



Efficient Articulated Trajectory Reconstruction Using Dynamic Programming and Filters

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Problem

An articulated structure is a graph G=(V,E) with edge labels $\ell:E o\mathcal{R}$ such that $\{i,j\} \in E \Rightarrow \|\mathbf{x}_i - \mathbf{x}_i\| = \ell_{ii}$



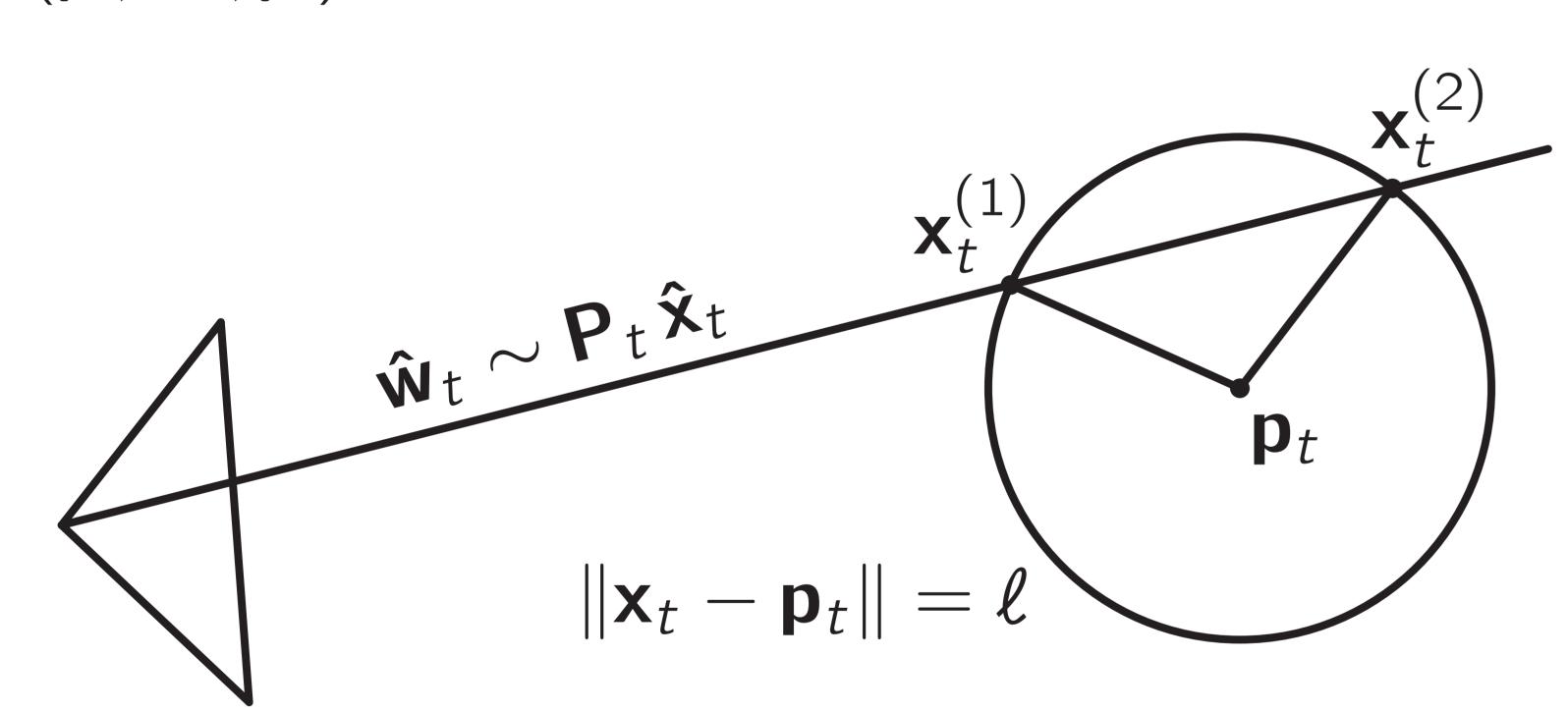
Given an articulated tree structure (G, ℓ) with, for $t = 1, \ldots, n$,

