Progressive Graph Matching: Making a Move of Graphs via Probabilistic Voting

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Graph Matching

Given two attributed graphs $\bar{G}^P = (\bar{V}^P, \bar{E}^P, \bar{A}^P)$ and $\bar{G}^Q = (\bar{V}^Q, \bar{E}^Q, \bar{A}^Q)$ with n^P and n^Q nodes respectively.

A result of graph matching is a subset of possible correspondences between those graphs, which can be represented in form of assignment matrix $X \in \{0,1\}^{n^P \times n^Q}$:

$$X_{ia} = \begin{cases} 1 & \text{node } v_i \in \bar{V}^P \text{matches } v_a \in \bar{V}^Q \\ 0 & \text{otherwise} \end{cases}$$

General formulation:

$$x^* = \arg\max S(x)$$

$$s.t. \begin{cases} x \in \{0,1\}^{n^P n^Q} \\ \sum_{i=1}^{n^P} x_{ia} \leq 1 \\ \sum_{a=1}^{n^Q} x_{ia} \leq 1 \end{cases}$$

The objective function $S(x)$ measures the similarity between the graph attributes.

Integer Quadratic Programming

Consider two types of similarity: node and edge similarity. Those can be combined in an affinity matrix W, where non-diagonal elements $W_{ia,jb}$ represent edge similarity of the edges $e_{ij} \in \bar{E}^P$ and $e_{ab} \in \bar{E}^Q$ and diagonal elements $W_{ia,ia}$ represent similarity between nodes $v_i \in \bar{V}^P$ and $v_a \in \bar{V}^Q$.
That leads to the integer quadratic optimization problem:

$$x^* = \arg\max x^T W x$$

$$\text{s.t.} \begin{cases} x \in 0, 1^{n^P n^Q} \\ \sum_{i=1}^{n^P} x_{ia} \leq 1 \\ \sum_{a=1}^{n^Q} x_{ia} \leq 1 \end{cases}$$

Issues

- Quadratic assignment problem is NP-complete
- Computation of W for a large graph is almost infeasible
- Reduction of the complexity often leads to worse matching results

Progressive Graph Matching

Refer to the initial graphs $\bar{G}^P$ and $\bar{G}^Q$ as maximal graphs. For each maximal graph a sub-graph induced by a reduced set of nodes is called active graph (G^P and G^Q respectively).

Idea: match maximal graphs by iteratively matching their active graphs $(t = 0, 1, \dots)$

- Graph Matching
  match current active graphs $G_t^P = (V_t^P, E_t^P, A_t^P)$ and $G_t^Q = (V_t^Q, E_t^Q, A_t^Q)$, $G_t^P \subset \bar{G}^P, G_t^Q \subset \bar{G}^Q$.
- Graph Progression
  update active graphs to improve matching score on the next matching step

Graph Matching

To reduce the complexity of graph matching consider a given set of candidate matches $C_t \subset V^P \times V^Q$.
The corresponding active graphs are defined by the nodes appeared in C_t.
This method reduces the size of active graphs and makes a affinity matrix more sparse.

Graph Progression I

Let $M_t = \{m_1, \ldots, m_{|M_t|}\} \subset C_t$ with $m_i = (v^P_{p_i}, v^Q_{q_i})$ be a result of graph matching of two active graphs and s_t it's score.
Consider conditional joint probability $p(V^P, V^Q | M_t)$:

$$\begin{aligned} p(V^P, V^Q | M_t) &= \sum_{m_i \in M_t} p(V^P, V^Q, M = m_i | M_t) \\ &= \sum_{m_i \in M_t} p(V^Q | V^P, M = m_i, M_t) \\ &\qquad p(V^P | M = m_i, M_t) p(M = m_i | M_t) \end{aligned}$$

Graph Progression II

$p(v_i^P, v_a^Q|M_t)$ conditional probability of match (v_i^P, v_a^Q) between two maximal graphs.
Base on the probability distribution $p(V^P, V^Q|M_t)$ new candidate set C_{t+1} consists of N_c best matches.
Given new candidate set C_{t+1} we obtain new active graphs G_{t+1}^P and G_{t+1}^Q.
The condition $M_t \subset C_{t+1}$ ensures that $s_{t+1} \geq s_t$, if M_t is an optimal matching.

