

Efficient Second Order Multi-Target Tracking with Exclusion Constraints

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Abstract

Current state of the art multi-target tracking (MTT) exists in an “either/or” situation. Either a greedy approach can be used, that can make use of second-order information which captures object dynamics, such as “objects tend to move in the same direction over adjacent frames”, or one can use global approaches that make use of the information contained in the entire sequence to resolve ambiguous sub-sequences, but are unable to use such second order information. However, the accurate resolution of ambiguous sequences requires both a good model of object dynamics, and global inference.

In this work we present a novel approach to MTT that combines the best of both worlds. By formulating the problem of tracking as one of global MAP estimation over a directed acyclic hyper-graph, we are able to both capture long range interactions, and informative second order priors. In practice, our algorithm is extremely effective, with a run time linear in the number of objects to be tracked, possible locations of an object, and the number of frames. We demonstrate the effectiveness of our approach, both on standard MTT data-sets that contain few objects to be tracked, and on point tracking for non-rigid structure from motion, which, with hundreds of points to be tracked simultaneously, strongly benefits from the efficiency of our approach.

<p>Initialisation</p> <pre> for t = 1 : F - 2 do ∀ a, b ∈ L, $\vec{M}_t(a, b) = \overleftarrow{M}_t(a, b) = -\infty$ ↓ $M_t = 0$ end for </pre>	<p>Message down</p> <pre> 1: $M_{o,t}(l) = \max_b (\vec{M}_{o,t}(l, b) + \overleftarrow{M}_{o,t}(l, b)$ 2: $-U_t(l) - P_t(l, b) - U_{t+1}(b))$ 3: for t = 1 : F do 4: $\hat{l} = \arg \max_l M_{o,t}(l)$ 5: if l ∉ O then 6: $M_t(\hat{l}) = \max_{a \neq \hat{l}} M_{o,t}(a) - M_{o,t}(\hat{l})$ 7: end for </pre>
<p>The Forward Procedure</p> <pre> 1: for t = 1 : F - 2 do 2: for all a ∈ l_t, b ∈ n_{t+1}(a), c ∈ n_{t+2}(b) do 3: $\vec{M}_{t+1}(b, c) = \max (\vec{M}_{t+1}(b, c),$ 4: $\vec{M}_t(a, b) + T(a, b, c))$ 5: end for 6: for all b ∈ l_{t+1}, c ∈ n_{t+2}(b) do 7: $\vec{M}_{t+1}(b, c) = \vec{M}_{t+1}(b, c) + U_{o,t+2}(c)$ 8: $+ P_{t+1}(b, c) + \downarrow M_{t+2}(c)$ 9: end for 10: end for </pre>	<p>Undo sent message</p> <pre> for T = 1 : F do if l ∉ O then ↓ $M_t(\hat{l}) = \max_{a \neq \hat{l}} M_{o,t}(a) - M_{o,t}(\hat{l})$ end for </pre>
<p>The Backward Procedure</p> <pre> 1: for t = 1 : F - 2 do 2: for all a ∈ l_t, b ∈ n_{t+1}(a), c ∈ n_{t+2}(b) do 3: $\overleftarrow{M}_t(b, c) = \max (\overleftarrow{M}_t(a, b),$ 4: $\overleftarrow{M}_{t+1}(b, c) + T(a, b, c))$ 5: end for 6: for all a ∈ l_t, b ∈ n_{t+1}(a) do 7: $\overleftarrow{M}_{t+1}(a, b) = \overleftarrow{M}_{t+1}(a, b) + U_{o,t}(a)$ 8: $+ P_t(a, b) + \downarrow M_t(a)$ 9: end for 10: end for </pre>	<p>Label set</p> <pre> 1: $g_{o,t}(l) = \max_{b \in n(l)} (\overleftarrow{M}_{o,t}(l, b))$ 2: $\hat{P}_{t-1}(a, b) = \begin{cases} 0 & \text{if } t - 1 = 0 \\ P_{t-1}(a, b) & \text{otherwise.} \end{cases}$ 3: $\hat{T}_{t-2}(a, b) = \begin{cases} 0 & \text{if } t - 2 \leq 0 \\ T_{t-2}(a, b, c) & \text{otherwise.} \end{cases}$ 4: for t = 1 : F do 5: if l ∉ O then 6: $x_{o,t} = \arg \max_l (f_{o,t}(l) + \hat{P}_{t-1}(x_{o,t-1}, l)$ 7: $+ \hat{T}_{t-2}(x_{o,t-2}, x_{o,t-1}, l))$ 8: end for </pre>
<p>Constraint Up</p> <pre> 1: for t = 1 : F do 2: if l ∉ O then 3: ↓ $M_t(x_{o,t}) = -\infty$ 4: end for </pre>	

