Multiple Hypothesis Tracking Revisited

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Pedestrian Tracking

Detect people and track them (a.k.a. tracking by detection).

Detector Output

Tracker Output

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Elements of Multi-target Tracking

• Data Association
• Appearance Modeling

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Elements of Multi-target Tracking

• Data Association
• Appearance Modeling

Challenge: combinatorial complexity

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Network Flow-based Method

Advantage: Global optimal solution can be found.
Disadvantage: Pairwise cost (pointed out in Collins 2012)

A. A. Butt. CVPR 2013, M. Hofmann. CVPR 2013, R. Collins. CVPR 2012, H. B. Shitrit. PAMI 2013,

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Multiple Hypothesis Tracking (MHT)

Advantage: Capability of modeling higher-order information
Disadvantage: Combinatorial explosion in the number of hypotheses

D. Reid. AC 1979, I. J. Cox. PAMI 1996, M. Han. CVPR 2001,
D. J. Papageorgiou. Optimization and Cooperative Control Strategies 2009

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3  2  1

Tree 1  Tree 2  ...  Tree N

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Multiple Hypothesis Tracking (MHT)

• Developed by the radar target tracking community and introduced to the vision community in the 90’s.
• Fell out of favor, now it is not even used as a baseline

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Multiple Hypothesis Tracking (MHT)

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- Fell out of favor, now it is not even used as a baseline

**Goal: Bring back MHT!**
Multiple Hypothesis Tracking (MHT)

What has changed compared to the 90’s?

• Better object detectors:
  
  Less ambiguity in data association ➔ we need fewer hypotheses

• Better appearance representations, long-term appearance modeling:
  
  More discriminative track score ➔ fewer mistakes in pruning
Contributions

• Efficient on-line method for MHT appearance modeling
  • Learned using multi-output least squares
  • New discriminative track score → efficient search of hypothesis space

• Reference implementation of classic MHT method
  • Surprisingly competitive on current datasets
  • It ranks #7 out of 35 on the leaderboard!
Goal: train and update the appearance model for each target over time

Tree 1

$t = 1$

$t = 2$

$t = 3$

Tree 2

\cdots

Tree N

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Appearance Modeling – MHT

How to train and update multiple appearance models efficiently in MHT?

Tree 1

Tree 2

... Tree N

$t = 1$

$t = 2$

$t = 3$

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Let’s look at a classifier for one hypothesis.

Tree 1

\[ t = 1 \]

\[ t = 2 \]

\[ t = 3 \]

Track Hypothesis 1

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Approach: Training Multiple Classifiers

Let’s look at a classifier for one hypothesis.

Tree 1

$t = 1$

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Track Hypothesis 1

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Let’s look at a classifier for one hypothesis.

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Approach: Training Multiple Classifiers

Repeat the same process for the next branch.

Tree 1

$t = 1$

$t = 2$

$t = 3$

Track Hypothesis 2

1st Decision boundary
Approach: Training Multiple Classifiers

Repeat the same process for the next branch.

Tree 1

- $t = 1$
- $t = 2$
- $t = 3$

Track Hypothesis 2

2$^{nd}$ Decision boundary
Correct hypothesis produces more consistent classifier than wrong hypothesis.
Correct hypothesis produces more consistent classifier than wrong hypothesis.

How to efficiently compute different weights for the combinatoric space of classifiers?
Least Squares Regression

Given $X$ and $\nu$ (all training samples and its labels), our task is to find the optimal $\nu$.

$$\min_w \|Xw - \nu\|^2 + \lambda \|w\|^2$$

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Multi-output Least Squares Regression

Given $X$ and $V$ (all training samples and its labels), our task is to find the optimal $W$.

$$\min_{W} \|XW - V\|_F^2 + \lambda \|W\|_F^2$$

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Multi-output Least Squares Regression

In MHT, data comes online $X, V \rightarrow X_t, V_t$ ($t = 1, 2, 3, \ldots, k$)

$$\min_W \|XW - V\|_F^2 + \lambda \|W\|_F^2$$

decomposed

$\min_{W_1} \|X_1W_1 - V_1\|_F^2 + \lambda \|W_1\|_F^2$

$t = 1$

$X_1$

$V_1$

$1$

$1$

$-1$

$-1$

$\ldots$

$\ldots$
Multi-output Least Squares Regression

In MHT, data comes online \( X, V \rightarrow X_t, V_t \) (\( t = 1,2,3, \ldots, k \))

\[
\min_{W} \|XW - V\|_F^2 + \lambda \|W\|_F^2
\]

\( t = 1 \)

\[
\begin{bmatrix}
1 & 1 & \ldots \\
-1 & -1 & \\
-1 & -1 & \\ 
\end{bmatrix}
\]

\[
\min_{W_1} \|X_1W_1 - V_1\|_F^2 + \lambda \|W_1\|_F^2
\]