Algorithm

Algorithmus 1 progressiveGraphMatching($\bar{G}^P$, $\bar{G}^Q$, N_c) [1]

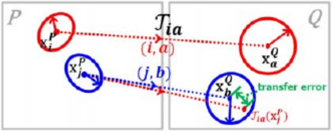
$C_0 = Find\_Initial\_Candidates(\bar{G}^P, \bar{G}^Q, N_c)$
$t = 0, s_0 = 0$
while score increases **do**
  $(M_t, s_t) = Graph\_Matching(C_t)$
  $p(v_p^P, v_q^Q|M_t) = 0 \;\; \forall v_p^P \in \bar{V}^P, v_q^Q \in \bar{V}^Q$
  for each $m_i = (v_p^P, v_q^Q) \in M_t$ **do**
    $N_A = \{v^P \in \bar{V}^Q | p(v^P|m_i, M_t) > \epsilon\}$
    for each $v_j^P \in N_A$ **do**
      $N_B = \{v^Q \in \bar{V}^Q | p(v^Q|v_j^P, m_i, M_t) > \epsilon\}$
      for each $v_b^Q \in N_b$ **do**
        $p(v_p^P, v_q^Q|M_t) = p(v_p^P, v_q^Q|M_t) + p(v_b^Q|v_j^P, m_i, M_t)p(v_j^P|m_i, M_t)p(m_i|M_t)$
      end for
    end for
  end for
  $C_{t+1} = N_c$ best matches based on $p(V^P, V^Q|M_t)$, which contains M_t
  $t = t + 1$
end while
return M_t

Matching of images I

Given two images.

- Detected features of the images represent nodes of the maximal graphs (and their geometric relations edges)
- Node similarity = similarity of feature descriptors of two graphs
- Edge similarity = Symmetric Transfer Error (STE) (see [3])

Derive affine homography transformation $\tau_{ia}(\cdot)$ between two features



The transfer error of (j, b) with respect to (i, a)

$$d_{jb|ia} = \|x_b^Q - \tau_{ia}(x_j^P)\|$$

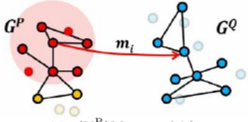
Edge similarity
$W_{ia,jb} = \max(0, \alpha - \frac{d_{jb|ia} + d_{bj|ai} + d_{ia|jb} + d_{ai|jb}}{4})$

Matching of images II

$$\mathbf{p}(\mathbf{V^P}, \mathbf{V^Q} | \mathbf{M_t}) = \sum_{\mathbf{m_i} \in \mathbf{M_t}} \mathbf{p}(\mathbf{V^Q} | \mathbf{V^P}, \mathbf{M} = \mathbf{m_i}, \mathbf{M_t}) \mathbf{p}(\mathbf{V^P} | \mathbf{M} = \mathbf{m_i}, \mathbf{M_t}) \mathbf{p}(\mathbf{M} = \mathbf{m_i} | \mathbf{M_t})$$

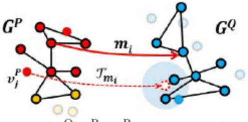
- $\mathbf{p}(\mathbf{M} = \mathbf{m_i} | \mathbf{M_t}) = score(m_i) / \sum_i score(m_i)$
- Assuming $m_i = (v^P_{p_i}, v^Q_{q_i})$ and use function $kNN(\cdot, k)$ to find k-nearest neighbours of a node

$$\mathbf{p}(\mathbf{V^P} = \mathbf{v^P_j} | \mathbf{M} = \mathbf{m_i}, \mathbf{M_t}) = \begin{cases} 1/k_1 & , \text{ if } v^P_j \in kNN(v^P_{p_i}, k_1) \\ 0 & , \text{ otherwise} \end{cases}$$



(a) $p(V^P | M = \mathbf{m}_i, \mathcal{M}_t)$

- Let $NN(\cdot)$ define a nearest neighbour of a node



(b) $p(V^Q | V^P = v_j^P, M = \mathbf{m}_i, \mathcal{M}_t)$

$$\mathbf{p}(\mathbf{V^Q} = \mathbf{v^Q_b} | \mathbf{V^P} = \mathbf{v^P_j}, \mathbf{M} = \mathbf{m_i}, \mathbf{M_t}) =$$

