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Recent Trends in 3D Computer Vision

Fusion4D: Real-time Performance Capture of Challenging Scenes

Recent trends in 3D computer vision

Technische Universität München
JOHNS HOPKINS
WHITING SCHOOL
of ENGINEERING

Fusion4D: Real-time Performance Capture of Challenging Scenes

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Microsoft Research

Conference: SIGGRAPH2016
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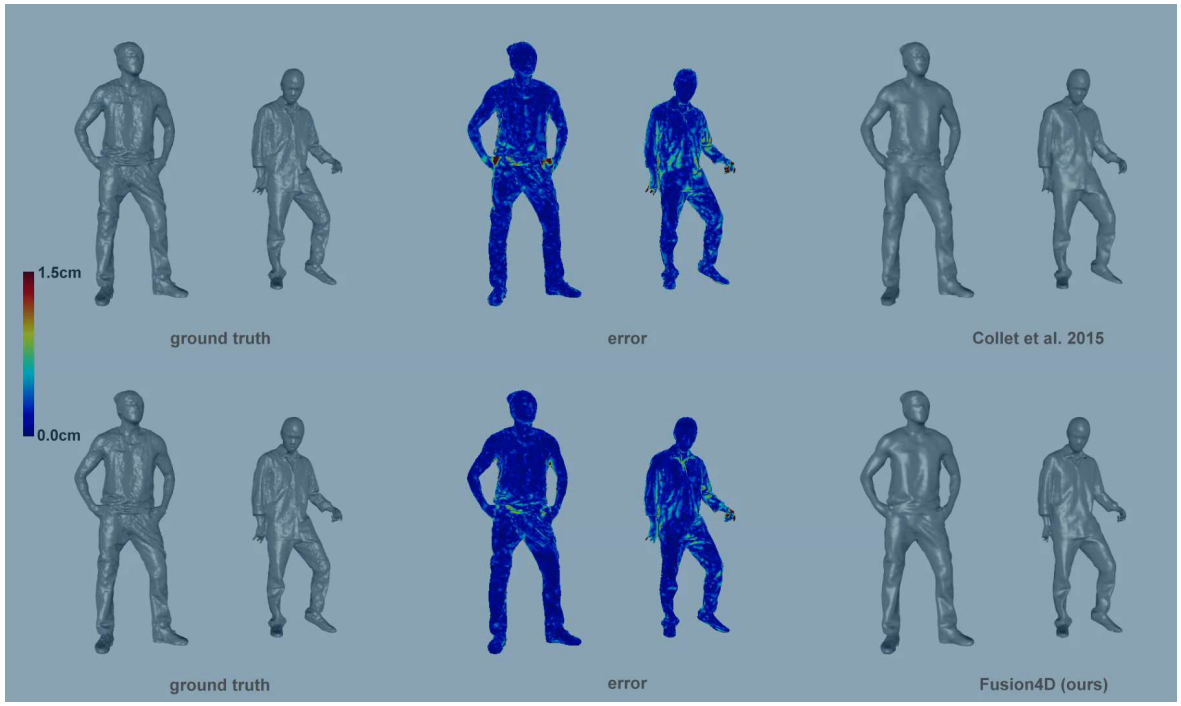
Technische Universität München + Johns Hopkins Whiting School of Engineering

Structure

- Related Work
- Overview
- Nonrigid Motion Field Estimation
- Fusion
- Results
- Conclusion
- Questions

Related Work

- Offline Approach Collet
  - 30s per frame
  - 106 cameras -> 24 depthmaps
  - controlled studio setting
- Dynamic Fusion 2015
  - incrementally updated Model
  - only slow motions
  - no topology-changes
- Zollhöfer 2014
  - Template-based
    - Fixed model



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Key Contributions

- No prior
- Robust to large motion and topology changes
- Multi-view RGBD
- Real-time

Overview

- Studio: (Bild aus Teaser)
  - Trinocular cameres (2xIR + 1xRGB) 1 megapixel
  - 24 cameras -> 8 depthmaps