\( t = 2 \)

\[
\begin{bmatrix}
1 & 1 & \ldots \\
-1 & -1 & \\
-1 & -1 & \\ 
\end{bmatrix}
\]

\[
\min_{W_2} \|X_1W_2 - V_1\|_F^2 + \|X_2W_2 - V_2\|_F^2 + \lambda \|W_2\|_F^2
\]

decomposed
Multi-output Least Squares Regression

In MHT, data comes online \( \mathbf{X}, \mathbf{V} \to \mathbf{X}_t, \mathbf{V}_t \) (\( t = 1,2,3, \ldots, k \))

\[
\min_{\mathbf{W}} \|\mathbf{XW} - \mathbf{V}\|^2_F + \lambda \|\mathbf{W}\|^2_F
\]

\[\text{decomposed}\]

\[
t = 1 \quad \mathbf{X}_1 \quad \mathbf{V}_1
\]

\[
t = 2 \quad \mathbf{X}_2 \quad \mathbf{V}_2
\]

\[
t = 3 \quad \mathbf{X}_3 \quad \mathbf{V}_3
\]
Multi-output Least Squares Regression

Recursive formulation (k frames) of Multi-output Least Squares Regression

$$\min_{W_k} \sum_{t=1}^{k-1} \| X_t W_k - V_t \|_F^2 + \| X_k W_k - V_k \|_F^2 + \lambda \| W_k \|_F^2$$

Optimal $W_k$: Only need to keep and update $H_k$ and $C_k$

$$W_k = (H_k + \lambda I)^{-1} C_k$$

$$H_k = \sum_{t=1}^k X_t^T X_t,$$

$$C_k = \sum_{t=1}^k X_t^T V_t$$

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Time Complexity for Model Updates

\[ W_k = (H_k + \lambda I)^{-1} C_k \]

- Updating \( H_k \) and decomposing \((H_k + \lambda I)\): \( O(m_k d^2 + d^3) \)
- Updating \( C_k \): \( O(dm_k n_k) \)  
  Linear dependence on \( n_k \)

\( n_k \): the number of hypotheses at \( k \) – combinatoric growth  
\( m_k \): the number of detections at \( k \) – typically 0~30  
\( d \): the feature dimension – fixed 256

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Evaluation

• Methods
  • MHT-DAM: MHT with Discriminative on-line Appearance Modeling
  • MHT: the baseline MHT that uses only the motion score

• Dataset
  - PETS2009 – 5 sequences
  - MOT Challenge: 11 training sequences, 11 testing sequences
## Tracking Benchmark: MOT Challenge

<table>
<thead>
<tr>
<th>Method</th>
<th>MOTA</th>
<th>MOTP</th>
<th>MT(%)</th>
<th>ML(%)</th>
<th>IDS</th>
<th>FM</th>
<th>Hz</th>
</tr>
</thead>
<tbody>
<tr>
<td>MHT-DAM</td>
<td>32.4</td>
<td>71.8</td>
<td>16.0%</td>
<td>43.8%</td>
<td>435</td>
<td>826</td>
<td>0.7</td>
</tr>
<tr>
<td>MHT</td>
<td>29.2</td>
<td>71.7</td>
<td>12.1%</td>
<td>53.3%</td>
<td>476</td>
<td>781</td>
<td>0.8</td>
</tr>
<tr>
<td>LP_SSVM</td>
<td>25.2</td>
<td>71.7</td>
<td>5.8%</td>
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<td>646</td>
<td>849</td>
<td>41.3</td>
</tr>
<tr>
<td>ELP</td>
<td>25.0</td>
<td>71.2</td>
<td>7.5%</td>
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<td>1,396</td>
<td>1,804</td>
<td>5.7</td>
</tr>
<tr>
<td>MotiCon</td>
<td>23.1</td>
<td>70.9</td>
<td>4.7%</td>
<td>52.0%</td>
<td>1,018</td>
<td>1,061</td>
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<tr>
<td>SegTrack</td>
<td>22.5</td>
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<td>54.8%</td>
<td>1,148</td>
<td>2,132</td>
<td>2.7</td>
</tr>
<tr>
<td>TBD</td>
<td>15.9</td>
<td>70.9</td>
<td>6.4%</td>
<td>47.9%</td>
<td>1,939</td>
<td>1,963</td>
<td>0.7</td>
</tr>
<tr>
<td>TC_ODAL</td>
<td>15.1</td>
<td>70.5</td>
<td>3.2%</td>
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<td>637</td>
<td>1,716</td>
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* The references for other published results could be found from [http://motchallenge.net/](http://motchallenge.net/)

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LP_SSVM, ELP, DP_NMS are Network flow-based methods.
Our baseline MHT performs better than them on MOT Challenge.

