For robust matching: literature

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Quick comparison

	Detector	Descriptor	Matching
corner detector	local extreme on gradient/saliency		NN
gradient based	local texture		NN
neighborhood	any	points distribution	hashing
robust matching	any	local texture	cool matching

*not very recent ;)

Papers on corner detector

Papers on corner detector

- A corner = The intersection of two edges.
- A point of local extreme.

	Detector
Moravec1980	low self-similarity
Harris1988	det. and trace of autocorrelation
Shi1994	use eigenvalue decomposition
Lindeberg1998	LoG (= saliency)
Mikolajczyk2004	multi-scale + LoG
Smith1997	SUSAN
Rosten2010	FAST

Papers on feature descriptor

Papers on feature descriptor

1. A feature descriptor for both detector and descriptor.
   – Normal papers proposing a feature descriptor.
2. Combination of different detector and descriptor.
   – Survey papers evaluating which descriptor is the best.

A feature descriptor for both detector and descriptor

- local gradient

	Detector
Matas2002	MSER
Forssen2007	multi-scale MSER + shape descriptor
Lowe2004	SIFT
Chandrasekhar2009,2012	CHoG
Tacks2010	RIFF
Wagner2008	Phony-SIFT
Tola2010	DAISY

A feature descriptor for both detector and descriptor

- binary descriptors

	Detector
Calonder2011	BRIEF
Rublee2011	ORB
Leutenegger2011	BRISK
Trzcinski2012	D-Brief (Discriminative BRIEF)
Strecha2012	LDAHash

Combination of different detector and descriptor

	Detector
Mikolajczyk2005	Harris is the best detector
Moreels2007	Hessian-affine and Harris-affine detector+SIFT
Gauglitz2011	concluded *it is difficult to derive universally valid recommendations or proclaim a single “winner.”*
Dalh2011	combination of DoF/MSER + SIFT/DAISY is best Harris is superior if scale change is low
Aanaes2012*	Harris, Hessian blob, and DoG.

*only for key-points detection algorithm

Papers on neighborhood feature descriptor

Papers on neighborhood feature descriptor

- Nakai2005: use cross ratio of key-points
- Uchiyama

	Detector	Descriptor	Matching
someone		neighborhood	Geometric Hashing
star tracker+		neighborhood	
Nakai2005	local extreme	a set of cross ratio	LLAH
Uchiyama2011a	local extreme	a set of area ratio of two triangles	LLAH
Uchiyama2011b	many*	a set of area ratio of two triangles	LLAH

+Their matching algorithm is robust for false positive detection.
*They tried many detectors and concluded that Harris is the best.

Papers on robust matching

Papers on robust matching

- They focus on matching two sets of key-points.
- Matching algorithms use the following components inside the alg.:
  - Feature vector of key-points.
  - Local appearance around key-points.
  - ...

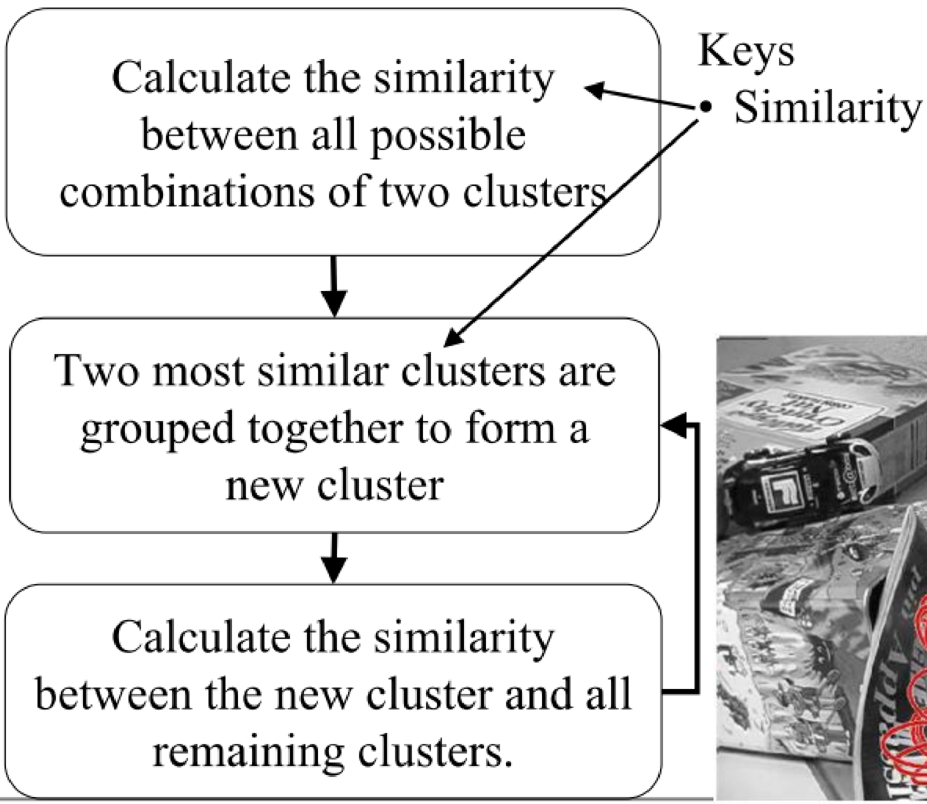
- The matching algorithm should handle deformation and false-positive and false-negative detection.

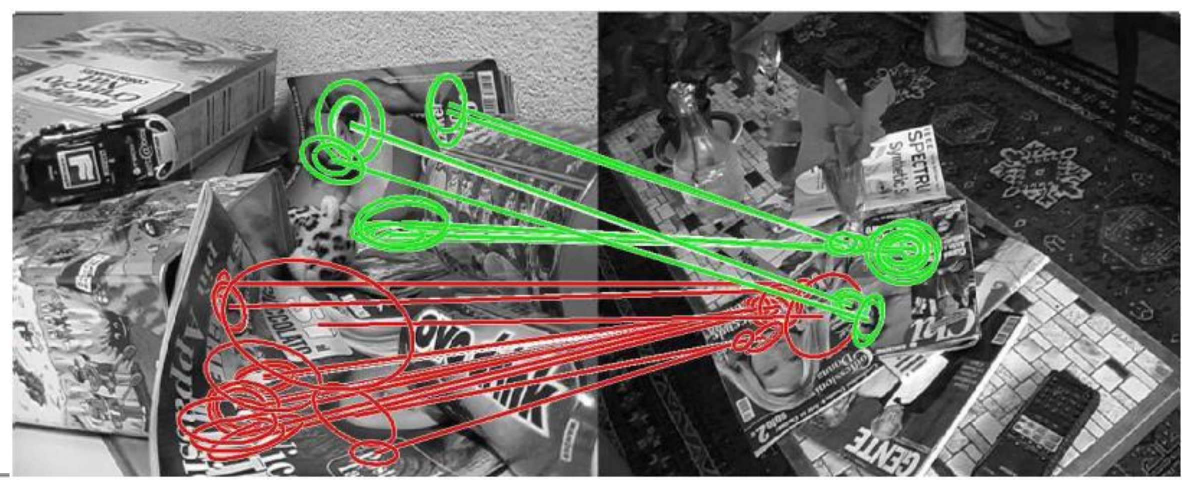
Papers on robust matching

	Detector	Descriptor	Matching
Cho2009	MSER	SIFT	Agglomerative Correspondence Clustering
Cho2010a	MSER	SIFT	Reweighted random walks on graph
Cho2010b	MSER+Har Aff	SIFT	multi-layer match-growing + Bayesian model for inter/intra matching
Lee2011	MSER	SIFT	Reweighted random walks on hyper-graph
Cho2012	MSER or MSER+Har Aff+HesAff		Progressive graph matching
Zhou2012			Factorized graph matching

Cho2009: Hierarchical clustering

- Bottom-up approach aggregation strategy: merge reliable matching neighbors.
- Connectedness between parts: deformed objects are locally connected by some mediating parts.





