Refining Graph Matching Using Inherent Structure Information
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1. Introduction
- Graphs are made up by nodes (vertices) and edges (links)
- Graph matching maps nodes of two graphs $G^A$ and $G^B$ by preserving relative structural relationships, which deals with:
  - non-rigid deformation
  - scale changes
- Graph matching challenges in real-world scenes:
  - unreliable nodes (do not necessarily have true matches)
  - false correspondences due to inaccurate descriptors
  - insufficient constraints of IQP (Integer Quadratic Programming) model [1]

2. Proposed Approach
- (Input) graph matching result $\chi \rightarrow$ (output) substructures $\hat{G}^A_{sub}$ and $\hat{G}^B_{sub}$ that:
  - comply with the graphs’ inherent structure
  - encode rich information describing the objects of interest
- Mining global and local information as refinement constraints:
  - global affinity $S_i(.)$ in the active association graph $G$:
    - connectivity $S_i(.)$ and stability $S_i(.)$. Inspired by [2]
  - local consistency $S_i(.)$ in two matched graphs $\hat{G}^A$ and $\hat{G}^B$:
    - common linkage information within neighbours. Inspired by [3]

3. Experiments
- Comparison with SM (Spectral Matching) [4] and RRWM (Re-weighted Random Walk Graph Matching) [5]
- CMU dataset: same object, deformation increases with temporal baseline
  - graph nodes: manually labeled points in images

<table>
<thead>
<tr>
<th>Method</th>
<th>Precision</th>
<th>Recall</th>
<th>F-score</th>
</tr>
</thead>
<tbody>
<tr>
<td>SM</td>
<td>0.5114</td>
<td>0.5507</td>
<td>0.5303</td>
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<tr>
<td>Refined SM</td>
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<td>0.4843</td>
<td>0.5637</td>
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<td>RRWM</td>
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<td>0.8559</td>
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</table>

- CMU dataset: different objects, various poses with different background
  - graph nodes: MSER (Maximally Stable Extremal Regions) feature points in images

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<th>Recall</th>
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<tbody>
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4. Conclusion
Promising direction to tackle graph matching in real-world scenes:
- analyse the individual graph structure
- explore graph’s own characteristic and hidden constraints

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References