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<th>Hz</th>
<th>Specs</th>
<th>Det.</th>
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<tr>
<td>TSML_CDE</td>
<td>5.8</td>
<td>49.1 ± 13.0</td>
<td>74.3</td>
<td>0.9</td>
<td>30.4%</td>
<td>26.4%</td>
<td>5,204</td>
<td>25,460</td>
<td>637 (10.9)</td>
<td>1,034 (17.7)</td>
<td>6.5</td>
<td>3.3 GHz, 4 Core</td>
<td>Private</td>
</tr>
<tr>
<td>NOMT</td>
<td>6.7</td>
<td>33.7 ± 16.2</td>
<td>71.9</td>
<td>1.3</td>
<td>12.2%</td>
<td>44.0%</td>
<td>7,762</td>
<td>32,547</td>
<td>442 (9.4)</td>
<td>823 (17.5)</td>
<td>11.5</td>
<td>2.4 GHz, 16 Core</td>
<td>Public</td>
</tr>
<tr>
<td>TDAM</td>
<td>9.8</td>
<td>33.0 ± 9.8</td>
<td>72.8</td>
<td>1.7</td>
<td>13.3%</td>
<td>39.1%</td>
<td>10,064</td>
<td>30,617</td>
<td>464 (9.2)</td>
<td>1,506 (30.0)</td>
<td>5.9</td>
<td>3.4 GHz, 1 Core</td>
<td>Public</td>
</tr>
<tr>
<td>MHT_DAM</td>
<td>9.6</td>
<td>32.4 ± 15.6</td>
<td>71.8</td>
<td>1.6</td>
<td>16.0%</td>
<td>43.8%</td>
<td>9,064</td>
<td>32,000</td>
<td>435 (9.1)</td>
<td>826 (17.3)</td>
<td>0.7</td>
<td>2 GHz, 4 Core</td>
<td>Public</td>
</tr>
<tr>
<td>MDP</td>
<td>13.9</td>
<td>30.3 ± 14.8</td>
<td>71.3</td>
<td>1.7</td>
<td>13.0%</td>
<td>38.4%</td>
<td>9,717</td>
<td>32,422</td>
<td>680 (14.4)</td>
<td>1,500 (31.8)</td>
<td>1.1</td>
<td>3.5 GHz, 8 cores</td>
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</tr>
<tr>
<td>CNNTCM</td>
<td>12.0</td>
<td>29.6 ± 13.9</td>
<td>71.8</td>
<td>1.3</td>
<td>11.2%</td>
<td>44.0%</td>
<td>7,786</td>
<td>34,733</td>
<td>712 (16.4)</td>
<td>943 (21.7)</td>
<td>1.7</td>
<td>2.6 GHz, 4 core</td>
<td>Public</td>
</tr>
<tr>
<td>CF_MCMC</td>
<td>16.2</td>
<td>29.4 ± 12.1</td>
<td>69.7</td>
<td>1.4</td>
<td>9.7%</td>
<td>41.6%</td>
<td>8,204</td>
<td>34,346</td>
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<td>12.3</td>
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<td>71.1</td>
<td>1.0</td>
<td>8.9%</td>
<td>47.3%</td>
<td>6,060</td>
<td>36,912</td>
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<tr>
<td>SiameseCNN</td>
<td>12.6</td>
<td>29.0 ± 15.1</td>
<td>71.2</td>
<td>0.9</td>
<td>8.5%</td>
<td>48.4%</td>
<td>5,160</td>
<td>37,708</td>
<td>639 (16.6)</td>
<td>1,316 (34.2)</td>
<td>52.8</td>
<td>3 Ghz 24 cores</td>
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</tr>
</tbody>
</table>

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# Tracking Benchmark: MOT Challenge

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Used their own detector:

- **MHT-DAM #3**

MHT #6.5  MOTA 29.2

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<td>71.9</td>
<td>1</td>
<td>442</td>
<td>2.4 GHz, 16 Core Public</td>
</tr>
<tr>
<td>TDA-M</td>
<td>9.8</td>
<td>33.0</td>
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**MT**

- 30.4
- 12.2
- 13.3
- **16.0**
- 13.2
- 11.2
- 9.7
- 8.9
- 8.5

**ID Sw.**

- 637
- 442
- 464
- **435**
- 680
- 712
- 798
- 604
- 639

*Used their own detector*

*C. Kim et al. Multiple Hypothesis Tracking Revisited. ICCV 2015*
Conclusion

• Classic MHT is surprisingly competitive.
  - It should be used as a benchmark!

• Our novel method for adaptive appearance modeling in MHT using multi-output least squares.
  - Efficiently learn multiple appearance models for different targets.
  - More discriminative than the original MHT score
  - More effective pruning

• MHT-DAM achieves state-of-the-art performance on standard datasets.

Code will be available in the project webpage soon.

http://cpl.cc.gatech.edu/projects/MHT/

Thank you!

C. Kim et al. Multiple Hypothesis Tracking Revisited. ICCV 2015