Cho2009: Hierarchical clustering

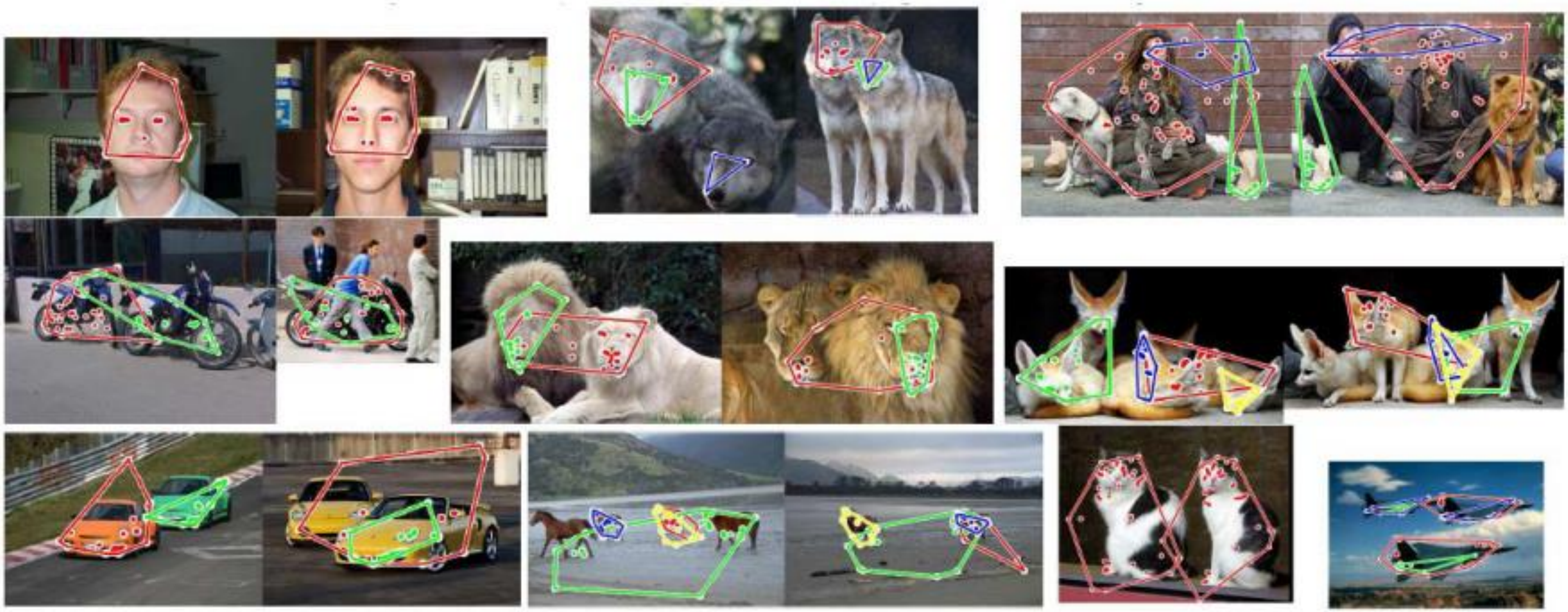
- Find known object in cluttered scene.

Cho2009: Hierarchical clustering

- Match objects in 2 unknown cluttered images.

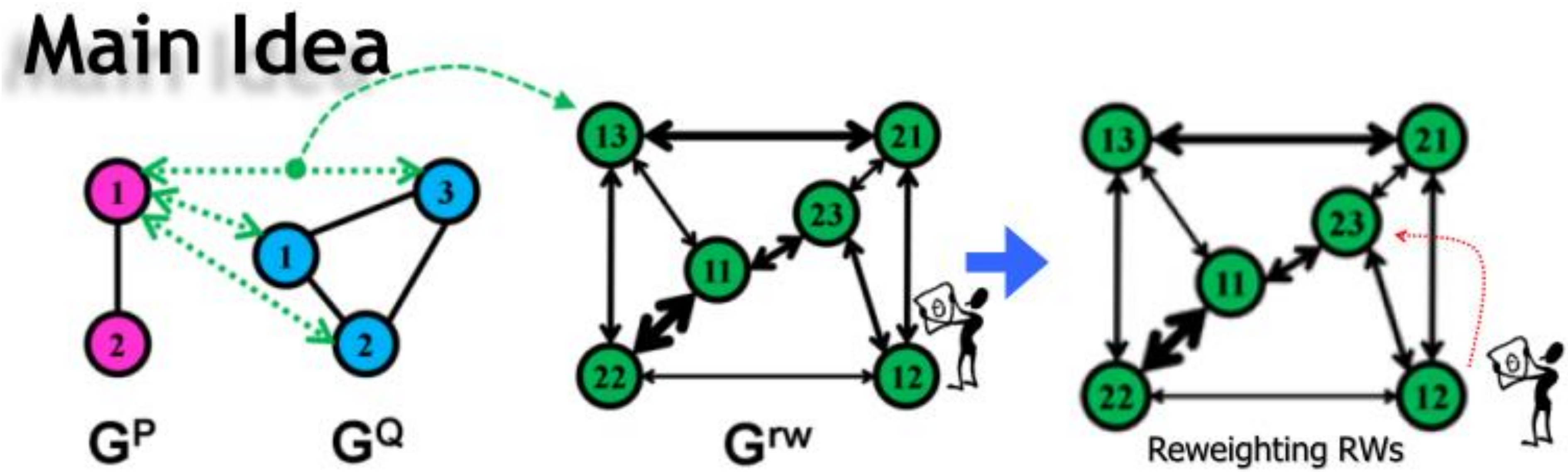
Cho2009: Hierarchical clustering

- Match objects in 2 unknown cluttered images.



