

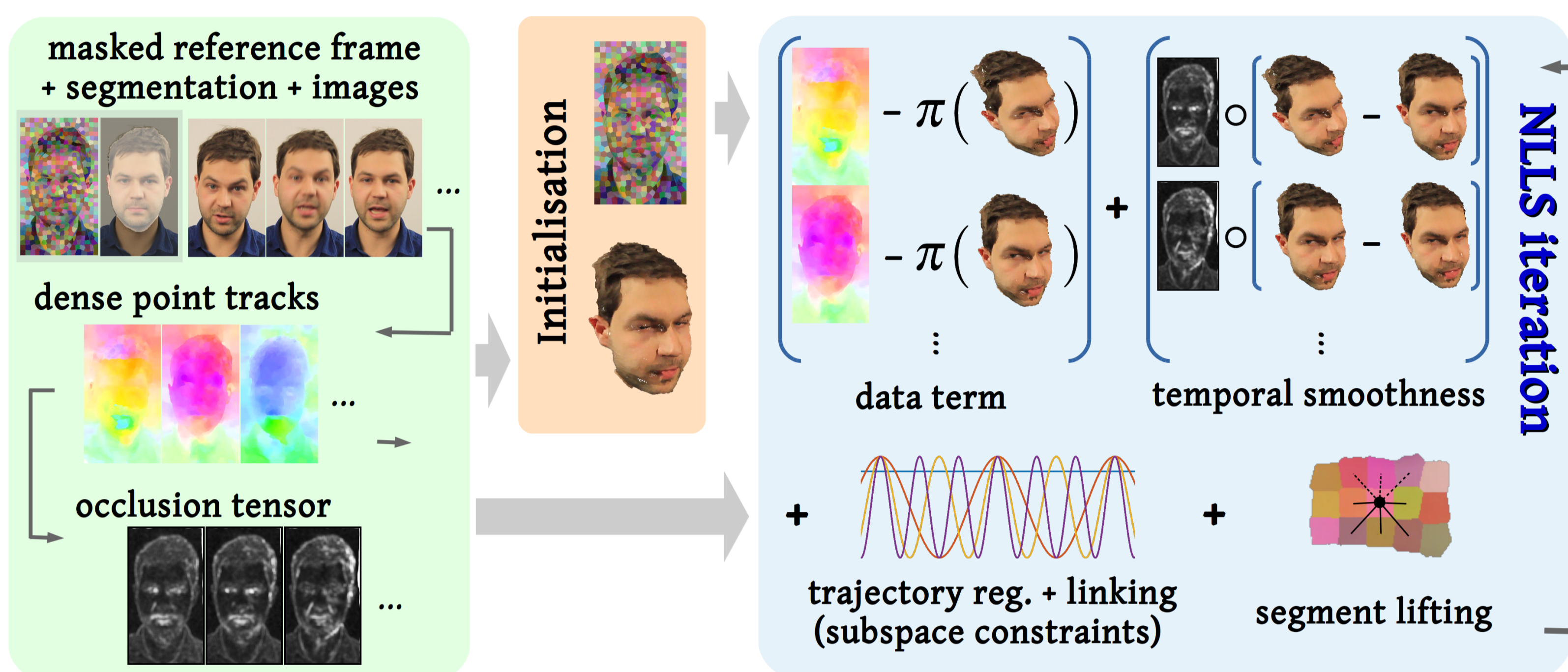
Consolidating Segmentwise Non-Rigid Structure from Motion

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Abstract

We introduce a new segmentwise technique which consolidates multiple principles for NRSfM into a single energy-based framework. The energy functional of our CMDR approach is optimised by NLLS and includes terms allowing to define the deformation model and additional constraints simultaneously in the metric and trajectory spaces. CMDR achieves high accuracy on several tested sequences while providing robustness and scalability due to the spatial scene segmentation and the new lifted spatial Laplacian term.