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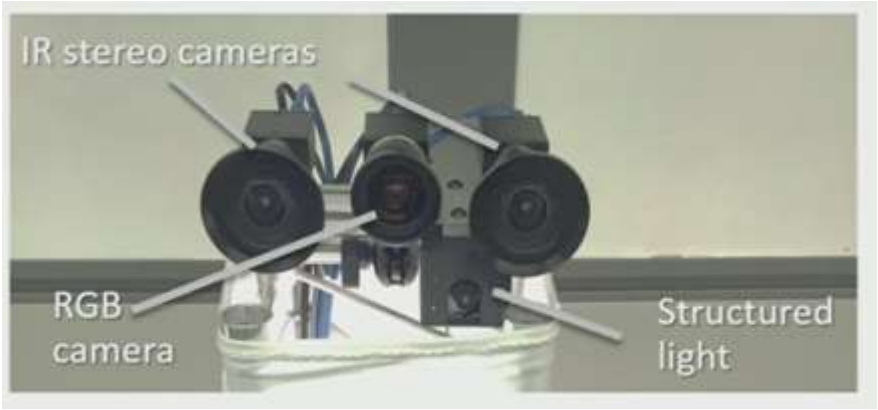

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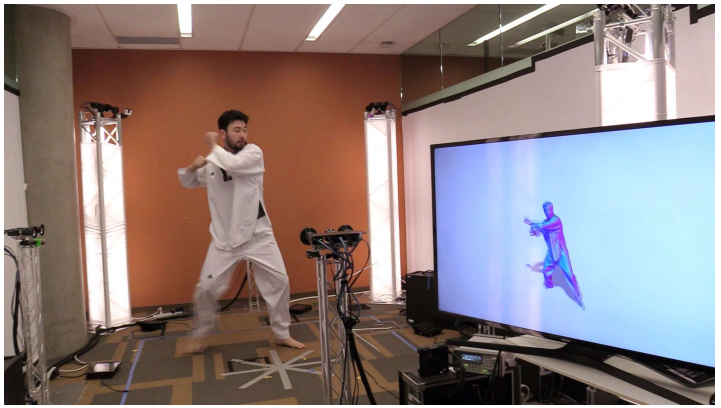
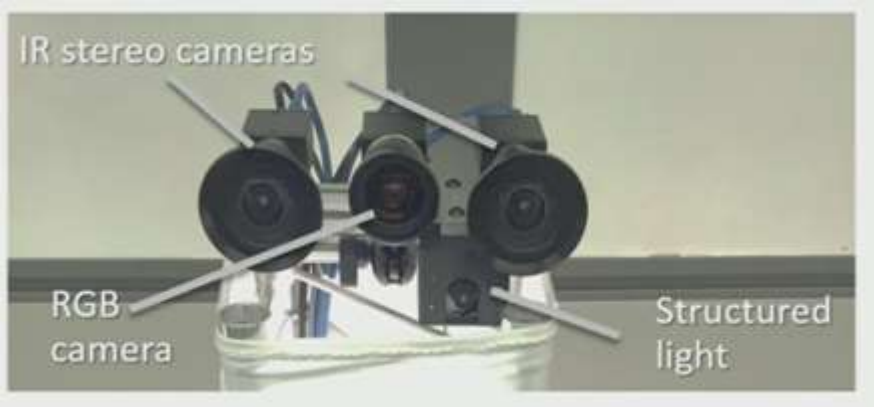
Overview – Setup