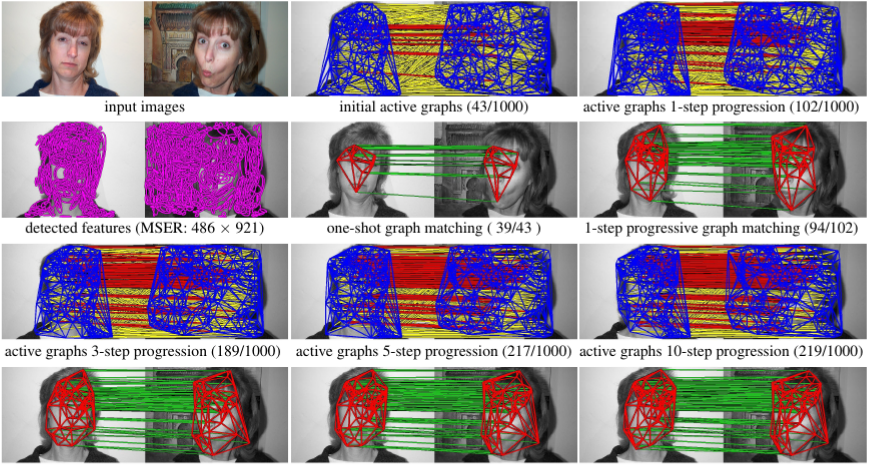
$$\begin{cases} 1 & , \text{ if } v^Q_b = NN(\tau_{m_i}(p^P_j)) \text{ and } (v^P_j, v^Q_b) \in M_t \\ \exp(-d_{jb|mi})/Z & , \text{ if } v^Q_b \in kNN(\tau_{m_i}(p^P_j), k_2) \text{ and } (v^P_j, NN(\tau_{m_i}(p^P_j))) \notin M_t \\ 0 & , \text{ otherwise} \end{cases}$$

$Z = \sum_{v^Q_b \in kNN(\tau_{m_i}(p^P_j), k_2)} \exp(-d_{jb|mi})$ is a normalization constant

Evaluation

- Parameters of the affinity matrix W: $\alpha = \mathbf{50}$, $\mathbf{k_1} = \mathbf{25}$, $\mathbf{k_2} = \mathbf{5}$
- Used Descriptors: **MSER** [4] and Harris-affine and Hessian-affine features [5]
- used graph matching methods:
  Graduate Assignment Algorithm (**SM**) [8]
  Spectral Matching with Affine Constraint (**SMAC**) [9]
  Probabilistic Graph Matching (**PM**) [7]
  Reweighted Random Walk Method (**RRWM**)[3]
  Integer Projected Fixed Point Method (**IPFP**) [6]
- Datasets: **VOC 2010**, **Caltech-101**, **MSRC**, **ETHZ** toys dataset

Evaluation: Progressive Graph Matching ($N_c = 1000$)



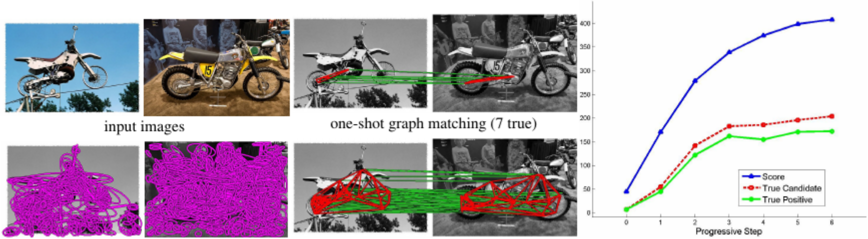
input images | initial active graphs (43/1000) | active graphs 1-step progression (102/1000)

detected features (MSER: 486 × 921) | one-shot graph matching (39/43) | 1-step progressive graph matching (94/102)

active graphs 3-step progression (189/1000) | active graphs 5-step progression (217/1000) | active graphs 10-step progression (219/1000)

3-step progressive graph matching (173/189) | 5-step progressive graph matching (184/217) | 10-step progressive graph matching (188/219)

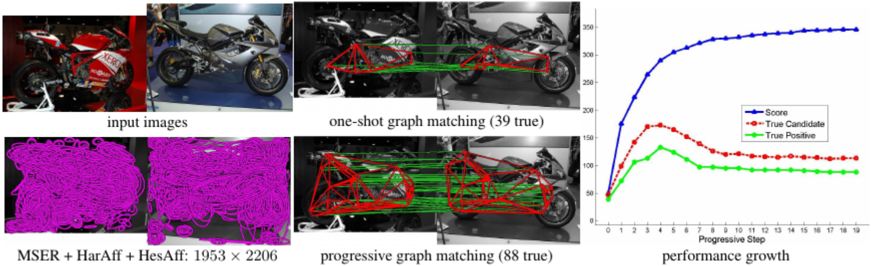
Evaluation: Progressive Graph Matching ($N_c = 3000$)