- root node position $\mathbf{x}_{t1} \in \mathcal{R}^3$,
- ▶ projections of other nodes $\mathbf{w}_{ti} \in \mathbb{R}^2$ for $i = 2, \ldots, |V|$,
- ightharpoonup perspective camera $\mathbf{P}_t \in \mathcal{R}^{3 imes 4}$,

find the smoothest trajectories which satisfy projections

Single articulated trajectory

Consider single trajectory $\mathbf{x} = (\mathbf{x}_1, \dots, \mathbf{x}_n)$ with fixed distance ℓ from a known parent trajectory $\mathbf{p}=(\mathbf{p}_1,\ldots,\mathbf{p}_n)$



Each point has exactly two solutions

$$\left\{ {{f x}_t}: \, {f{\hat w}}_t \sim {f P}_t {f{\hat x}}_t, \,\, \left\| {{f x}_t - {f p}_t}
ight\| = \ell
ight\} = \left\{ {f x}_t^{(1)}, {f x}_t^{(2)}
ight\}$$

2ⁿ possible trajectories parameterised by binary variables

$$\mathbf{x}_t = (1 - y_t) \mathbf{x}_t^{(1)} + y_t \mathbf{x}_t^{(2)},$$

$$y_t \in \{0, 1\}$$

$$x = Ay + b$$

 $y \in \{0, 1\}^n$

Branch and bound solution (Park and Sheikh, 2011)

Minimise component orthogonal to a low-frequency trajectory basis

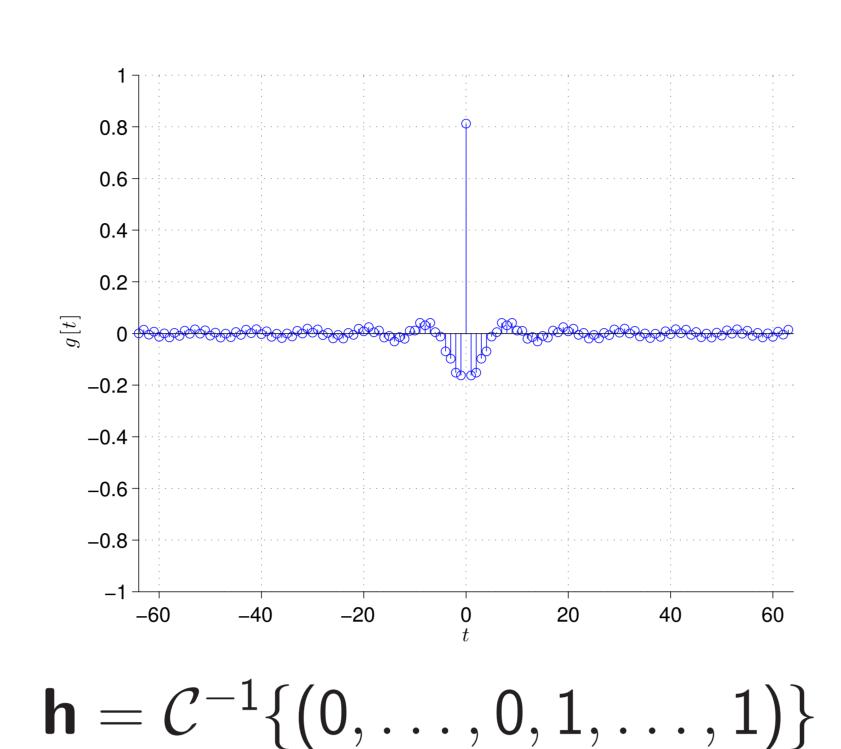
$$\mathbf{y}^* = \arg\min_{\mathbf{y}} \left\| (\mathbf{I} - \mathbf{\Theta} \mathbf{\Theta}^T) (\mathbf{A} \mathbf{y} + \mathbf{b}) \right\|$$
 subject to $\mathbf{y} \in \{0, 1\}^n$