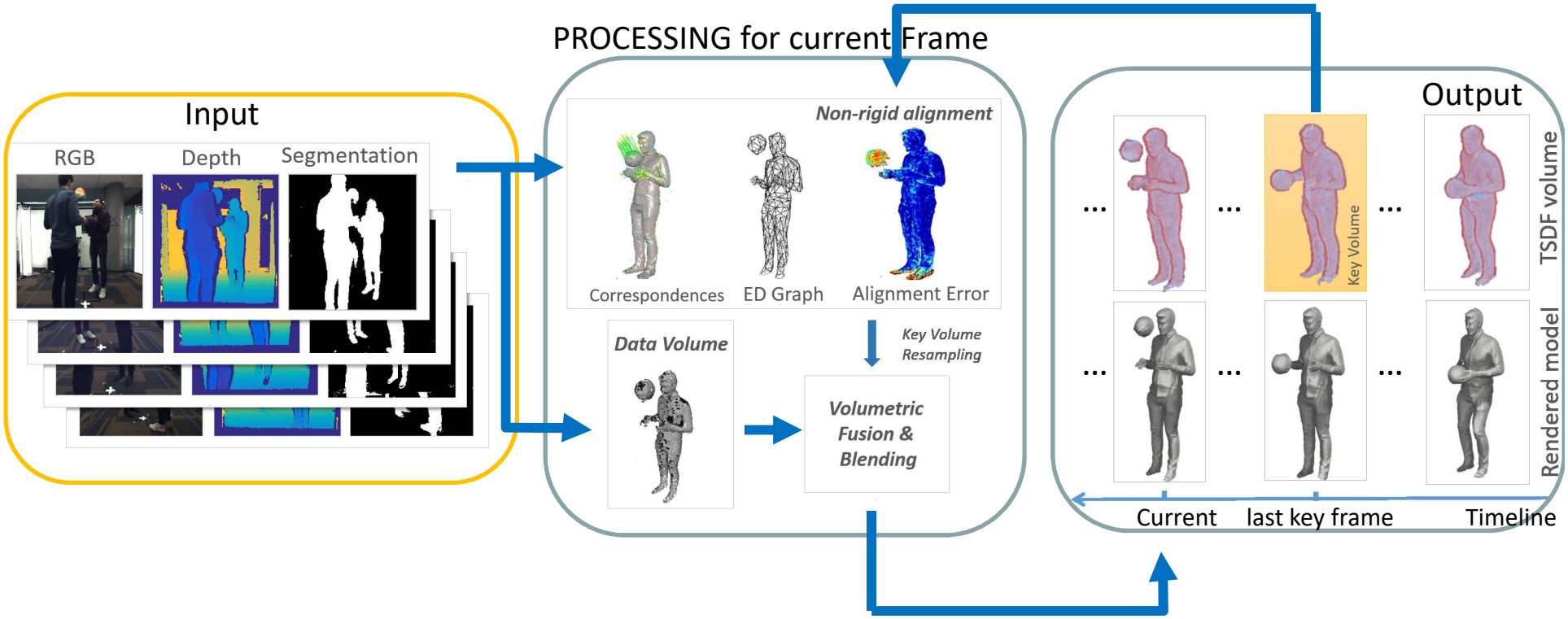


- Studio:
  - Trinocular cameres (2xIR + 1xRGB) 1 megapixel
  - 24 cameras -> 8 depthmaps

- Hardware:
  - 12 Computer (Intel Core i7, 3.4GHz CPU, 16GB of RAM and it uses 2 NVIDIA Titan X GPUs)
  - Master Computer (same, but with a single NVIDIA Titan X)



Overview - Pipeline



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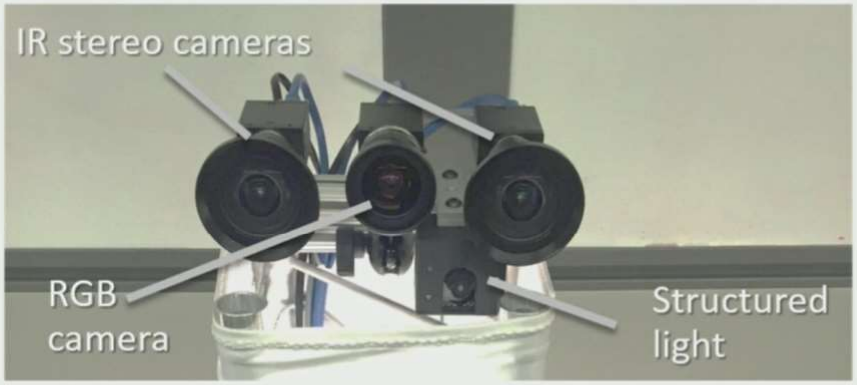
Depth Acquisition