Method Overview



Energy Functional and Optimisation

Segmentwise data term:

$$E_{\text{data}}(\mathbf{R}, \mathbf{T}) = \sum_{f=1}^F \left\| \mathbf{W}_f - \pi \left(\mathbf{R}_f [g(\mathbf{T}_1^f, \mathbf{S}_1) \dots g(\mathbf{T}_L^f, \mathbf{S}_L)] \right) \right\|_{\epsilon}^2$$

+ Segment trajectory smoothness:

$$E_{\text{temp}}(\mathbf{T}) = \sum_{f=2}^F \sum_{l=1}^L \left\| \Phi_f^l \circ (\mathbf{T}_l^f - \mathbf{T}_l^{f-1}) \right\|_{\epsilon}^2$$

+ Subspace constraints on segment trajectories:

$$E_{\text{linking}}(\mathbf{S}, \mathbf{A}) = \left\| \Psi - (\Theta \otimes \mathbf{I}_3)_{3F \times 3K} \mathbf{A}_{3K \times L} \right\|_{\epsilon}^2$$

$$\text{where } \Psi = \begin{bmatrix} g(\mathbf{T}_1^1, \mathbf{S}_1) & g(\mathbf{T}_2^1, \mathbf{S}_2) & \dots & g(\mathbf{T}_L^1, \mathbf{S}_L) \\ g(\mathbf{T}_1^2, \mathbf{S}_1) & g(\mathbf{T}_2^2, \mathbf{S}_2) & \dots & g(\mathbf{T}_L^2, \mathbf{S}_L) \\ \vdots & \vdots & \ddots & \vdots \\ g(\mathbf{T}_1^F, \mathbf{S}_1) & g(\mathbf{T}_2^F, \mathbf{S}_2) & \dots & g(\mathbf{T}_L^F, \mathbf{S}_L) \end{bmatrix} \text{ and } \Theta = \begin{pmatrix} \theta_{11} & \dots & \theta_{1K} \\ \vdots & \ddots & \vdots \\ \theta_{F1} & \dots & \theta_{FK} \end{pmatrix}$$

+ Trajectory coefficient regularisation:

$$E_{\text{reg.}}(\mathbf{A}) = \sum_{l=1}^L \sum_{k=1}^K w(l) \left\| \nabla \mathbf{A}_{k,l} \right\|_{\epsilon}^2$$

+ Segment coherency regulariser

(segment lifting for detection of topological changes):

$$E_{\text{lifting}}(\mathbf{T}, \mathbf{w}) = \sum_{f=1}^F \sum_{j \neq h} \left(\zeta_1 \left\| w_{j,h}^2 (\mathbf{T}_j - \mathbf{T}_h) \right\|_2^2 + \zeta_2 \left\| (1 - w_{j,h}^2) \right\|_2^2 \right)$$

= **The energy functional of CMDR** $M = FP + L(10F + 7)$

$Q = 3F + 7LF + 3KL + 8L$ parameters:

$3F$ for global poses

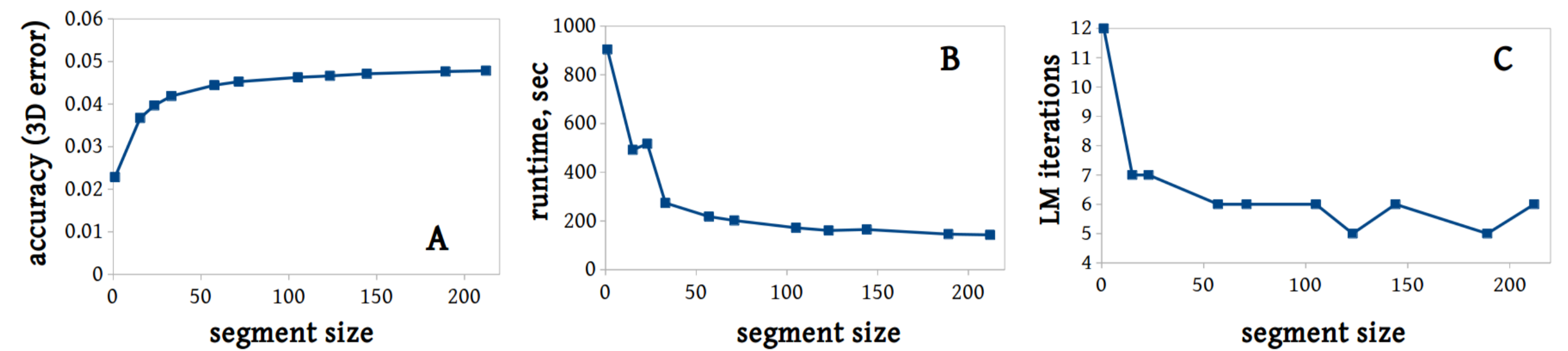
$3KL$ for DCT coefficients

$7LF$ for segment orientations per every frame

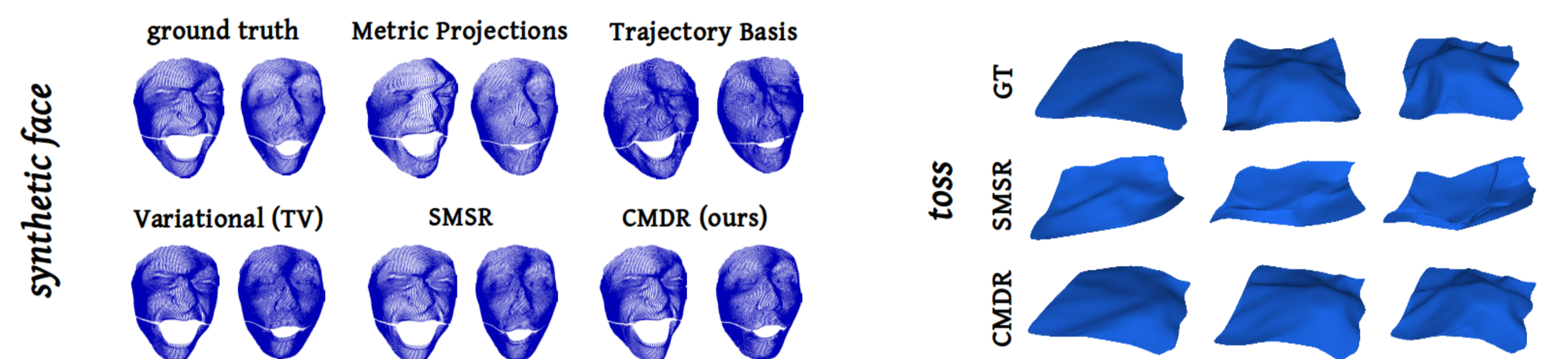
$8L$ for the lifting weights

$\mathbf{F}(\mathbf{x}) : \mathbb{R}^Q \rightarrow \mathbb{R}^M$ (optimised with Levenberg-Marquardt)

Experimental Results



3D error, runtime and number of Gauss-Newton solver iterations as the functions of the segment size, for the actor mocap sequence



	TB	MP	VA	DSTA	CDF	SMSR	GM	CMDR
Seq. 3	0.1252	0.0611	0.0346	0.0374	0.0886	0.0304	0.0294	0.0324
Seq. 4	0.1348	0.0762	0.0379	0.0428	0.0905	0.0319	0.0309	0.0369