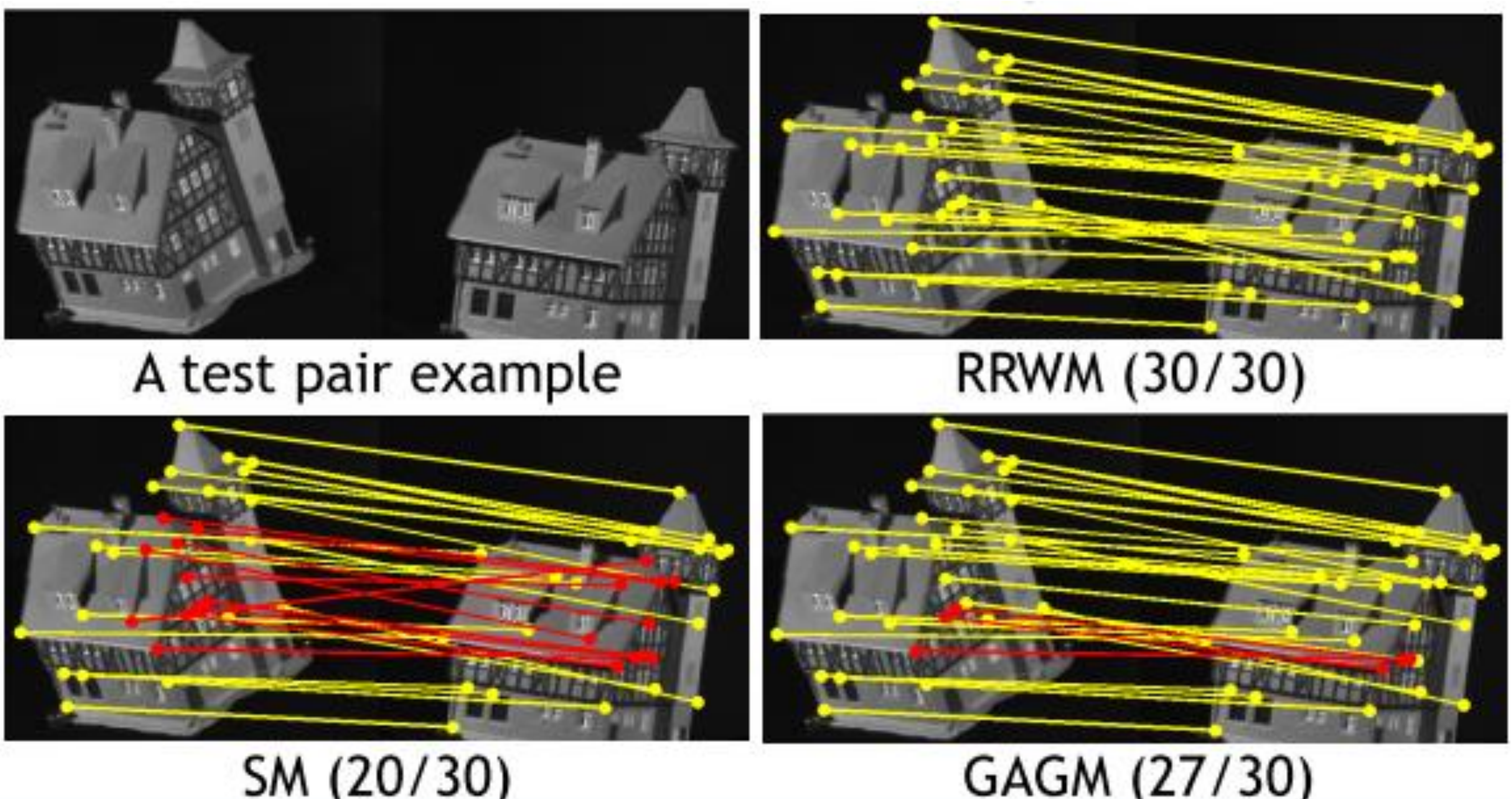
Cho2010a: reweighted random walks

- robust to deformation and outliers by reweighted random walks.
  - Affinity-preserving Random Walks
  - Reweighting Random Walks



