Associating People Dropping off and Picking up Objects

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BMVC07
The Task
Tracking people and detecting objects

The video is a sequence of periods of activity
Tracking people and detecting objects

The video is a sequence of periods of activity
Associating drops with picks
Discriminating drops from picks - people
Discriminating drops from picks - people
Discriminating drops from picks - objects

Masked edges

‘before’ reference image

‘after’ reference image
Possible assignments for a period of activity

\[ d(p_i, o_j) = \begin{cases} 
1 - \max_{\infty} \left( \frac{\text{Box}(p_i) \cap \text{Box}(o_j)}{\text{min}(\text{Box}(p_i), \text{Box}(o_j))} \right) & \text{if } \text{interval}(p_i) \subset \text{interval}(o_j) \\
\infty & \text{otherwise}
\end{cases} \]

Assignments set 1:
- drop(Person1, Bike1)
- none(Person2)
- drop(Person3, Bike1)
- drop(Person4, Bike1)
- none(Person5)
- drop(Person6, Bike2)
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Tree of hypotheses: sequences of assignments

Period of activity

1
2
Tree of hypotheses: sequences of assignments

Period of activity

1

2
Tree of hypotheses: sequences of assignments

Period of activity

1

2
Tree of hypotheses: sequences of assignments

Period of activity

1 2 3
Tree of hypotheses: sequences of assignments

Period of activity

K-best – k-min-cost
Tree of hypotheses: sequences of assignments

Period of activity

1

2

3

K-best – k-min-cost
Tree of hypotheses: sequences of assignments

Period of activity

1

2

3

K-best – k-min-cost
Tree of hypotheses: sequences of assignments
Tree of hypotheses: sequences of assignments
Constrained optimisation

\[ f_{p_{kd}p}(p_i, o_j, p_k, o_l) = d(p_i, o_j) + d(o_j, o_l) + d(p_k, o_l | o_j) \]
\[ f_{dp}(p_i, o_j) = f_{pk}(p_i, o_j) = d(p_i, o_j) + \alpha \]
\[ f_{none}(p_i) = \beta \]

\[ f(e) = \sum_{C_{pk dp}} f_{p_{kd}p}(p_i, o_j, p_k, o_l) + \sum_{C_{dp}} f_{dp}(p_i, o_j) + \sum_{C_{pk}} f_{pk}(p_i, o_j) + \sum_{C_{none}} f_{none}(p_i) \]

Each person should be involved in exactly one event
Post-segmentation

\[
d(o_i, o_j) = \begin{cases} 
1 - \frac{\sum_{x,y} (o_i(x,y) \land o_j(x,y))}{\min(\sum_{x,y} o_i(x,y), \sum_{x,y} o_j(x,y))} & \text{if } o_i \in \text{picked} \land o_j \in \text{dropped} \land I(o_i) > I(o_j) \\
\infty & \text{otherwise}
\end{cases}
\]

\[
d(p_k, o_l \mid o_j)
\]
Experiments & Results

- 3 experiments
  - 1 hour (45 events)
  - 50 minutes (22 events)
  - Full day (9 hours and 30 mins) (40 events)

<table>
<thead>
<tr>
<th>Exp #</th>
<th>Unconstrained</th>
<th>Constrained</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>75.86</td>
<td>93.10</td>
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<tr>
<td>2</td>
<td>70.37</td>
<td>92.59</td>
</tr>
<tr>
<td>3</td>
<td>83.59</td>
<td>96.09</td>
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</tbody>
</table>
Application to bicycle theft detection

- 8×8×8 scale-normalized equal-bin-size colour histogram
- Scale-by-max
- Median histogram

<table>
<thead>
<tr>
<th>Actual</th>
<th>Predicted</th>
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<tbody>
<tr>
<td>Thief</td>
<td>10</td>
</tr>
<tr>
<td>Non-Thief</td>
<td>17</td>
</tr>
</tbody>
</table>

ROC Curve for the three experiments

Threshold = 0.7
Summary

- Deal with ambiguity in the visual data through the use of global constraints on what is possible.
- Comparison with unconstrained and partially-constrained solutions (in the paper).
- Ambiguities in the observations are expressed as multiple hypotheses.
- Hypotheses can then be verified or invalidated by future observations.
Thank you for listening

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