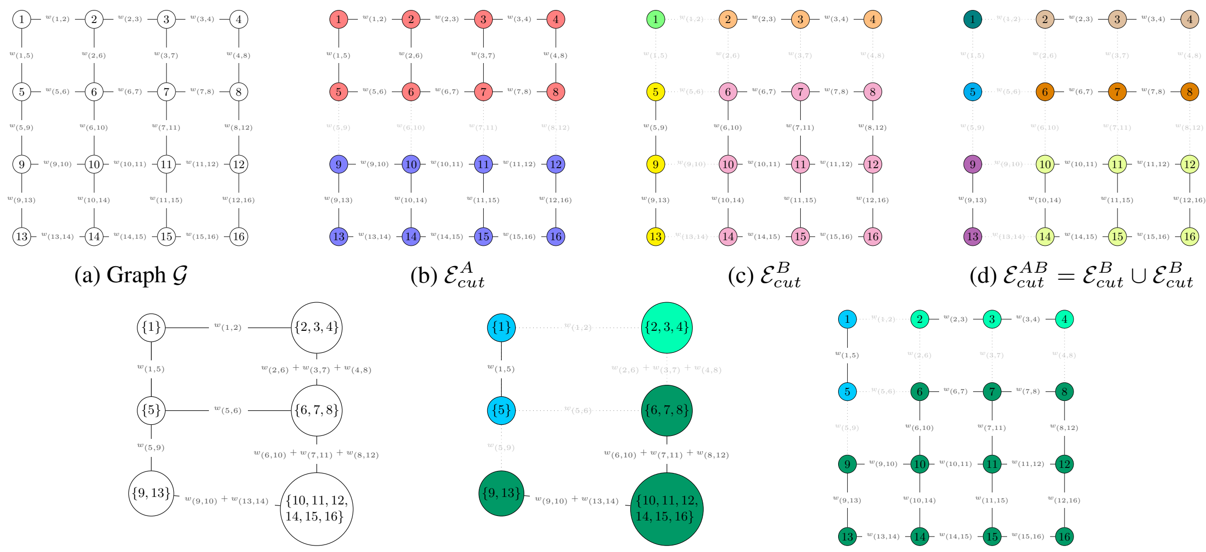
[2] S. Bagon and M. Galun. Large scale correlation clustering optimization. *CoRR*, abs/1112.2903, 2011. 1

[3] T. Beier, T. Kroeger, J. H. Kappes, U. Koethe, and F. Hamprecht. Cut, Glue & Cut: A Fast, Approximate Solver for Multicut Partitioning. In *IEEE Conference on Computer Vision and Pattern Recognition 2014*, 2014. 1

[4] J. H. Kappes, T. Beier, and C. Schnörr. Map-inference on large scale higher-order discrete graphical models by fusion moves. In *International Workshop on Graphical Models in Computer Vision*, 2014. Oral. 1

[5] J. H. Kappes, M. Speth, B. Andres, G. Reinelt, and C. Schnörr. Globally optimal image partitioning by multicuts. In *EMMCVPR*, pages 31–44. Springer, 2011. 1

[6] J. Yarkony, A. Ihler, and C. C. Fowlkes. Fast planar correlation clustering for image segmentation. In *ECCV*. Springer, 2012. 1



(a) Graph $\mathcal{G}$ (b) $\mathcal{E}^{A}_{cut}$ (c) $\mathcal{E}^{B}_{cut}$ (d) $\mathcal{E}^{AB}_{cut} = \mathcal{E}^{B}_{cut} \cup \mathcal{E}^{B}_{cut}$

(e) $\bar{\mathcal{G}} = \textbf{contract}(\mathcal{E} \backslash \{\mathcal{E}^{AB}_{cut}\})$ (f) $\mathcal{E}^{\bar{\mathcal{G}}}_{cut}$ (g) $\mathcal{E}^{\mathcal{G}}_{cut} = \textbf{projectBack}(\mathcal{E}^{\bar{\mathcal{G}}}_{cut})$