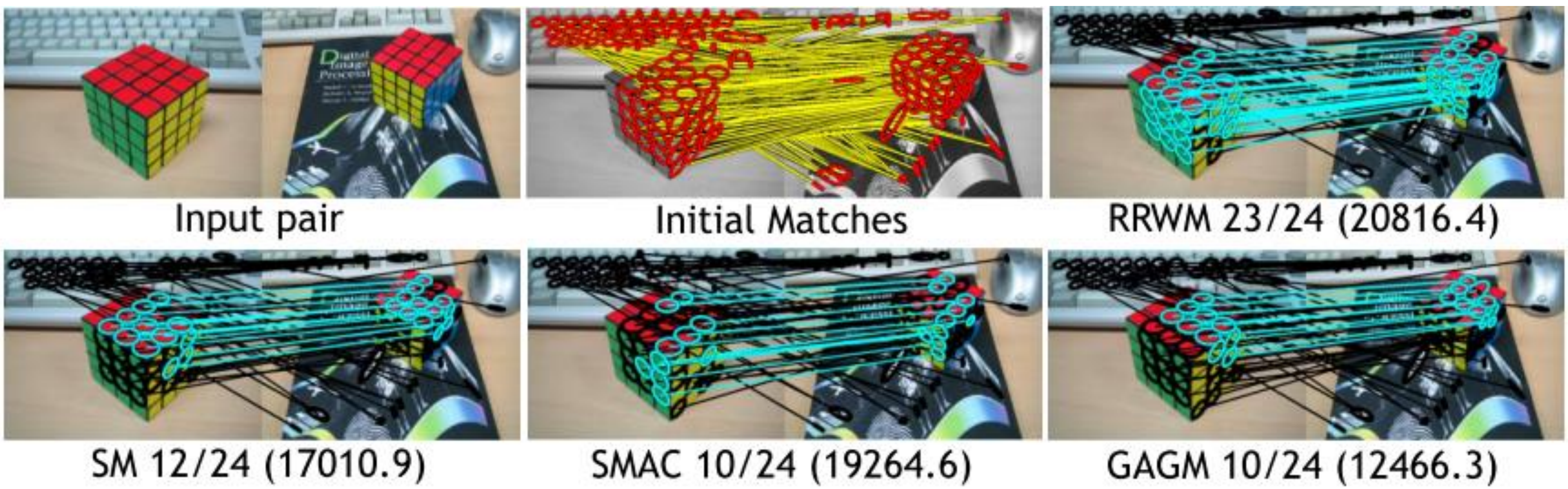
Cho2010a: reweighted random walks

- Matching on ideal images



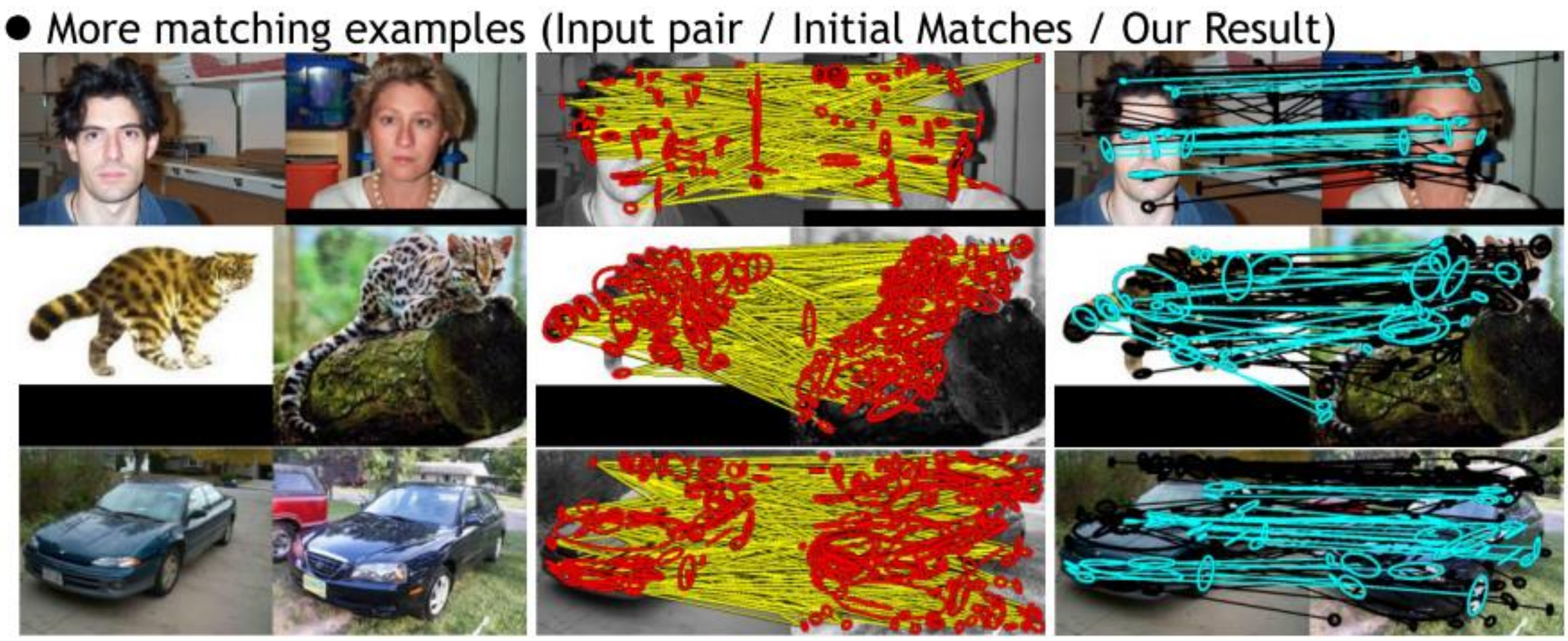
Cho2010a: reweighted random walks

- Matching in cluttered scene.
- Comparison with state-of-the-art (RRWM is the proposed)



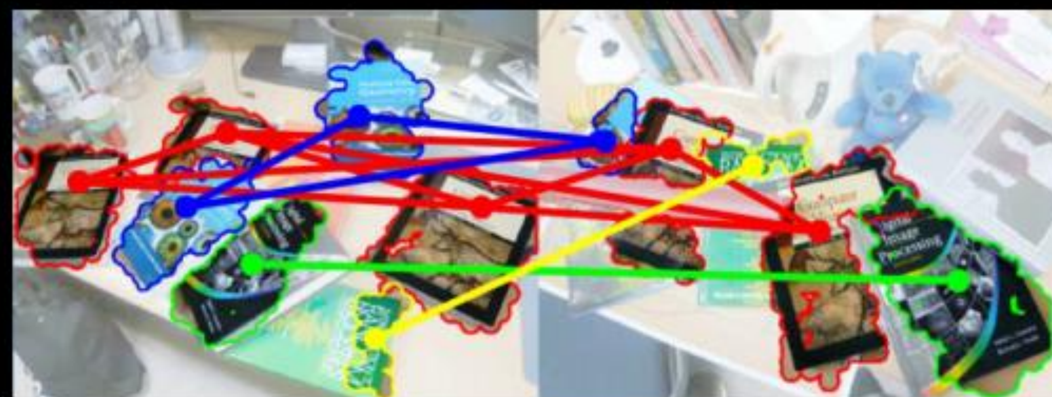
Cho2010a: reweighted random walks

- Matching in cluttered scene.



Cho2010b: inter/intra object matching

- UNSUPERVISED detection, segmentation, and grouping of identical objects from a single or multiple images



- Direct object discovery from images

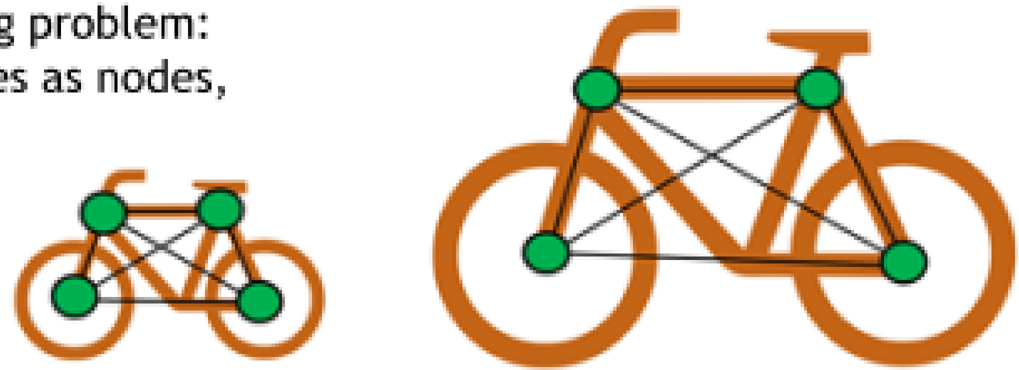
'Object Correspondence Networks'

  - Each network represents a set of identical objects

Lee2011:

Feature Matching by Hyper-graph Matching

- Establishing feature correspondence is essential task for vision problem
- Well formulated as graph matching problem:
  Represent object or image features as nodes,
  features' relations as edges
- Why hyper-graph?
  Exploiting higher-order relations
  Ex. Distances are varying
  Angles are not varying
- Find the solution which best preserves graph attributes



Challenges & Motivations

Outlier Noise → Challenging NP-hard Problem ← Deformation Noise

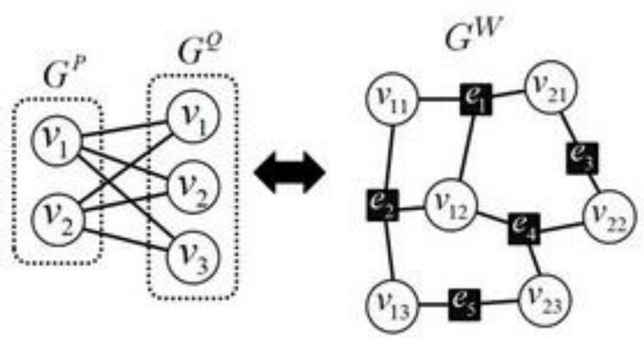
- Due to background clutters
  Imperfect feature detector

