Object Tracking, Trajectory Analysis and Event Detection in Intelligent Video Systems

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Outlines

- Motivation
- Object Tracking
- Trajectory Analysis
- Event Detection
- Conclusions and Future Work
Motivation

- **Advantage** of Video-based systems
  - Being able to capture a large variety of information
  - Relatively inexpensive
  - Easier to install, operate, and maintain

- **Applications**
  - Security surveillance
  - Home care surveillance
  - Intelligent transportation systems

- There is an urgent need for **intelligent video systems** to replace **human operators** to monitor the areas under surveillance.
System Modules for Intelligent Event Detection Systems

Image Frames → Video Object Segmentation → Tracking System → Feature Extraction → Recognition Model → Semantics and Events
Challenges for Robust Tracking

- Segmentation errors
- Change of lighting conditions
- Shadows
- Occlusion
Inter-Object Occlusion
Initial Occlusion
Background Occlusion
Proposed Tracking Mechanism
Background Estimation and Updating

- Based on **Gaussian mixture models** [Stauffer 1999]
- Model the recent history of each pixel by a mixture of K Gaussian distributions.
- Every pixel value is checked among the existing K Gaussian distributions for a match.
- Update the weights for the K distributions and the parameters of the matched distribution.
- The k\textsuperscript{th} Gaussian is ranked by \( \frac{w_k}{\sigma_k} \) \( \left( \sum_k = \sigma_k^2 I \right) \)
- The top-ranked Gaussians are selected as the background models.
- Pixel values that belong to background models are accumulated and averaged as the background image.
- The background image is updated for every certain interval of time.
Moving Object Segmentation

- Based on background subtraction
- Fourth order moment


\[
\mu_d^{(4)}(x, y) = \frac{1}{N_{\eta}} \sum_{(s, t) \in \eta(x, y)} (\text{diff} \_ \text{img}(s, t) - \hat{m}_d)^4
\]

- Thresholding

\[
S(x, y) = \begin{cases} 
1, & \text{if } \mu_d^{(4)}(x, y) \geq \theta \\
0, & \text{if } \mu_d^{(4)}(x, y) < \theta 
\end{cases}
\]
Kalman Filter

Kalman filters are modeled on a Markov chain built on **linear operators** perturbed by **Gaussian noises**.

- At time $k$, each target has state $x_k$

  $$x_k = F_k x_{k-1} + w_k$$

  , where $w_k \sim N(0, Q_k)$

  and observation (measurement) $y_k$

  $$y_k = H_k x_k + v_k$$

  , where $v_k \sim N(0, R_k)$

Kalman Filter Phases

Predicted State $\hat{x}_{k|k-1}$

Updated State Estimate $\hat{x}_{k|k}$

Predict

Observed Measurements $y_k$

$F_k = \begin{bmatrix} 1 & 0 & 1 & 0 \\ 0 & 1 & 0 & 1 \\ 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 1 \end{bmatrix}$

$H_k = \begin{bmatrix} 1 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 \\ 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 1 \end{bmatrix}$

$x_k = y_k = [u_k \ v_k \ \dot{u}_k \ \dot{v}_k]^T$
Kalman Filter Phases

**Predict Phase**
- Predicted State
  \[ \hat{x}_{k|k-1} = F_k \hat{x}_{k-1|k-1} \]
- Predicted Estimate Covariance
  \[ P_{k|k-1} = F_k P_{k-1|k-1} F_k^T + Q_k \]

**Update Phase**
- Updated State Estimate
  \[ \hat{x}_{k|k} = \hat{x}_{k|k-1} + K_k \tilde{y}_k \]
- Updated Estimate Covariance
  \[ P_{k|k} = (I - K_k H_k) P_{k|k-1} \]
- Kalman Gain
  \[ K_k = P_{k|k-1} H_k^T S_k^{-1} \]
- Innovation Covariance
  \[ S_k = H_k P_{k|k-1} H_k^T + R_k \]
- Innovation (Measurement) Residual
  \[ \tilde{y}_k = y_k - H_k \hat{x}_{k|k-1} \]
Constructing Measurement
Candidate List

Find measurements within the validation gate of a target

Size matches?  No

Object matching around predicted and previous positions

Overlapping area > Thres OR Dis-similarity < Thres

No

Any measurement in the List?  Yes

Proceed to data association

No

Error handling
Searching for measurement
candidate representation points

• Search for \( q_1 \) and \( q_2 \) in the two \( nxn \) windows centered around \( p_1 \) and \( p_2 \), respectively.

\[
q_1 = \arg \max_{q \in \eta_1(x,y)} \text{Area}(O(q) \cap S_c)
\]

\[
q_2 = \arg \max_{q \in \eta_2(x,y)} \text{Area}(O(q) \cap S_c)
\]

• Compute the dissimilarities between the target object and the potential measurement candidates.
Data Association

- To associate measurements with targets when performing updates
- Nearest Neighbor Data Association
  For all the measurement in the validation gate of a target, select the nearest measurement.
  \[
  [y_k - H_k x_k]^T S_k^{-1} [y_k - H_k x_k] \leq \gamma^2
  \]
- Probabilistic Data Association (PDA)
- Joint Probabilistic Data Association (JPDA)
Consider a single target independently of others.

