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Multi-target Data Association by Tracklets with Unsupervised Parameter Estimation

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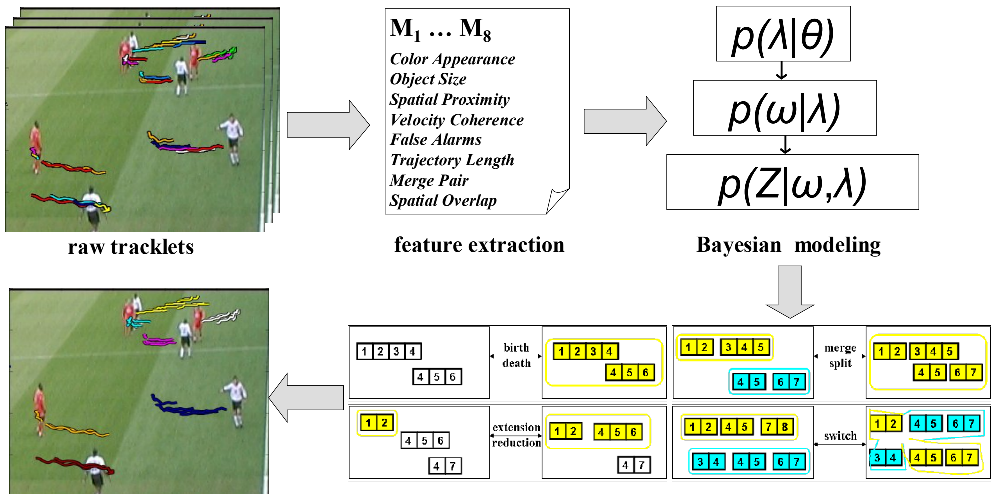
Introduction

We consider multi-target tracking via probabilistic data association among tracklets (trajectory fragments), a mid-level representation that provides good spatio-temporal context for efficient tracking. Model parameter estimation and the search for the best association among tracklets are unified naturallywithin a MCMC sampling procedure. We adopt Markov Chain Monte Carlo Data Association (MCMCDA) to estimate a varying number of trajectories and the optimal model parameters in an unsupervised manner.

Method

To recover the trajectories of moving foreground objects in the video, we first extract short-term tracklets from overlapping temporal windows by running a tracker within a short time period. The resulting partial trajectories are less prone to drift and occlusion than a long trajectory. Then we extract eight types of tracklet-level features Z to model the prior and likelihood of desirable tracklet partitions based on spatial, motion, and appearance consistencies. MCMCDA is used to automatically infer the optimal model parameters λ and the tracklet partition ω based on stochastic mode seeking in the combinatorial solution space. Several reversible moves are carefully designed for efficient sampling.



raw tracklets — feature extraction — Bayesian modeling

estimated tracklet partition — MCMC moves

Models

- $p(Z|\omega,\lambda)$ – the likelihood of observing the tracklet features Z given the tracklet partition ω
- $p(\omega|\lambda)$ – the prior distribution of the tracklet partition ω governed by the model parameters λ
- $p(\lambda|\theta)$ – the distribution of the parameters is chosen to be the conjugate Gamma distribution for computational convenience

$$p(\lambda|\theta) \sim \texttt{Gamma}(\theta^0,\theta^1)$$

$$p(\omega|\lambda) = \lambda_5\lambda_6^K\lambda_7\lambda_8^K e^{-\Sigma_{j=5}^{8}\lambda_j M_j}$$

$$p(Z|\omega,\lambda) = \prod_{j=1}^{4}\lambda_j^{\Sigma_k|\tau_k|-K}e^{-\lambda_j M_j}$$

$$p(\lambda_j|-) \sim \texttt{Gamma}(\alpha_j,\beta_j)$$

$$p(\omega|-) \propto \prod_{j=1}^{4}\lambda_j^{\Sigma_k|\tau_k|-K}\lambda_6^K\lambda_8^K e^{-\lambda M^T}$$

Inference

Algorithm 1 MCMCDA with parameter estimation

Input: Z, n_{mc}, ω_0, θ Output: λ^*, ω^*

Initialization: $\omega \leftarrow \omega_0$, $\lambda \sim \texttt{Gamma}(\theta^0,\theta^1)$, $(\lambda^*,\ \omega^*) = (\lambda,\ \omega_0)$

for $n = 1$ to n_{mc}

update ω sample a move m from the distribution $p_\omega(m)$

propose ω' from the move specific proposal $p_m(\omega|\lambda)$

sample $U \sim \texttt{Uniform}(0,1)$

$\omega \leftarrow \omega'$ if $\log(U) < \log(A(\omega,\omega'))$

update λ update α, β according to Eqn. 13

sample $\lambda \sim \texttt{Gamma}(\alpha,\beta)$

$(\lambda^*,\ \omega^*) \leftarrow (\lambda,\ \omega)$ if $p(\omega,\lambda|Z) > p(\omega^*,\lambda^*|Z)$

Results

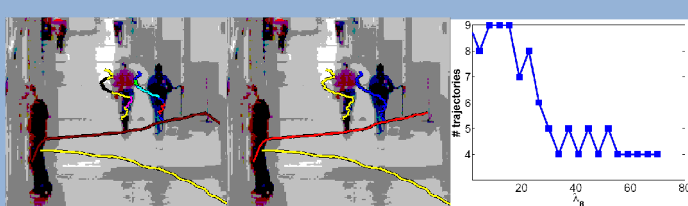


Illustration of multi-target data association by tracklets and the influence of one model parameter that penalizes spatial overlap. **Left**: a "bad" partition of tracklets where more than four trajectories were estimated because the parameter value is set too low. **Middle**: increasing the value yields a "good" partition of tracklets into sets associated with individual objects, each drawn in a different color. **Right**: Plot showing how the total estimated number of targets varies while changing this single model parameter. There are many such parameters in our model, and fine tuning all of them manually would be infeasible. This provides the motivation for our automated Bayesian approach.

Raw fragmented tracklets and snapshots of estimated trajectories for two different scenes: Soccer (**top**) and ArtFest (**bottom**). The estimated model parameters λ are (11, 22.1,5.2,804,10.1,3.2, 67, 1343) and (28,50,7,858.9,12.9,5.7,87,1299) respectively.