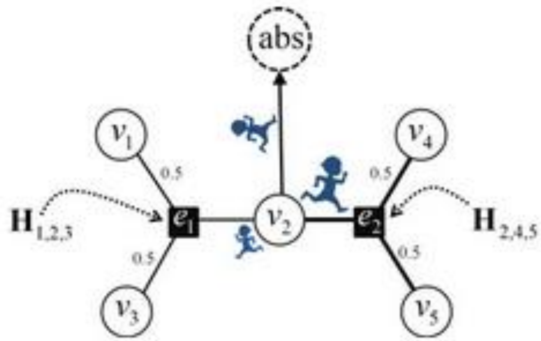
- Object motion
  View-point change

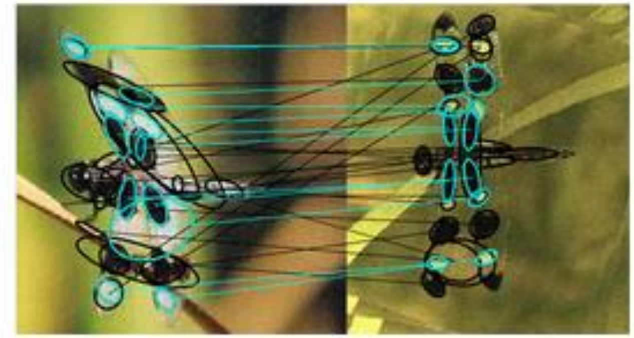
Lee2011:

Our Contribution

- Generalization the hyper-graph matching formulation to mixed orders
- A state-of-the-art hyper-graph matching method robust to deformation & outliers
- Extensive comparison with recent hyper-graph matching methods

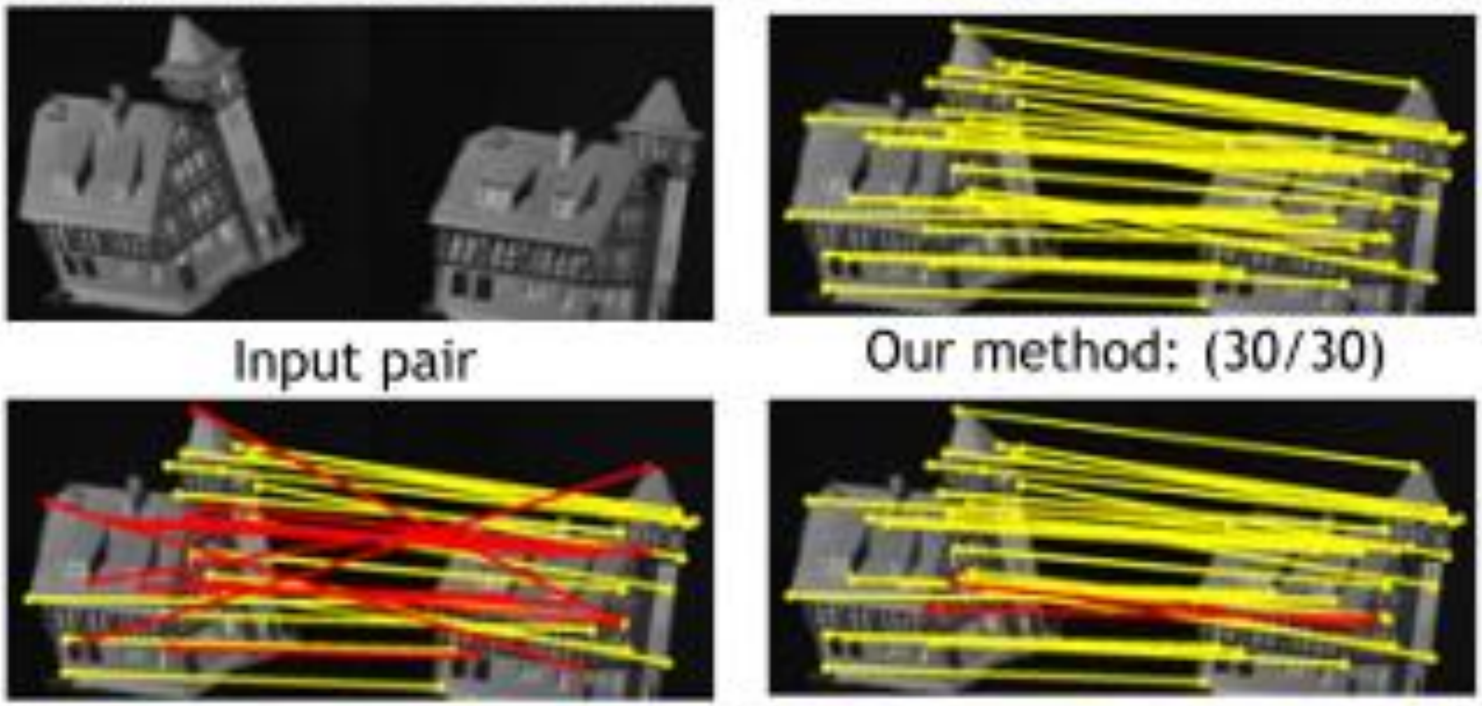






Lee2011:

- Triplet distance: differences of angles of two triangles



Input pair

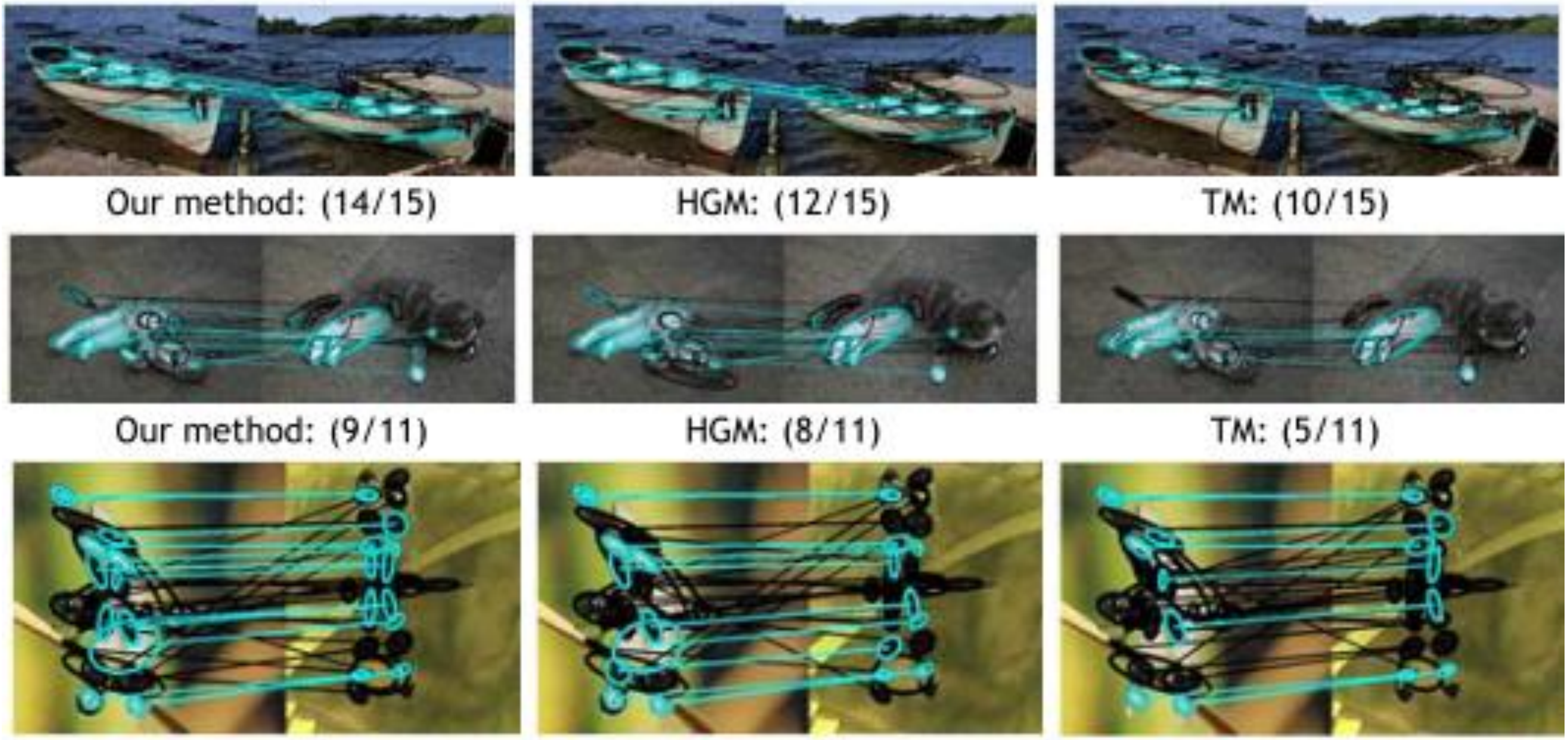
Our method: (30/30)

HGM: (10/15)

TM: (27/30)

Lee2011:

- Matching examples

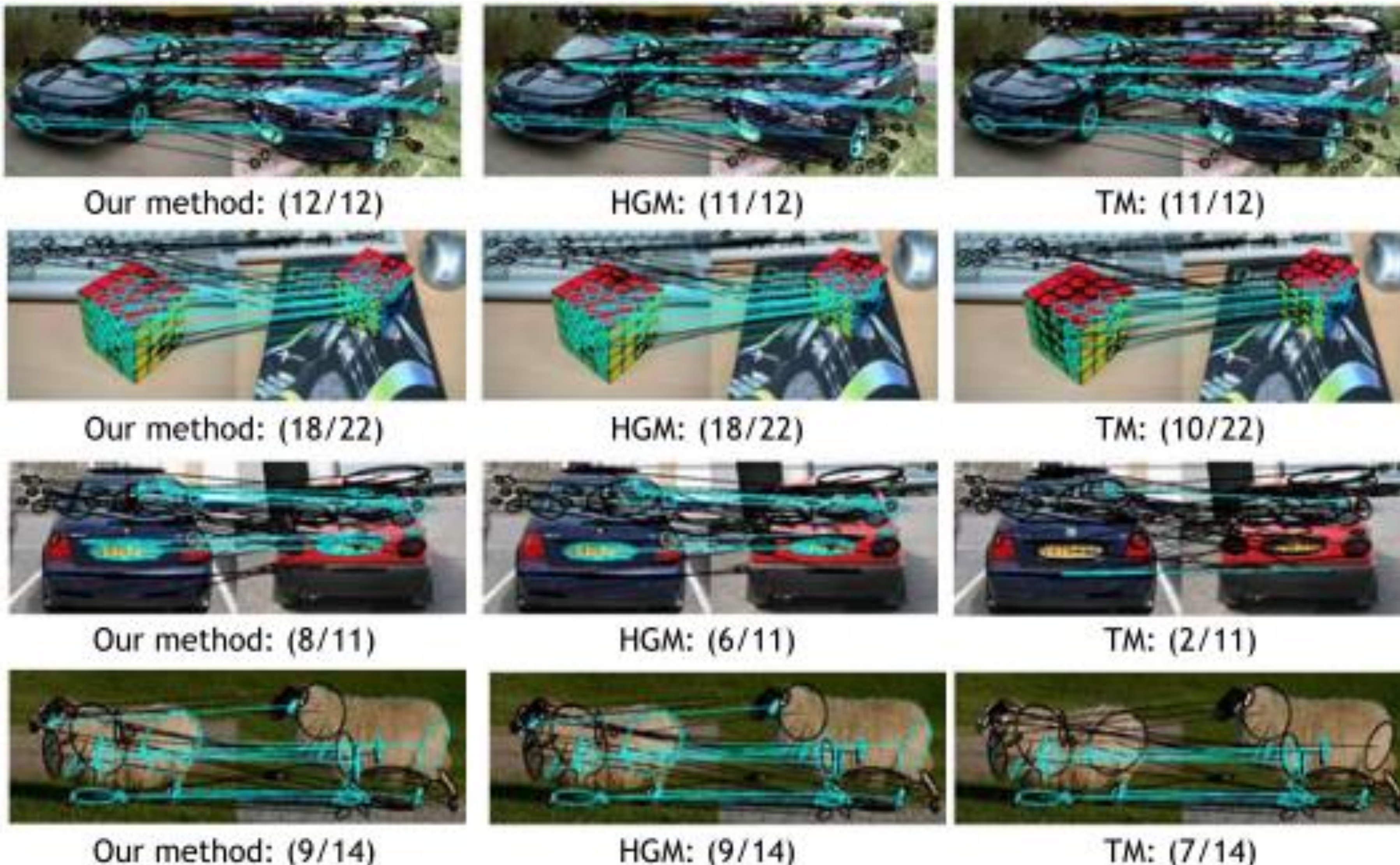


Our method: (14/15) | HGM: (12/15) | TM: (10/15)