Figure 1: Pseudo code for the procedures referenced in Algorithm 1. See also section 3.1 of main paper.

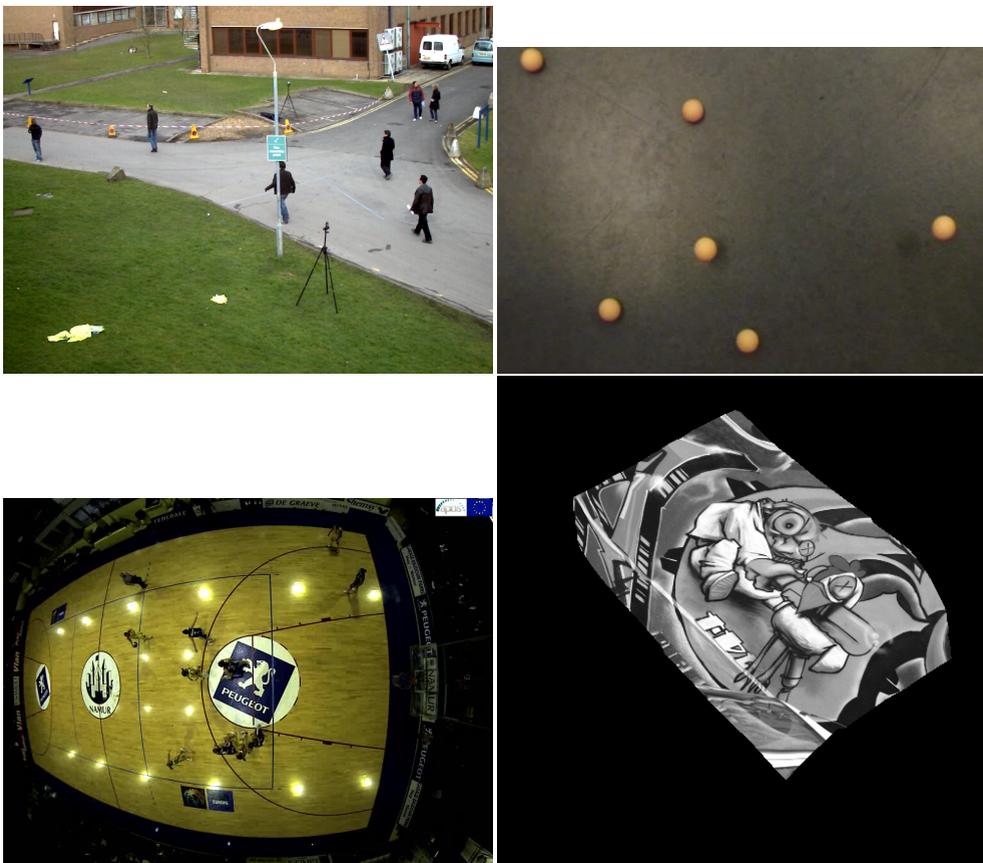


Figure 2: Sample frames from the PETS2009, balls, basketball, and flag dataset. See section 4 of main paper.