Sparse Dynamic 3D Reconstruction from Unsynchronized Videos

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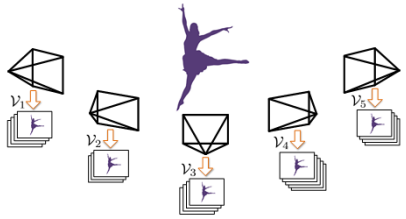
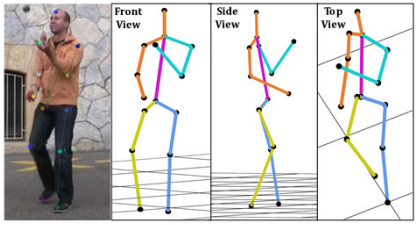
Problem

- **Input**: unsynchronized videos

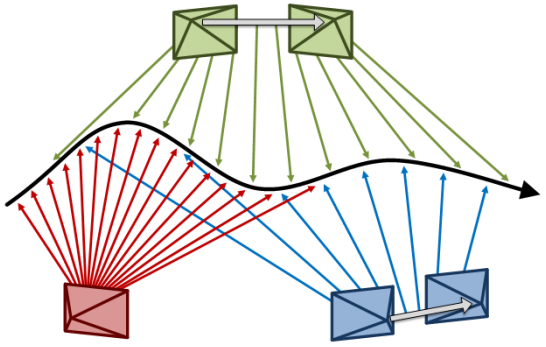


- **Output**: Sparse 3D reconstruction of dynamic points



Challenge

- **Challenge**: (1) non-coincidental capture, (2) possible different frame rate, (3) projective camera model



Preliminary

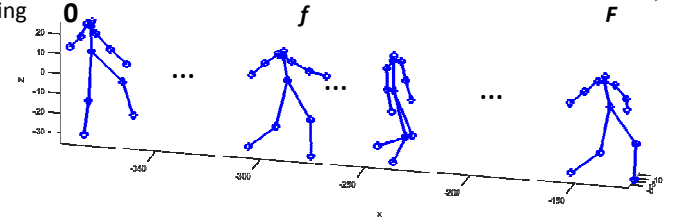
- Camera poses are computed by structure from motion and the static background scene.
- 2D correspondence across images are available.
- The 3D points lie on the viewing ray:

$$\mathbf{X}_{(f,p)} = \mathbf{C}_f + d_{(f,p)}\mathbf{r}_{(f,p)}$$

Principle

- Assume the 3D shape $\mathbf{S}_f$ at frame f is known

Shape $\mathbf{S}_0$ $\mathbf{S}_f$ $\mathbf{S}_F$
Timing 0 f F



- $\mathbf{S}_f$ is closely related to $\mathbf{S}_{f-1}$ and $\mathbf{S}_{f+1}$

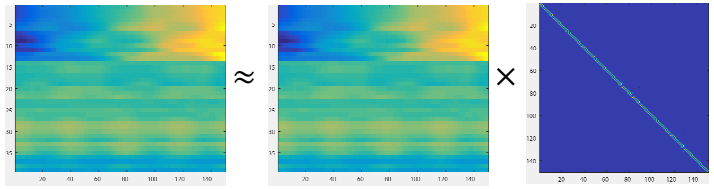
$$\mathbf{S}_f \approx t \times \mathbf{S}_{f-1} + (1-t) \times \mathbf{S}_{f+1} + 0 \times \cdots + 0 \times \cdots \cdots$$

$$\mathbf{S}_f = \mathbb{X}\mathbf{T}_f \quad (\mathbb{X} = [\mathbf{S}_1 \ \cdots \ \mathbf{S}_F],\ \mathbf{T}_f = (t_{(f,1)}, \ldots, t_{(f,f-1)}, 0, t_{(f,f+1)}, \ldots, t_{(f,F)})^\top)$$

- $\mathbf{T}_f$ is sparse

$$\min_{\mathbf{T}_f} \ ||\mathbf{S}_f - \mathbb{X}\mathbf{T}_f||_2^2 + \lambda||\mathbf{T}_f||_1$$

$$\min_{\mathbf{T}_f} \ ||\mathbf{S}_f - \mathbb{X}\mathbf{T}_f||_2^2 \quad \text{subject to} \quad \mathbf{T}_f \cdot \mathbf{1}_{F\times 1} = 1, \ \mathbf{T}_f > 0$$



$\mathbb{X}$ $\approx$ $\mathbb{X}$ $\times$ $\mathbb{T}$

Our method

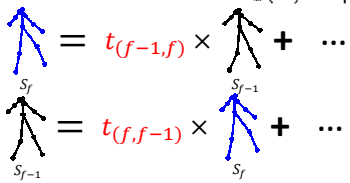
- Both the 3D shape $\mathbb{X}$ and coefficients $\mathbb{T}$ are unknown

$$\min_{\mathbb{X},\mathbb{T}} \quad ||\mathbb{X} - \mathbb{X}\mathbb{T}||_{\mathrm{F}}^2 + \lambda_1\Psi_1(\mathbb{T}) + \lambda_2\Psi_2(\mathbb{X})$$

$$\text{subject to} \quad \mathbb{T}_f \in \Delta_f, f = 1, \cdots, F;$$

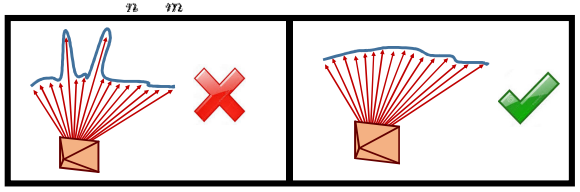
- Non-convex problem.
- Optimize over $\mathbb{X}$ and $\mathbb{T}$ alternatively.
  -- If $\mathbb{T}$ is fixed, quadratic problem without constraint.
  -- If $\mathbb{X}$ is fixed, we develop a efficient solver based on ADMM

- Relation between coefficients: $\Psi_1(\mathbb{T}) = ||\mathbb{T} - \mathbb{T}^\top||_{\mathrm{F}}^2$



- Sequencing information within each video:

$$\Psi_2(\mathbb{X}) = \sum_n^N \sum_m^{|\mathcal{V}_n|} ||\mathbf{X}_{(n,m)} - \mathbf{X}_{(n,m+1)}||_2^2$$



Result

- Evaluation on synthetic and real datasets

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