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MMTrack:
Max-Margin Offline Pedestrian Tracking with Multiple Cues

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Outline

1. Overview and Previous Works
2. MMTrack
3. Learning Procedure
4. Features
5. Experimental Results

Single Object Tracking

How to combine the features?

Prior Works

- Online selection of discriminative tracking features [Collins et al, PAMI05]
- MILTrack [Babenko et al, CVPR09]

○ Single type of features
○ Appearance model

- Tracking with multiple observers [Stenger et al, CVPR09]

○ Combine complete trackers
○ Independent learning of relative weightings

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MMTrack

Different feature types
Test frames
Training sequences
Learning
Model Parameters
Inference
Includes Motion Model
Joint parameter learning
Track result

Learned Appearance Parameters

Learned Motion Parameters

First Order Model

Trajectory Scoring

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Structural SVM Learning

- Objective: find parameters that produce 'good' tracks
- How to measure 'goodness' of a track? Loss function $\Delta(y_i, y)$
- We use total Euclidean distance

Structural SVM Formulation

$$\min_{\boldsymbol{w},\boldsymbol{\varepsilon}} \frac{1}{2}\|\boldsymbol{w}\|^2 + \frac{C}{N}\sum_{i=1}^{N} \varepsilon_i, \text{s.t.}\ \forall_i, \varepsilon_i \geq 0$$

Regularizer

Slack variables

$$\forall i, \forall y \backslash y_i : \langle \phi(x_n, y_i), w \rangle - \langle \phi(x_n, y), w \rangle \geq \Delta(y_i, y) - \varepsilon_i$$

Score for ground truth y_i

Exponentially large number of constraints!

Score for hypothesized track y

[Tsochantaridis et al, ICML04]

Structural SVM Learning

Structural SVM Learning

$$\min_{w,\varepsilon} \frac{1}{2}\|w\|^2 + \frac{C}{n}\sum_{i=1}^{N} \varepsilon_i, \text{s.t.} \forall_i, \varepsilon_i \geq 0$$

Regularizer

Slack variables

$$\forall i, \forall y \backslash y_i : \langle \phi(x_n, y_i), w \rangle - \langle \phi(x_n, y), w \rangle \geq \Delta(y_i, y) - \varepsilon_i$$

Large Score for 'most violated constraint':

$$\forall i, \forall y \backslash y_i : \langle \phi(x_n, y_i), w \rangle \geq \Delta(y_i, y) + \langle \phi(x_n, y), w \rangle - \varepsilon_i$$

$$\underset{y}{\operatorname{argmax}}\, \Delta(y_i, y) + \langle \phi(x_n, y), w \rangle$$

[Tsochantaridis et al, ICML04]

Structural SVM Learning

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Structural SVM Learning

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Features – HOG Score Map

- Histogram of Oriented Gradient [Dalal&Triggs, CVPR05]

Features – Appearance Templates

- Object templates from initial and previous frames
- Compute sum of absolute difference at nearby locations

Features – Color Histogram Distance

Features

12 features: HOG + 9 histogram difference + 2 appearance template

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UBC Dataset

Experimental Results

- Left: HOG + 9 histogram
- Middle: HOG + appearance templates
- Right: HOG + 9 histogram + appearance templates

Experimental Results

Tracker	#CDT (max=22)	Avg CT	Avg Error
MMTrack: all features	21	0.66	7.01
MMTrack: HOG + Hist	10	0.47	14.40
MMTrack: HOG + Template	14	0.52	22.24
MILTrack [1]	19	0.61	19.87
Collins-Liu [2]	14	0.54	21.24

[1]. B. Babenko et al, CVPR09
[2]. R. Collins et al, PAMI05

More Experimental Results