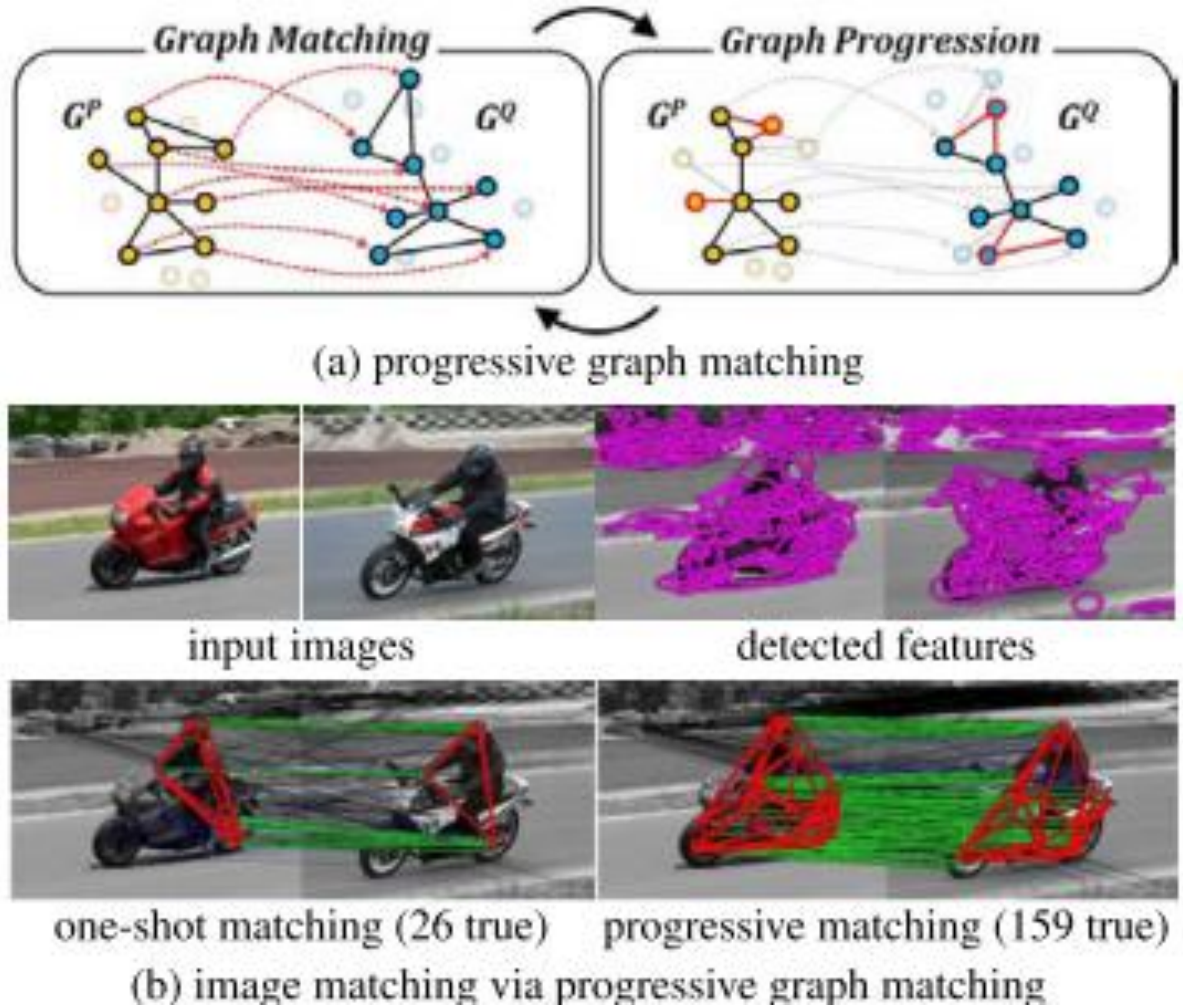
Our method: (9/11) | HGM: (8/11) | TM: (5/11)

Our method: (12/15) | HGM: (10/15) | TM: (8/15)

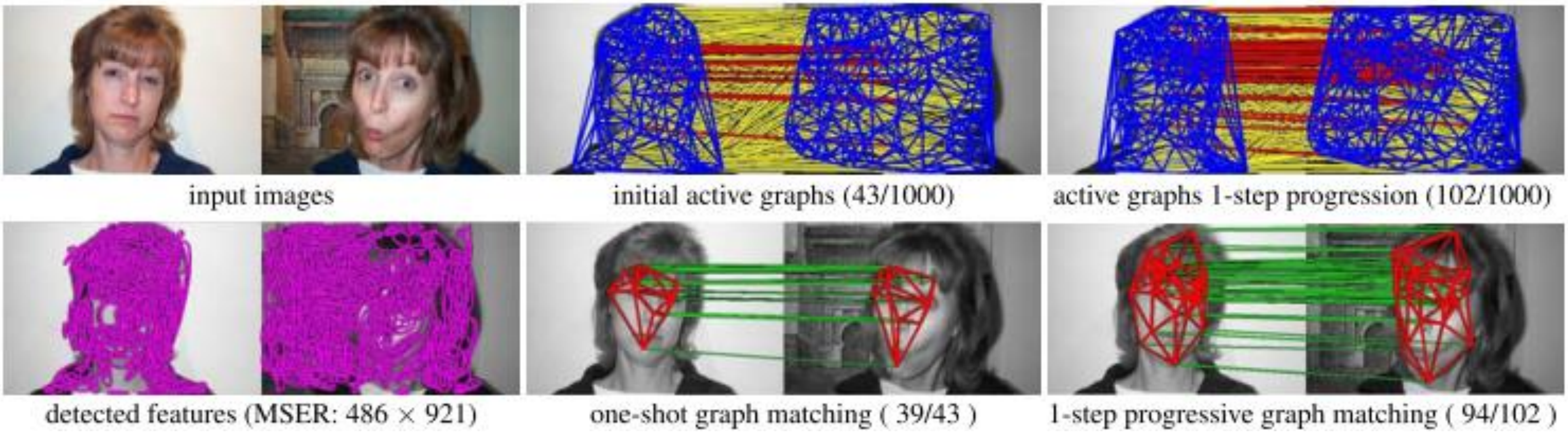
Lee2011:


Our method: (12/12)
HGM: (11/12)
TM: (11/12)
Our method: (18/22)
HGM: (18/22)
TM: (10/22)
Our method: (8/11)
HGM: (6/11)
TM: (2/11)
Our method: (9/14)
HGM: (9/14)
TM: (7/14)