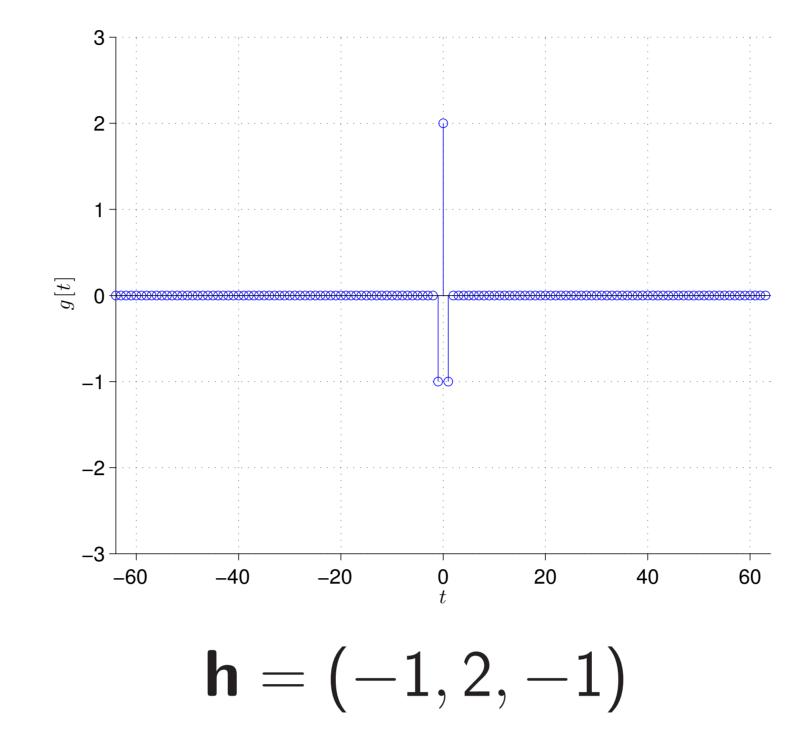
Branch and bound with the convex relaxation $0 \le y \le 1$, worst case $\mathcal{O}(2^n)$ time

DCT basis and convolution (Valmadre and Lucey, 2012)

Low-frequency DCT basis ⇔ symmetric convolution with a high-pass "brick wall" filter $\|(\mathbf{I} - \mathbf{\Theta}\mathbf{\Theta}^T)\mathbf{x}\| = \|\operatorname{diag}(0, \dots, 0, 1, \dots 1)\mathcal{C}\{\mathbf{x}\}\| = \|\mathbf{h} * \mathbf{x}\|$

 $\mathcal{C}\{\cdot\}$ is a Discrete Cosine Transform and **h** is the impulse response





Resulting filter \sim compact support

Simple filters have physical motivation:

- \blacktriangleright (-1,1) minimises kinetic energy,
- \blacktriangleright (-1,2,-1) assumes Gaussian i.i.d. forces

Dynamic programming (Felzenszwalb and Zabih, 2011)

Objectives of the form

$$f(\mathbf{y}) = \sum_{t=1}^{n-m+1} g_t(y_t, \dots, y_{t+m-1})$$
 $\mathbf{y} \in \{1, \dots, k\}^n$

can be minimised in $\mathcal{O}(nk^m)$ time and $\mathcal{O}(nk^m)$ memory

Based on recursive partial solution

$$f_i^*(y_{i+1}, \dots, y_{i+m-1}) = \min_{y_1, \dots, y_i} \sum_{t=1}^{r} g_t(y_t, \dots, y_{t+m-1})$$

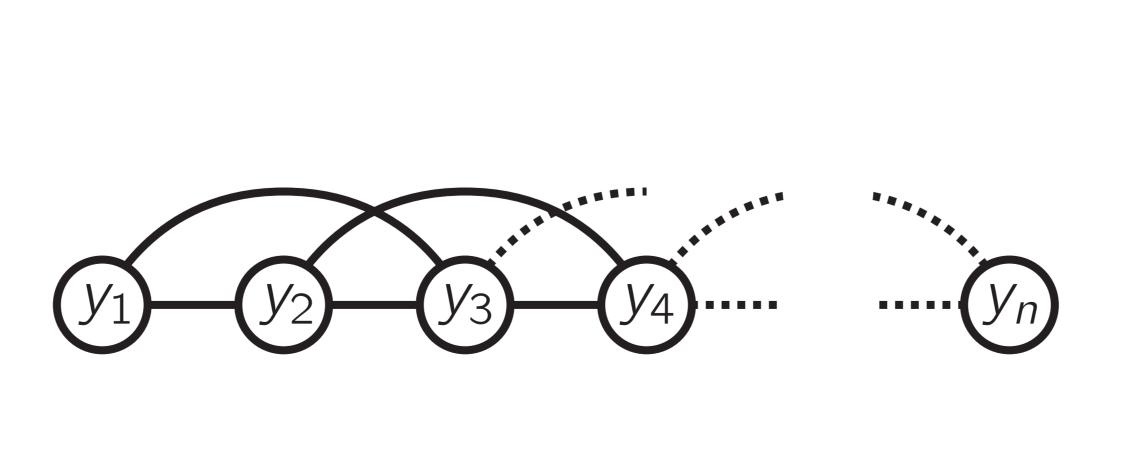
$$= \min_{y_i} \left\{ g_i(y_i, \dots, y_{i+m-1}) + f_{i-1}^*(y_i, \dots, y_{i+m-2}) \right\}$$