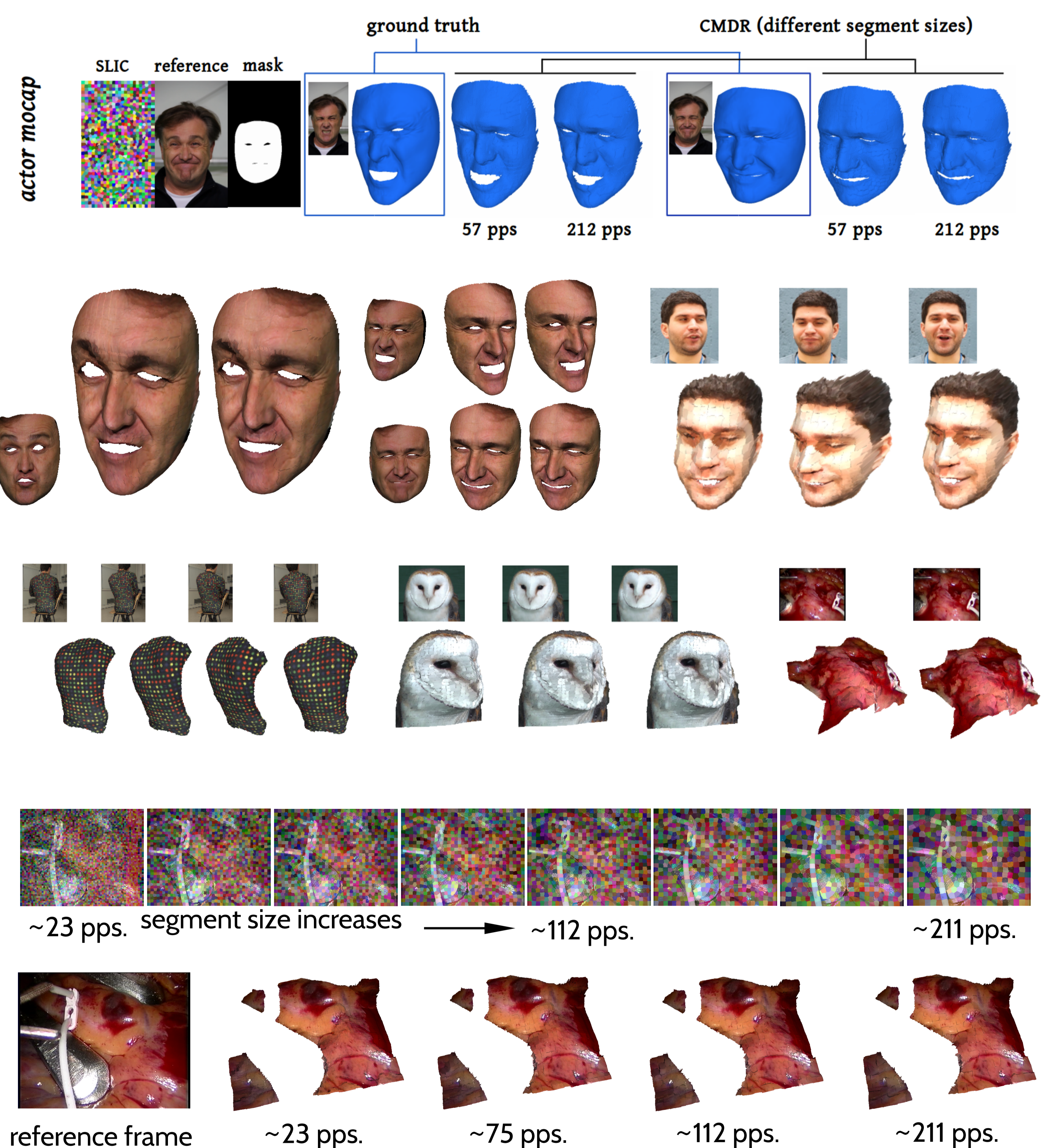
Comparison of methods on synthetic faces [3], observed by two different camera settings. CMDR achieves the third highest accuracy with a volatile difference to SMSR [6] and GM [7]

approach	coin	toss	flag mocap	synth. flag	actor mocap	actor mocap #2
SMSR [23]	0.2424	0.4003	0.196	0.1467	0.054	0.0145
CMDR	0.0696	0.3064	0.0792	0.084	0.0257	0.0228

SMSR [6] vs. CMDR (ours) on multiple sequences [3, 8, 9]

seq.	all terms	no $E_{\text{reg.}}$	no $E_{\text{lift.}}$	$E_{\text{data.}}$ and $E_{\text{lift.}}$	$E_{\text{temp.}}$ and $E_{\text{lift.}}$	$E_{\text{data.}}$ and $E_{\text{temp.}}$
Seq. 3	0.0627	0.0616	0.0906	0.0622	0.0622	0.0681
Seq. 4	0.0678	0.0678	0.0967	0.0682	0.0682	0.0736

results of the ablation study (actop mocap)



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