Holoportation: Virtual 3D Teleportation in Real-time
Orts-Escolano et al. [UIST '16]

(1)

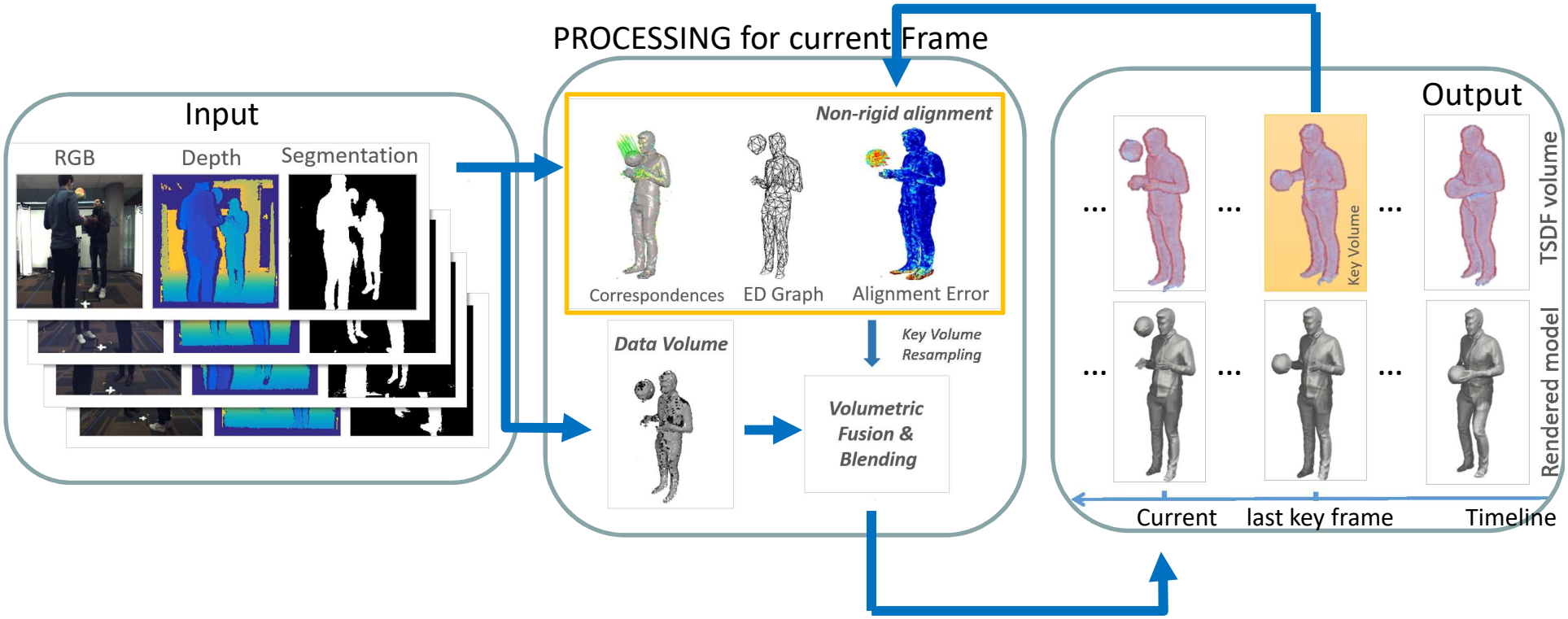
Depth Acquisition

Real-time foreground/background segmentation

Krähenbühl et al. [ICML ’13], Vineet et al. [CVPR ’08]