Figure 3: Describe Method here

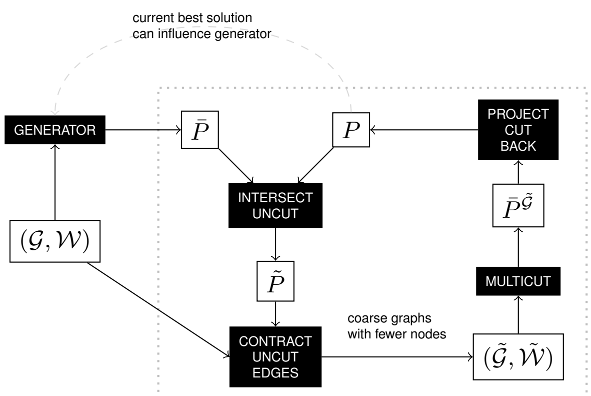


Figure 1: The proposed algorithm works in the following way: Given a graph $\mathcal{G}$, edge weights $\mathcal{W}$ and a proposal generator, the current best solution P is iteratively improved. A proposal generator generates different versatile proposal partitions $\bar{P}$. The proposal $\bar{P}$ is intersected with P which results in $\tilde{P}$. Contracting each each which is not cut in $\tilde{P}$ leads to a coarser graph $\tilde{\mathcal{G}} = (\tilde{\mathcal{V}}, \tilde{\mathcal{E}})$ with new edge weights $\tilde{\mathcal{W}}$. If $\bar{P}$ and P have a small fraction of cut edges, $\tilde{\mathcal{G}}$ will be small ($|\tilde{\mathcal{V}}| << |\mathcal{V}|$ and $|\tilde{\mathcal{E}}| << |\mathcal{E}|$). The multicut objective on the smaller graph $\tilde{\mathcal{G}}$ can be optimized magnitudes faster than on $\tilde{\mathcal{G}}$. It is guaranteed that the optimal multicut partitioning $\bar{P}^{\tilde{\mathcal{G}}}$ on $\tilde{\mathcal{G}}$ projected back to $\mathcal{G}$ as a lower or equal energy than any of the two input partitions P and $\bar{P}$, therefore we store the result of fusion as new best state P and repeat the procedure.

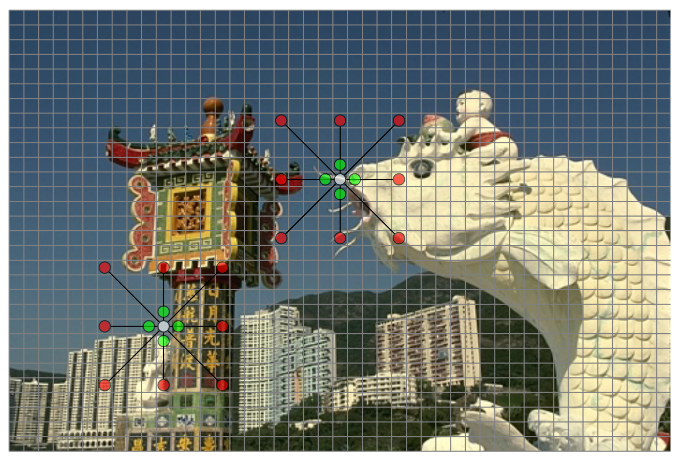


Figure 2: Pixel Level Multicut: every pixel (white nodes) is connected to its 4 *local* neighbors (green nodes). Furthermore each pixel is connected to some *non-local* neighbors within a certain radius (red nodes). The local neighbors are connected with a *positive* edge weight. If the edge indicator (as gradient magnitude) is very high, the local edge weight should be close to zero. The non-local edge weights are *negative* to encourage label transitions. The weight of the non-local edge weights can be the negative value of the maximum gradient magnitude along a line between the red and white node. If there is evidence for a cut between red and white, the weight should be strongly(?) negative.