\( \mathcal{X}_{j} \) denotes the event that the \( j^{th} \) measurement belongs to that target.

**Combined (Weighted) Innovation**

\[
\tilde{y}_k = \sum_{j=1}^{m} \beta_j \tilde{y}_{kj} = \sum_{j=1}^{m} \beta_j (y_{kj} - H_k \hat{x}_{k|k-1})
\]

Modified PDA for Video Object Tracking

• To handle video objects (regions), incorporate the following factor when computing $\beta_j$

$$\alpha \sum_{i=1}^{m} \text{Similarity}_i + (1-\alpha) \sum_{i=1}^{m} \text{OverlapArea}_i$$

$0 < \alpha < 1$

• Similarity measure: cross correlation function

$$C_R = \frac{\sum_{m} \sum_{n} (A_{mn} - \bar{A})(B_{mn} - \bar{B})}{\sqrt{\sum_{m} \sum_{n} (A_{mn} - \bar{A})^2 (\sum_{m} \sum_{n} (B_{mn} - \bar{B})^2)}}$$
Experimental Videos
Vehicle Tracking Results 1
Vehicle Tracking Results 2
Human Tracking Results
## Object Tracking Statistics

<table>
<thead>
<tr>
<th>Video</th>
<th>Sequence 1</th>
<th>Sequence 2</th>
<th>Sequence 3</th>
<th>Sequence 4</th>
</tr>
</thead>
<tbody>
<tr>
<td>Ground Truth</td>
<td>71</td>
<td>64</td>
<td>92</td>
<td>130</td>
</tr>
<tr>
<td>Object Detected</td>
<td>72</td>
<td>61</td>
<td>93</td>
<td>128</td>
</tr>
<tr>
<td>Miss</td>
<td>0</td>
<td>3</td>
<td>0</td>
<td>5</td>
</tr>
<tr>
<td>False Alarm</td>
<td>1</td>
<td>0</td>
<td>1</td>
<td>3</td>
</tr>
<tr>
<td>Correctly Detected</td>
<td>71</td>
<td>61</td>
<td>92</td>
<td>125</td>
</tr>
<tr>
<td>Correctly Tracked</td>
<td>70</td>
<td>58</td>
<td>92</td>
<td>120</td>
</tr>
<tr>
<td>Detection Precision</td>
<td>0.986</td>
<td>1.000</td>
<td>0.989</td>
<td>0.977</td>
</tr>
<tr>
<td>Detection Recall</td>
<td>1.000</td>
<td>0.953</td>
<td>1.000</td>
<td>0.962</td>
</tr>
<tr>
<td>Tracking Success Rate</td>
<td>0.986</td>
<td>0.951</td>
<td>1.000</td>
<td>0.960</td>
</tr>
</tbody>
</table>

\[
\text{Detection Precision} = \frac{\text{Correctly Detected}}{\text{Object Detected}}
\]

\[
\text{Detection Recall} = \frac{\text{Correctly Detected}}{\text{Ground Truth}}
\]

\[
\text{Tracking Success Rate} = \frac{\text{Correctly Tracked}}{\text{Correctly Detected}}
\]

Occluded Object Tracking Success Rate: **0.855**
Trajectory Analysis

Class 1

Class 2

Class 3

Class 4

Class 5

Class 6
Trajectory Smoothing

- Sample the trajectory
- Perform cubic spline interpolation
Angle Feature Extraction

Relative Angle

\((x'_t, y'_t)\)

\((-\theta_p\rightharpoonup\theta_p\leftarrow)\)

\((x'_{t+k}, y'_{t+k})\)

\((x'_{t-k}, y'_{t-k})\)

(a)

Absolute Angle

\(\theta_p = \cos^{-1}\left(\frac{\vec{v}_1 \cdot \vec{v}_2}{|\vec{v}_1| |\vec{v}_2|}\right)\)

\(\theta_h = \cos^{-1}\left(\frac{\vec{v}_h \cdot \vec{v}_2}{|\vec{v}_h| |\vec{v}_2|}\right)\)

\(\vec{v}_1 = (\tilde{x}_t - \tilde{x}_{t-k}, \tilde{y}_t - \tilde{y}_{t-k})\)

\(\vec{v}_2 = (\tilde{x}_{t+k} - \tilde{x}_t, \tilde{y}_{t+k} - \tilde{y}_t)\)
Hidden Markov Model