(1)

Overview - Pipeline



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Nonrigid Motion Field Estimation

- TSDF of N Depthmaps
- Embedded Deformation(ED)-model to warp the model to align with the raw depth maps
- Energy function E(G) for optimization of the ED-Model

Deformation field

- (Embedded Deformation)ED-model
  - Set of K ED-nodes with sampling locations $g_k \in R^3$ from the mesh

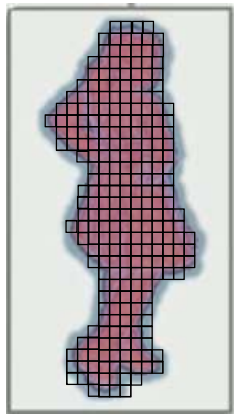
- Deformation (warp) of each point then is:

(1)

$$\mathcal{T}(vm;G) = R \sum_{k \in s_m} w_k^m [A_k(v - g_k) + g_k + t_k] + T$$

- and the normal $\mathcal{T}^{\perp}(n_m;G) = R \sum_{k \in s_m} w_k^m A_k^{-T} n_m$

Deformation field



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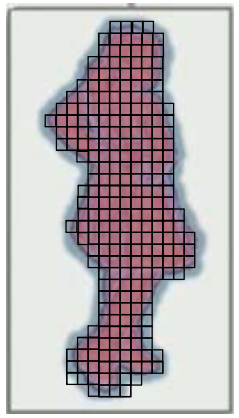

- (Embedded Deformation)ED-model
  - Set of K ED-nodes with sampling locations $g_k \in R^3$ from the mesh
- Deformation (warp) of each point then is:

Global Rotation — sample location — global Translation

$$\mathcal{T}(vm;G) = R \sum_{k \in s_m} w_k^m [A_k(v - g_k) + g_k + t_k] + T$$

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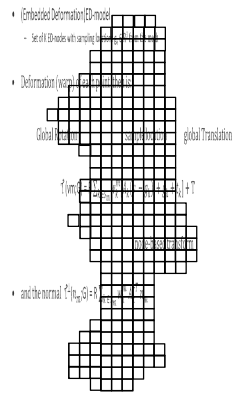
Deformation field



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  - Set of K ED-nodes with sampling locations $g_k \in R^3$ from the mesh
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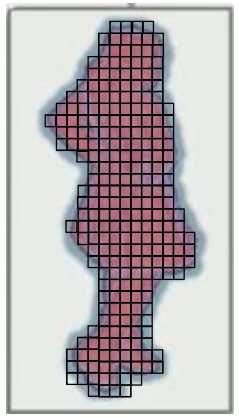
$$\mathcal{T}(vm;G) = R \sum_{k \in s_m} w_k^m [A_k(v - g_k) + g_k + t_k] + T$$

node-based transform

- and the normal $\mathcal{T}^{\perp}(n_m;G) = R \sum_{k \in s_m} w_k^m A_k^{-T} n_m$

Deformation field



- (Embedded Deformation)ED-model
  - Set of K ED-nodes with sampling locations $g_k \in R^3$ from the mesh
- Deformation (warp) of each point then is:

Global Rotation — global Translation

$$\mathcal{T}(v_m;G) = R \sum_{k \in s_m} w_k^m [A_k(v - g_k) + g_k + t_k] + T$$

weighted by distance — node-based transform

- and the normal $\mathcal{T}^{\perp}(n_m;G) = R \sum_{k \in s_m} w_k^m A_k^{-T} n_m$

Energy Functions – Data Term

$$E(G) = \lambda_{data}\, E_{data}(G) + \lambda_{hull} E_{hull}(G) + \lambda_{corr} E_{corr}(G) + \lambda_{rot} E_{rot}(G) + \lambda_{smooth} E_{smooth}(G)$$

Accumulated Misalignment :

$$E_{data}(G) = \sum_{n=1}^{N} \sum_{m=1}^{M} \min_{x \in P(D_n)} \| \mathcal{T}(v_m; G) - x \|^2$$