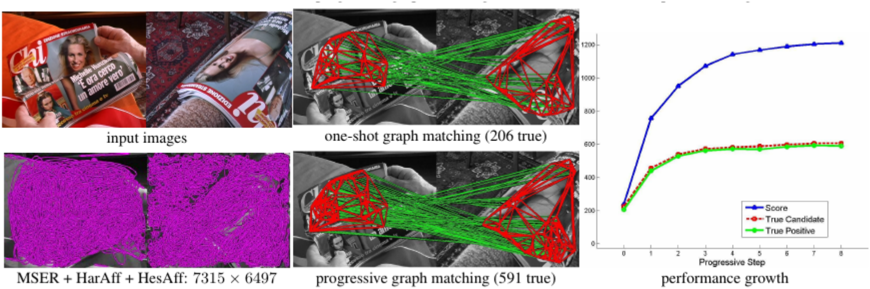
input images | one-shot graph matching (7 true)

MSER: 292 × 703 | progressive graph matching (172 true) | performance growth

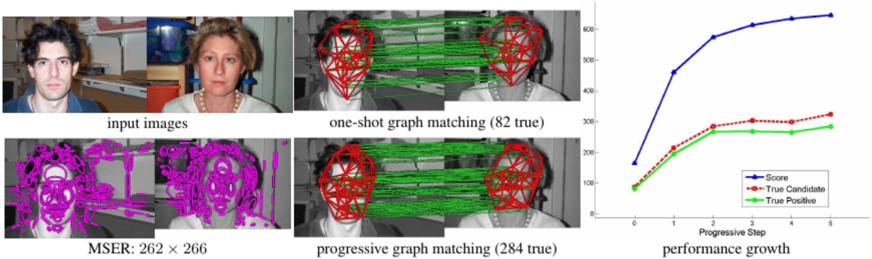
Evaluation: Progressive Graph Matching ($N_c = 3000$)



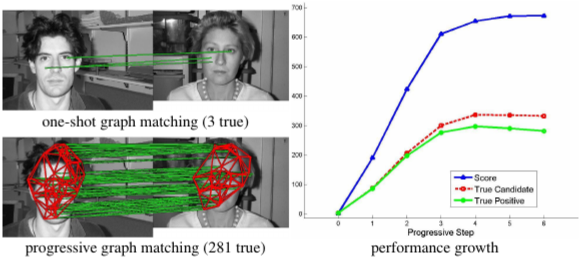
Evaluation: Progressive Graph Matching ($N_c = 3000$)

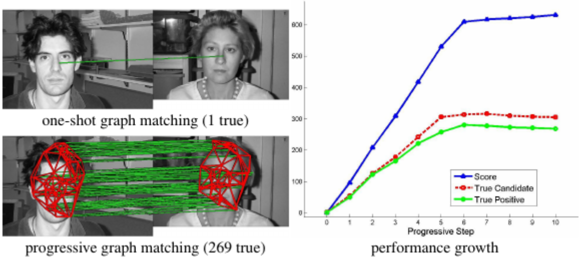


Evaluation: Robustness to initial active graph ($N_c = 3000$) I



Evaluation: Robustness to initial active graph ($N_c = 3000$) II





Evaluation: Different matching algorithms

	Graph Matching Module				
One-Shot	SM	SMAC	PM	RRWM	IPFP
Accuracy (%)	62.6	57.6	63.7	73.6	71.9
Progressive	SM	SMAC	PM	RRWM	IPFP
Accuracy (%)	68.2	63.6	66.7	81.2	78.2
Prog. vs. One-Shot	SM	SMAC	PM	RRWM	IPFP
Score Growth (%)	+65.0	+38.7	+92.1	+65.7	+63.8
Inlier Growth (%)	+59.6	+17.0	+85.1	+65.6	+69.7

Figure: Dataset of 30 image pairs. Accuracy boost 3% $\sim$ 8%

Conclusions

- graph progression significantly increases one-step graph matching
- algorithm is suitable for large graphs

- (?) convergence of the algorithm
- (?) number of the candidate matches
- (?) running time
- (?) geometric graphs

The End

Thank you for your attention!

References I

[1] Minsu Cho and Kyoung Mu Lee. Progressive graph matching: Making a move of graphs via probabilistic voting. *Proc. Computer Vision and Pattern Recognition (CVPR)*, 2012.

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[3] Minsu Cho, Kyoung Mu Lee, and Jungmin Lee. Reweighted random walks for graph matching. *European Conference on Computer Vision (ECCV)*, 2010.

[4] Matas. J, Chum. O, Urban. M, and Pajdla. T. Robust wide baseline stereo from maximally stable extremal regions. *BMVC*, 2002.

References II

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[6] Leordeanu. M and Herbert. M. An integer projected fixed point method for graph matching and map interface. *NIPS*, 2009.

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[9] Cour. T, Srinivasan. P, and Shi. J. Balanced graph matching. *NIPS*, 2007.