

# U-Phylogeny: Undirected Provenance Graph Construction

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## Problem

**Provenance:** tracing the place of origin or earliest known history of something

### Why solve Image Provenance?

- Existence of multiple copies of the same media
- Prevalence of photo manipulation in popular culture
- Which is the original image and where did it come from?

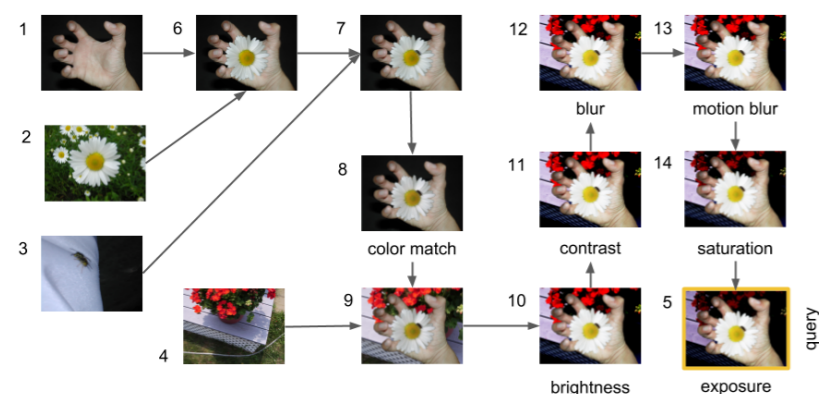


### Limitations of Existing Methods

- No multi-composite scenarios
- Only works in constrained environments
- Not much exploration of dissimilarity computation
- Not invariant to many transformations
- Unavailability of sufficient information to perform mappings (compression artifacts for non-JPEG images)

### What is U-Phylogeny\*?

- Undirected provenance graph construction method that can be extended to obtain directed phylogenetic tree
- Generalized and more efficient method for > 2 donors without image format restrictions

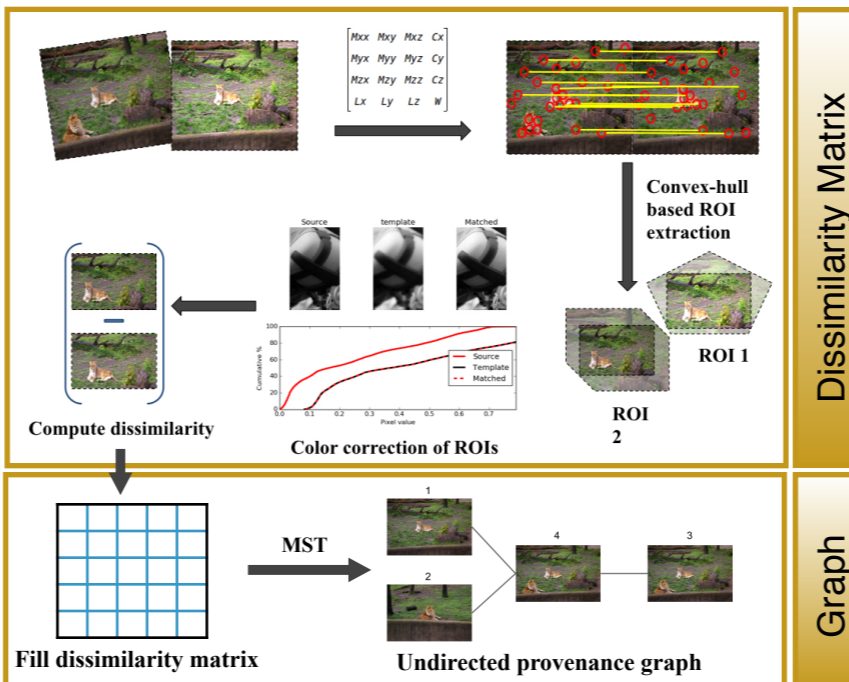


\* Bharati, A., Moreira, D., Pinto, A., Brogan, J., Bowyer, K., Flynn, P., Scheirer, W. and Rocha, A., 2017. U-Phylogeny: Undirected Provenance Graph Construction in the Wild. IEEE International Conference on Image Processing, 2017. Code: <https://gitlab.com/notredame-provenance/u-phylogeny>