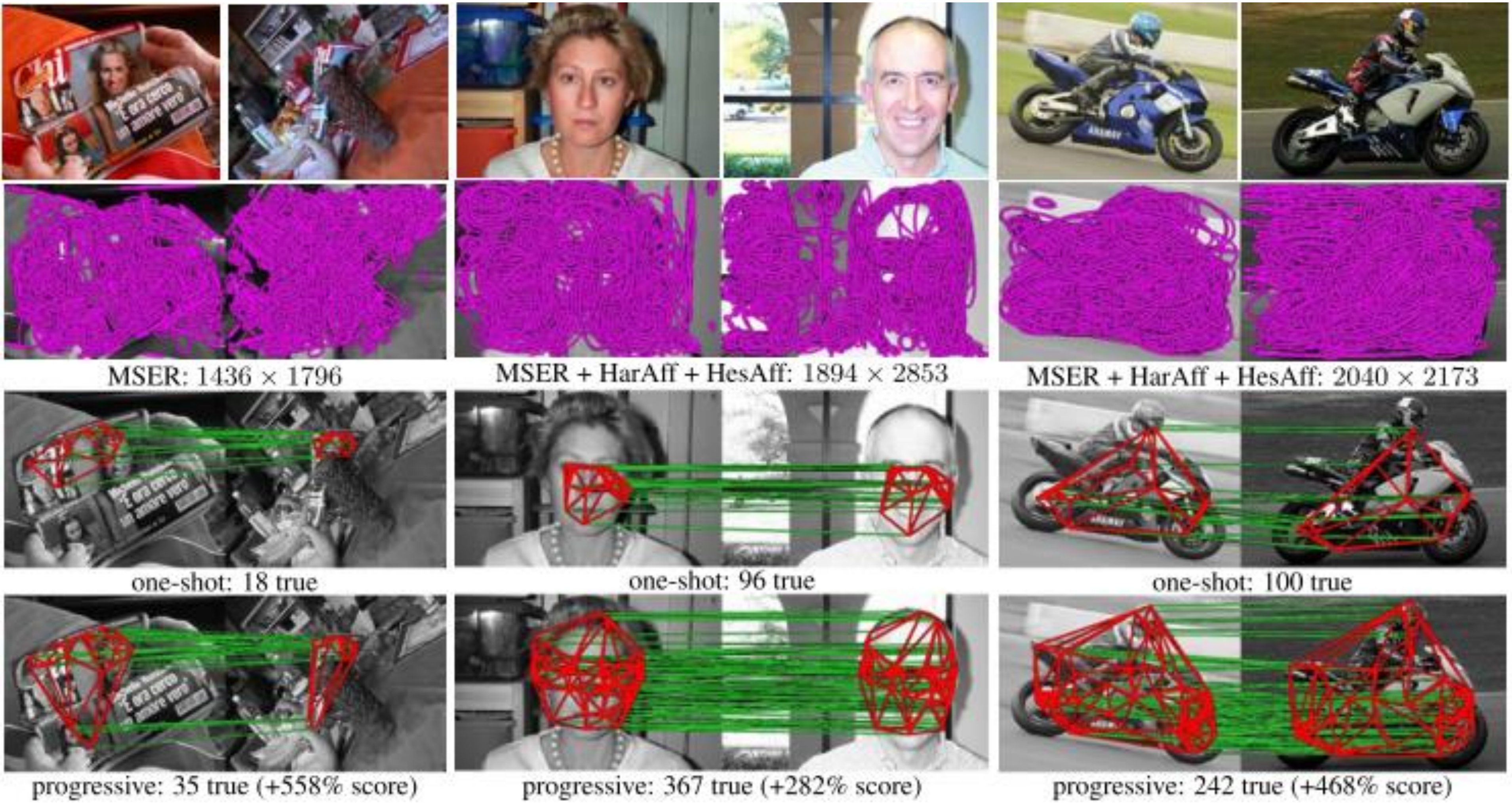
Cho2012:


Graph Matching
Graph Progression
G^P
G^Q
G^P
G^Q
(a) progressive graph matching
input images
detected features
one-shot matching (26 true)
progressive matching (159 true)
(b) image matching via progressive graph matching

Cho2012:


input images
initial active graphs (43/1000)
active graphs 1-step progression (102/1000)
detected features (MSER: 486 × 921)
one-shot graph matching (39/43)
1-step progressive graph matching (94/102)

Cho2012:


MSER: 1436 × 1796
MSER + HarAff + HesAff: 1894 × 2853
MSER + HarAff + HesAff: 2040 × 2173
one-shot: 18 true
one-shot: 96 true
one-shot: 100 true
progressive: 35 true (+558% score)
progressive: 367 true (+282% score)
progressive: 242 true (+468% score)

Cho2012:

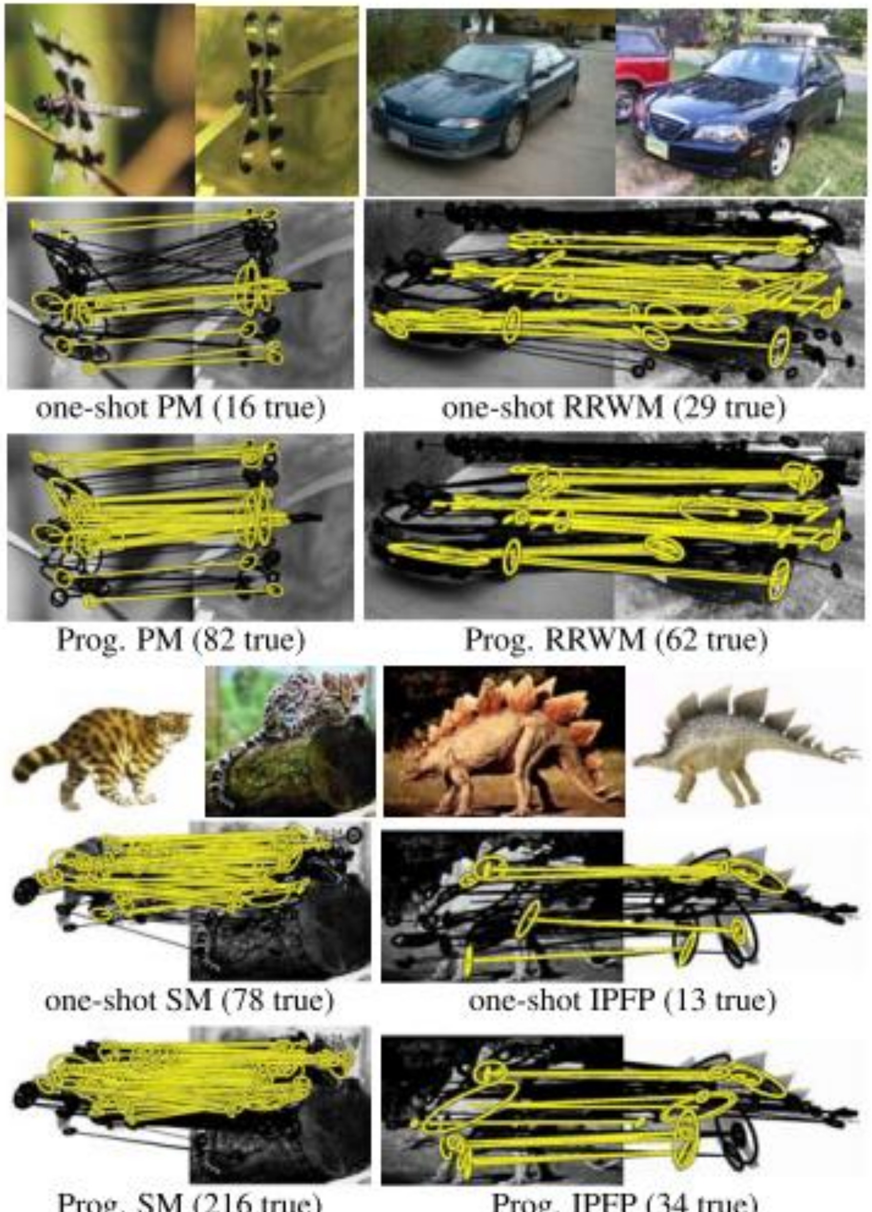


Figure 8. Example results on the benchmark dataset of 30 pairs.