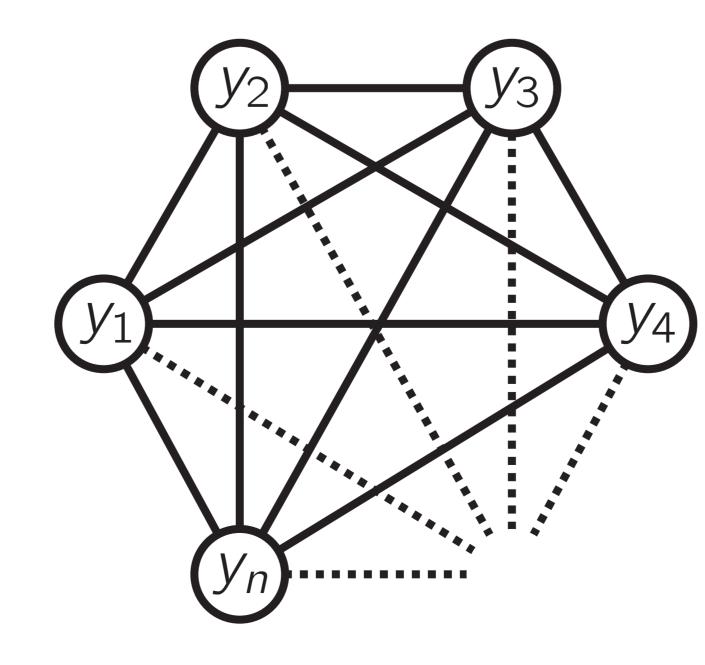
Our solution

Minimise response of feasible trajectory to compact filters (k = 2, m = 3)