## Methodology

### Pipeline:

1. Detection and description of points of interest (SURF)
2. Keypoint matching using L2 distance
3. Match filtering
  - Geometrically Consistent Matching (GCM)
4. Dissimilarity computation
  - Number of GCM's, Distance of GCM's
  - Difference in pixel distribution (MSE, Mutual Information) (extended U-phylogeny)
5. Kruskal's min/max spanning tree algorithm



Dissimilarity Matrix

Graph

**Dataset Used:** 59 provenance cases from NIST's Nimble 2017 challenge dataset

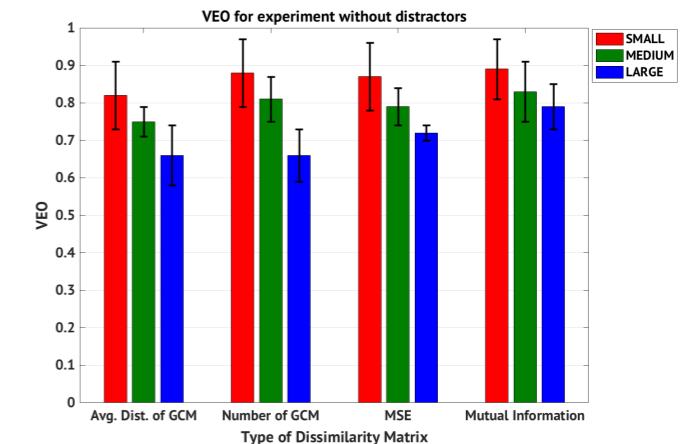
- 59 queries and 10446 gallery images (750 related)
- Average graph order = 12.7, Range - [3, 82]
- Small (<=12 nodes) Medium (13-20 nodes) Large (>20 nodes)

**Evaluation Metrics:** web graph similarity metrics

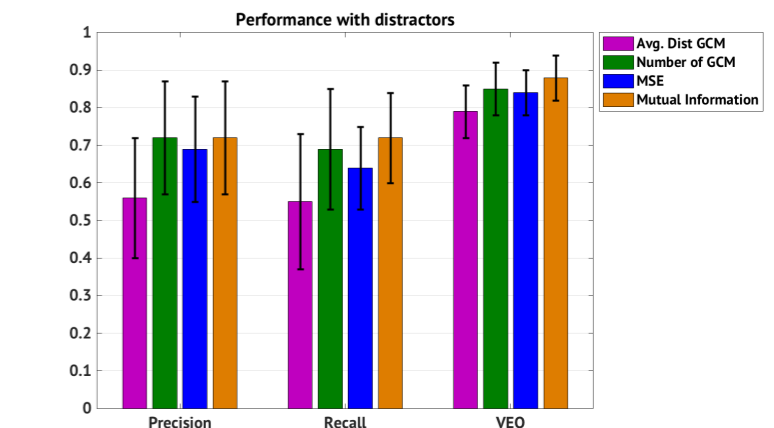
$$VEO(G, G') = \frac{|\text{nodes}(G') \cap \text{nodes}(G)| + |\text{edges}(G') \cap \text{edges}(G)|}{|\text{nodes}(G')| + |\text{nodes}(G)| + |\text{edges}(G')| + |\text{edges}(G)|}$$

## Results

### Experiment 1: Without distractors



### Experiment 2: With distractors (25 images/case)



### Conclusion

- Effectiveness decreases with the size of graphs irrespective of dissimilarity metrics
- Extended U-Phylogeny performs better on average but reduced efficiency
- U-Phylogeny is robust to the presence of distractors (VEO = 88%)
- Mutual Information yields better performance than MSE

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