

# Unordered feature tracking made fast and easy

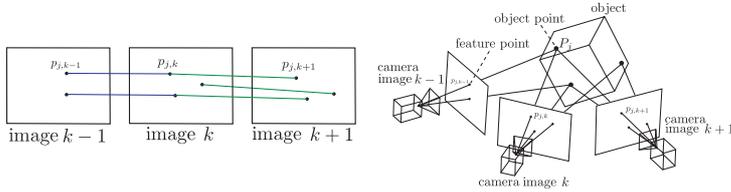
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## MOTIVATION & CONTRIBUTION

Considering  $n$  pairwise feature correspondences we want sets of corresponding matching features across multiple images, i.e., *tracks*.



Track identification in a set of images is an important task in computer vision. It allows solving geometry-related problems like:

- region tracking, match-moving, video stabilization,
- image-stitching,
- structure from motion [4] and odometry.

We present an efficient algorithm to fuse two-view correspondences into multi-view consistent tracks that is:

- **simple**,
- **efficient**: lower computational complexity than [2, 3],
- **reliable**: able to identify all tracks, contrary to [2, 3].

## THE TRACK COMPUTATION PROBLEM

The problem of feature point tracking consists in linking multi-view correspondences from pairwise matches that share a common point. It consists of a correspondence fusion problem.

Detected Features: Putatives matches: Geometric matches: Tracks:

Pairwise hypothesis: Remaining pairs:

## THE UNION-FIND SOLUTION

- We see the correspondence fusion problem as set unions,
- It can be solve efficiently using the Union-Find [1] algorithm.

Consider a graph  $\mathcal{G}$ :

- vertices: features  $\{ImageId, FeatureId\} = \mathbf{sets}$ ,
- edges: correspondences  $\{LeftFeature, RightFeature\} = \mathbf{sets\ union}$ ,
- $\Rightarrow$  Tracks are connected components of  $\mathcal{G}$ .

Our algorithm enumerates edges (pairwise correspondences) and fuses the sets containing the edges' endpoints (features).

### Algorithm 1 Unordered feature tracking

**Input:** list of pairwise correspondences

**Output:** tracks

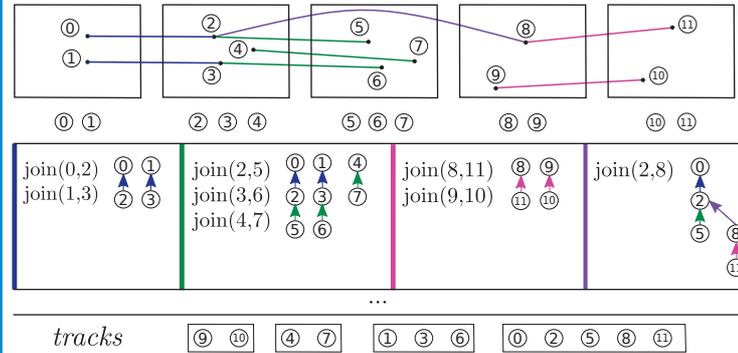
create a singleton for each feature

**for** each pairwise match **do**

    join(*leftMatch*, *rightMatch*)

**end for**

return each connected set as a track



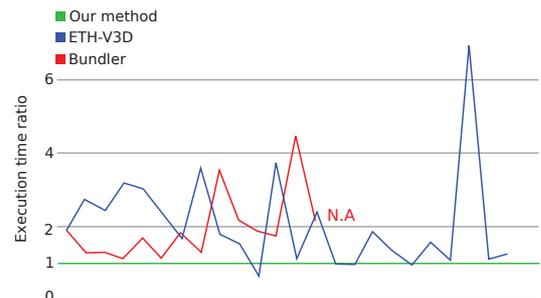
- **Union-Find algorithm allows efficient:**
  - fusion:  $\Rightarrow \text{join}(a,b) = \text{union}(\text{find}(a), \text{find}(b))$ ,
  - connected set search and traversal.

## COMPLEXITY & PERFORMANCE

Experimental results on small to large datasets (10 to 2,600 images), largest dataset with more than 41 million pairwise matches, yielding a million tracks.

|                      | Bundler [2]   | ETH-V3D [3]   | Our approach    |
|----------------------|---------------|---------------|-----------------|
| Complexity           | $O(n \log n)$ | $O(n \log n)$ | $O(n\alpha(n))$ |
| Execution time ratio | 1.57          | 2.09          | 1.00            |
| Track count          | 78%           | 90%           | 100%            |
| Lines of code (C++)  | $\approx 200$ | $\approx 150$ | $\approx 100$   |

$\alpha(\cdot)$  is the inverse Ackermann function, quasi-constant in practice.



## AVAILABLE SOLUTIONS

Available algorithms do not solve the problem in an optimal way:

| Bundler [2]                    | ETH-V3D [3]                        |
|--------------------------------|------------------------------------|
| • requires a start image index | • requires many sorting operations |
| • depends on image pair order  | • heavy memory consumption         |

Neither approach is able to identify all valid tracks.

## CONCLUSION

Our approach is quasi-linear. It does not depend on the image pair order. Open source implementation is available in the openMVG library [4].

## REFERENCES

[1] B. A. Galler and M. J. Fischer. An improved equivalence algorithm. In ACM, V7, I5, May 1964.  
 [2] N. Snavely, S. M. Seitz and R. Szeliski. Photo tourism: exploring photo collections in 3D. In SIGGRAPH 2006.  
 [3] C. Zach. ETH-V3D Structure-and-Motion software. © 2010-2011. ETH Zurich.  
 [4] P. Moulon, P. Monasse and R. Marlet. Adaptive Structure from Motion with a *contrario* model estimation. In ACCV 2012.