 $\Rightarrow \mathcal{O}(n)$ instead of $\mathcal{O}(2^n)$

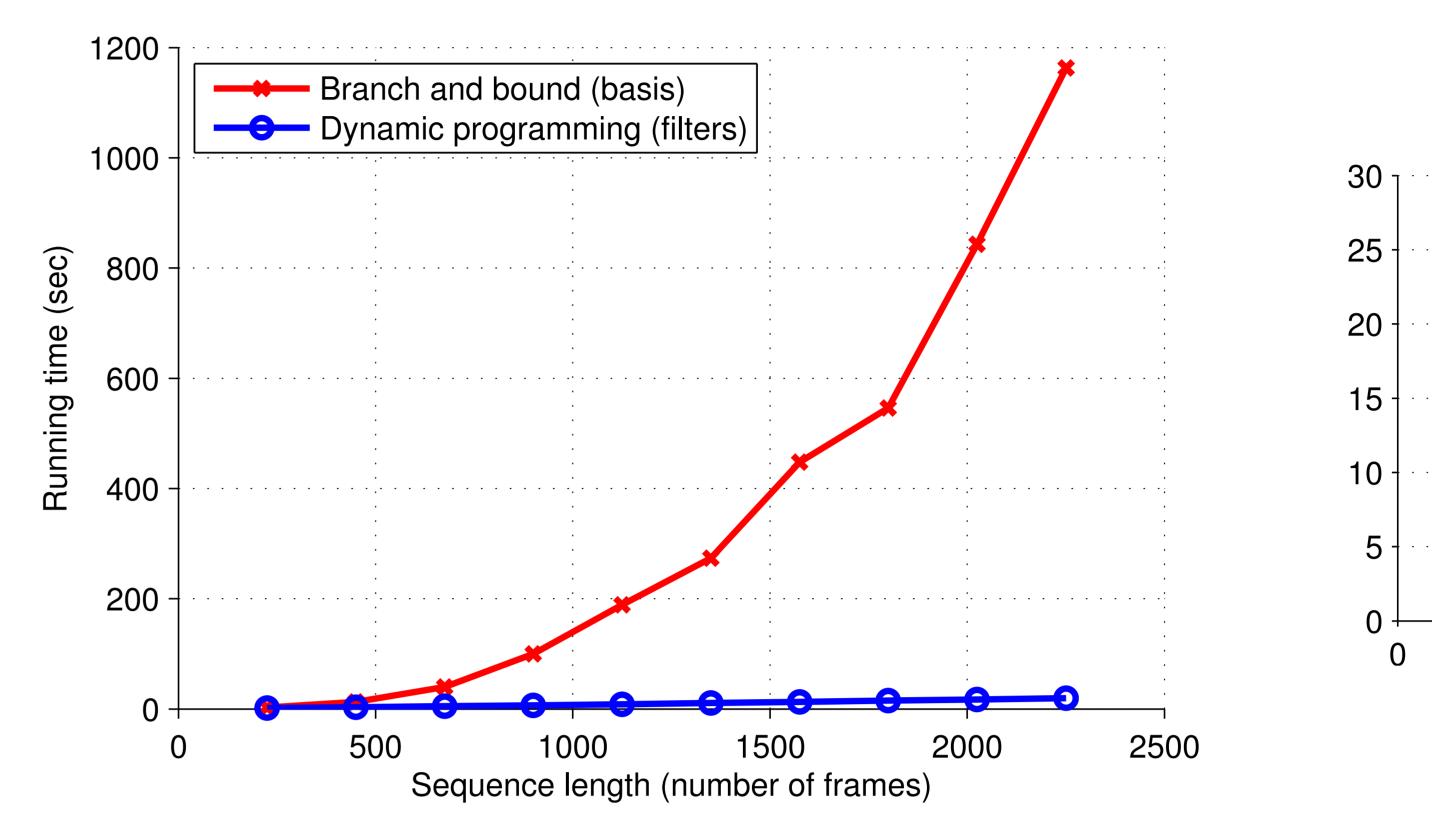
Takes advantage of the inherent locality, whereas a basis requires inner products