- N states \( S_i, i=1,\ldots, N \)
- Transition probability \( a_{ij} \)
- Initial probability \( \pi_i \)
- Observation symbol probability \( b_j(k) \)
- A complete model \( \lambda=(A,B,\Pi) \)
  - \( A=\{a_{ij}\} \)
  - \( B=\{b_{jk}\} \)
  - \( \Pi=\{\pi_i\} \)

<table>
<thead>
<tr>
<th></th>
<th>Sunny</th>
<th>Cloudy</th>
<th>Rainy</th>
</tr>
</thead>
<tbody>
<tr>
<td>P(walk)</td>
<td>0.5</td>
<td>0.4</td>
<td>0.2</td>
</tr>
<tr>
<td>P(bike)</td>
<td>0.4</td>
<td>0.3</td>
<td>0.1</td>
</tr>
<tr>
<td>P(bus)</td>
<td>0.1</td>
<td>0.3</td>
<td>0.7</td>
</tr>
</tbody>
</table>
Example of HMM

Observation sequence \( O = \{ \text{walk, bike, bus, bus, bike, walk, ...} \} \)
Three Problems in HMM

- Given $\lambda$, compute the probability that $O$ is generated by this model
  How likely did $O$ happen at this place? 
  forward-backward algorithm

- Given $\lambda$, find the most likely sequence of hidden states that could have generated $O$
  How did the weather change day-by-day? 
  Viterbi algorithm

- Given a set of $O$, learn the most likely $\lambda$
  Train the parameters of the HMM 
  Baum-Welch algorithm
Left-to-right HMM for Trajectory Classification

\[
\begin{align*}
a_{00} & \\
b_0(k) & \\
\end{align*}
\]

\[
\begin{align*}
a_{ij} & \neq 0 \text{ for } j = i, i+1, i+2 \\
b_i(k) & \\
\end{align*}
\]

State 0 \rightarrow State 1 \rightarrow State 2 \rightarrow \cdots \rightarrow State N
K-means Clustering of Feature Points
### Number of Training and Test sequences

Video for both training and testing

<table>
<thead>
<tr>
<th>Trajectory Class</th>
<th>Training Trajectories</th>
<th>Testing Objects</th>
<th>Testing Trajectories</th>
</tr>
</thead>
<tbody>
<tr>
<td>Class 1</td>
<td>12</td>
<td>64</td>
<td>307</td>
</tr>
<tr>
<td>Class 2</td>
<td>11</td>
<td>18</td>
<td>66</td>
</tr>
<tr>
<td>Class 3</td>
<td>13</td>
<td>27</td>
<td>27</td>
</tr>
<tr>
<td>Class 4</td>
<td>5</td>
<td>20</td>
<td>20</td>
</tr>
<tr>
<td>Class 5</td>
<td>8</td>
<td>26</td>
<td>32</td>
</tr>
<tr>
<td>Class 6</td>
<td>8</td>
<td>29</td>
<td>45</td>
</tr>
</tbody>
</table>

Video for testing only
## Trajectory Classification Statistics

<table>
<thead>
<tr>
<th></th>
<th>C 1</th>
<th>C 2</th>
<th>C 3</th>
<th>C 4</th>
<th>C 5</th>
<th>C 6</th>
<th>Accuracy</th>
</tr>
</thead>
<tbody>
<tr>
<td>Class 1</td>
<td>307</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>100%</td>
</tr>
<tr>
<td>Class 2</td>
<td>0</td>
<td>64</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>2</td>
<td>97.4%</td>
</tr>
<tr>
<td>Class 3</td>
<td>2</td>
<td>0</td>
<td>25</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>92.6%</td>
</tr>
<tr>
<td>Class 4</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>20</td>
<td>0</td>
<td>0</td>
<td>100%</td>
</tr>
<tr>
<td>Class 5</td>
<td>1</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>31</td>
<td>0</td>
<td>96.8%</td>
</tr>
<tr>
<td>Class 6</td>
<td>0</td>
<td>2</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>43</td>
<td>95.5%</td>
</tr>
</tbody>
</table>
Anomalous Trajectories
Event Detection

- **Type I Events**
  - Simple rule-based decision logic
  - Entering a dangerous region
  - Stopping in the scene
  - Driving on the road shoulder

- **Type II Events**
  - Based on trajectory classification results via HMM using angle features
  - Illegal U-turns or left turns
  - Anomalous trajectories

- **Type III Events**
  - Based on trajectory classification results via HMM using speed features
  - Speed change
Conclusions and Future Works

- **Tracking**
  - Kalman filtering for prediction
  - Modified PDA for data association

- **Basic Events**
  - Simple rule-based decision logic
  - HMM

- **Higher Level Events**
  - Combining basic events
  - More flexible models