Solving Person Re-identification in Non-overlapping Cameras using Efficient Gibbs Sampling

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Person Re-identification: Problem Formulation

Same camera in a network

Different camera (overlapping)

Different camera (non-overlapping)
Person Re-identification: Problem Formulation

Applications:
Behaviour analysis, Surveillance, Logistics...

Solution:
Appearance-based features and temporal information

Issues:
Appearance variations across time and cameras
Loss of temporal information (non-overlapping views)
High computational complexity
Person Re-identification: Algorithm Overview

Problem formulation

Unsupervised person trajectory re-identification in non-overlapping network addressing:

Illumination variation
Camera gain variation
High computational complexity

Solution overview

Probabilistic graphical model
Infer person labels using efficient Gibbs sampling
Closed-form analytical updates of absolute appearance, gain and illumination variation parameters
Person Re-identification: Probabilistic Graphical Model

\[ \mathbf{X} = [x_1, \ldots, x_n] \quad \text{(Set of observations)} \]

\[ \mathbf{Z} = [z_1, \ldots, z_n] \quad \text{(Set of labels to be solved)} \]

\[ \mathbf{x}_i = [a_i, l_i, e_i, t_i] \quad \text{(ith trajectory)} \]

- \( a_i \): average raw RGB color model
- \( l_i \): camera label
- \( e_i \): trajectory entrance time
- \( t_i \): trajectory leaving time
Person Re-identification: Analytical Update

Appearance = gain * (rgb + cam illumination noise)

**Analytical Update**

- **Distributions**
  - Transitions probability: Multinomial distribution
  - Transition time: Gamma distribution
  - Gain: Gaussian distribution
  - Appearance: Gaussian distribution
  - Illumination variation: Gaussian distribution

- **Conjugate prior**
  - Gain(*unknown mean and precision*) Normal-gamma
  - RGB, Appearance (*mean, precision*) Normal-Wishart
  - RGB, Illumination (*mean, precision*) Normal-Wishart

- **Known labels**
- **Efficient Bayesian inference using Markov blanket**
- **Closed-form analytical solution posterior**
Person Re-identification: Probabilistic Graphical Model

Known labels
Efficient inference

Unknown labels
Inefficient inference

(Markov blanket is complete set of observation and labels)
Person Re-identification: Efficient Gibbs Sampling

- Gibbs sampling based MCMC

\[
p(z_i | z_{-i}, X) = \frac{p(X | z) p(z_i)}{\sum_{z_i=1}^{N} p(X | z) p(z)}
\]

- Computational complexity over observations
  - Naive Gibbs sampling: \textbf{quadratic}
    \[
    \begin{align*}
    p(z_i | z_{-i}, X) & \quad \text{linear} \\
p(z) & \quad \text{constant} \\
p(X | z) & \quad \text{linear}
    \end{align*}
    \]
  - Gibbs sampling with book keeping: \textbf{linear}
    \[
    \begin{align*}
    p(z_i | z_{-i}, X) & \quad \text{constant} \\
p(z) & \quad \text{constant} \\
p(X | z) & \quad \text{linear}
    \end{align*}
    \]
Person Re-identification: Book Keeping

Given $z=[z_1\ldots, z_n]$ (Set of person labels)

- **Store** $b=[b_1\ldots, b_n]$ (Set of previous indices associated with $z$)
- **Store** $f=[f_1\ldots, f_n]$ (Set of future indices associated with $z$)
- **Compute** $p(X \mid z)$

For each new label $z_i'$,

1) **Compute** $p(X \mid z_i', z_{-i})$ in constant time given $p(X \mid z)$

$$p(X \mid z_{-i}, z_i') = p(X \mid z) \times \frac{p(x_i' \mid z_i', b_i') p(x_{f_i} \mid z_{f_i}, b_i) p(x_{f_i'} \mid z_i', x_i)}{p(x_i \mid z_i, b_i) p(x_{f_i} \mid z_{f_i}, x_i) p(x_{f_i'} \mid z_i', x_{b_{f_i'}})}$$

2) **Modify** $f$ and $b$

$$f_{b_i} \leftarrow f_i \quad b_{f_i} \leftarrow b_i \quad f_i \leftarrow f_i' \quad b_i \leftarrow b_{f_i} \quad b_{f_i} \leftarrow i \quad f_{b_i} \leftarrow i$$
Person Re-identification: Book Keeping

Calculate $b$ and $f$

Modify $b$ and $f$ for new label for $i$th observation
Person Re-identification: Experimental Results

- Ceiling-mounted multiple camera datasets
  - 2 Datasets with 5-13 cameras and 5-10 people
- Comparative experiments
  - Pasula sampler
  - MCMC: transition by swapping random observation pairs
  - Maximum-Likelihood
- Algorithm parameter
  - Naïve appearance model (Raw rgb)
Person Re-identification: Experimental Results

Comparative (5 trials)

<table>
<thead>
<tr>
<th>Dataset</th>
<th>PGM-based</th>
<th>Pasula sampler</th>
</tr>
</thead>
<tbody>
<tr>
<td>1 -5 sub</td>
<td>87.3+4.3%</td>
<td>67.5 + 6.1%</td>
</tr>
<tr>
<td>1-10 sub</td>
<td>86+ 5.2%</td>
<td>65.0 + 8.1%</td>
</tr>
<tr>
<td>2-5 sub</td>
<td>84+ 4.1 %</td>
<td>62.5 + 7.3%</td>
</tr>
</tbody>
</table>

Algorithm parameters (5 trials)

<table>
<thead>
<tr>
<th>Dataset</th>
<th>PGM-based</th>
<th>Naïve appearance</th>
</tr>
</thead>
<tbody>
<tr>
<td>1 -5 sub</td>
<td>87.3+4.3%</td>
<td>75 + 5.1%</td>
</tr>
<tr>
<td>1-10 sub</td>
<td>86+ 5.2%</td>
<td>74.3 + 4.6%</td>
</tr>
<tr>
<td>2-5 sub</td>
<td>84+ 4.1 %</td>
<td>73.2 + 5.3%</td>
</tr>
</tbody>
</table>

Computational Complexity

Frames

<table>
<thead>
<tr>
<th>Frames</th>
<th>Mean and Std. Dev</th>
</tr>
</thead>
<tbody>
<tr>
<td>200</td>
<td>72.5+5.6%</td>
</tr>
<tr>
<td>600</td>
<td>77+5.2%</td>
</tr>
<tr>
<td>1000</td>
<td>81.6+4.6%</td>
</tr>
<tr>
<td>1400</td>
<td>82.1+3.9%</td>
</tr>
<tr>
<td>2000</td>
<td>84+4.1%</td>
</tr>
</tbody>
</table>
Person Re-identification: Summary

- Unsupervised person trajectory re-identification in non-overlapping network addressing:
  - Illumination variation
  - Camera gain variation
  - High computational complexity
- Using probabilistic graphical model
- Infer person labels using efficient Gibbs sampling
- Closed-form analytical updates of appearance, gain and illumination variation parameters
- Significantly improved performance
Thank you