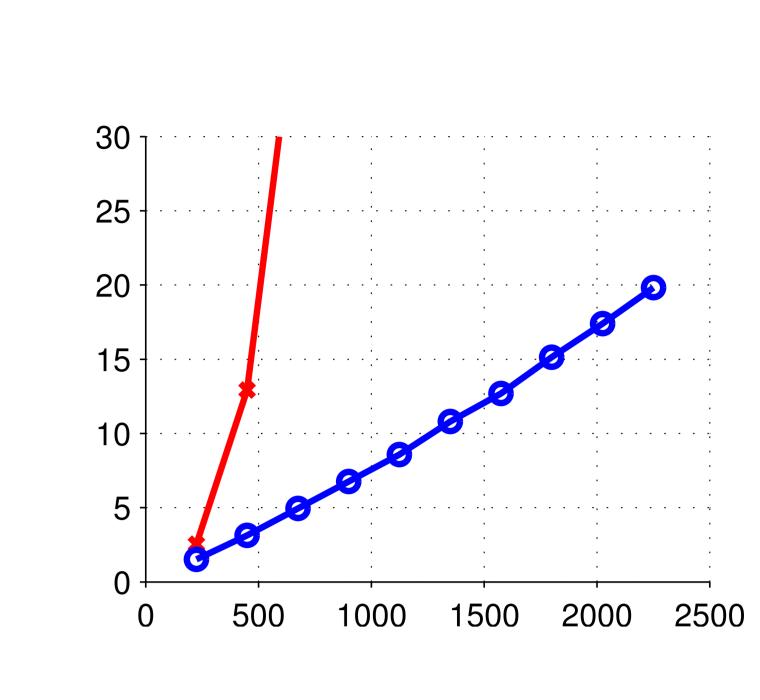




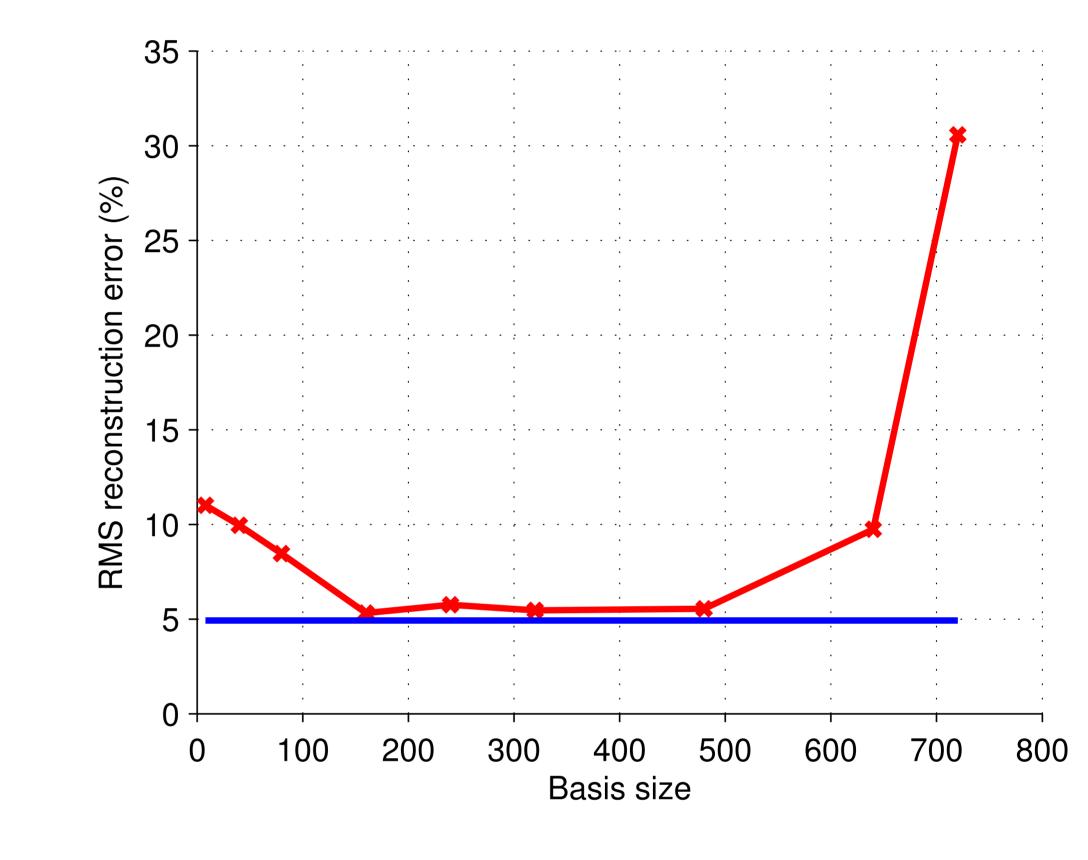
Results

Running time (synthetic sequences)





Reconstruction error (synthetic sequences)



Real sequences: see videos

Calibration-less reconstruction

Assume that

- smoothness is preserved in the camera reference frame,
- the root trajectory is smooth,
- orthographic projection is a good approximation,
- each link is observed near parallel to the image plane,

and then take

- ▶ all cameras to be identity $P_t = [1 \ 0]$,
- the root node depth to be zero,
- the length of each edge to be its maximum projection $\ell_{ii} = \max_t \|\mathbf{w}_{ti} \mathbf{w}_{ti}\|$

References

- ► H. S. Park and Y. A. Sheikh, 3D reconstruction of a smooth articulated trajectory from a monocular image sequence, ICCV 2011
- ▶ J. Valmadre and S. Lucey, General trajectory prior for non-rigid reconstruction, CVPR 2012
- ▶ P. F. Felzenszwalb and R. Zabih, Dynamic programming and graph algorithms in computer vision, PAMI 2011