-> expensive

Energy Functions – Data Term

$E(G) = \lambda_{data}\ E_{data}(G) + \lambda_{hull}E_{hull}(G) + \lambda_{corr}E_{corr}(G) + \lambda_{rot}E_{rot}(G) + \lambda_{smooth}E_{smooth}(G)$

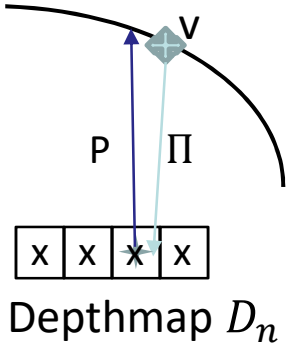
Projective point-to-plane approximation of every visible point in depthmap N

$$E_{data}(G) = \sum_{n=1}^{N} \sum_{m \in V_n(G)} \left(\mathcal{T}^{\perp}(n_m; G)^T \left(\mathcal{T}(v_m; G) - \Gamma_n(\mathcal{T}(v_m; G))\right)\right)^2$$

$\Gamma_n(v) = P_n(\Pi_n(v))$:

$\Pi_n(v)$: projection of v to a pixel in depthmap n

$P_n(p)$: projection of pixel in depthmap n into 3D



Energy Functions – Data Term

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Projective point-to-plane approximation of every visible point in depthmap N

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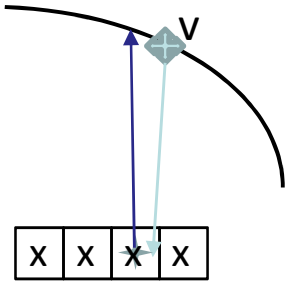
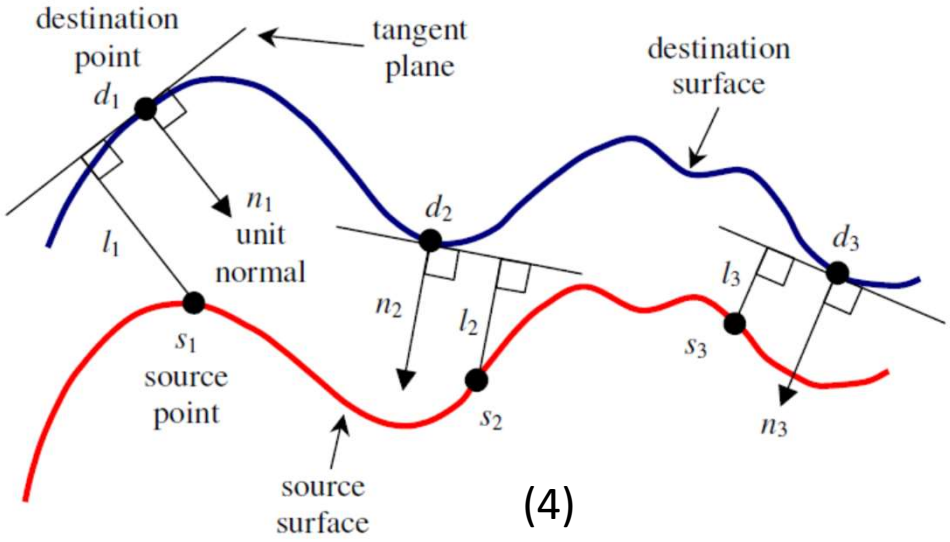
Point-to-plane

$\Gamma_n(v) = P_n(\Pi_n(v))$:



Depthmap D_n



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Energy Functions – Regularization Terms

$$E(G) = \lambda_{data}\, E_{data}(G) + \lambda_{hull} E_{hull}(G) + \lambda_{corr} E_{corr}(G) + \lambda_{rot} E_{rot}(G) + \lambda_{smooth} E_{smooth}(G)$$

Restriction of the class of allowed deformations:

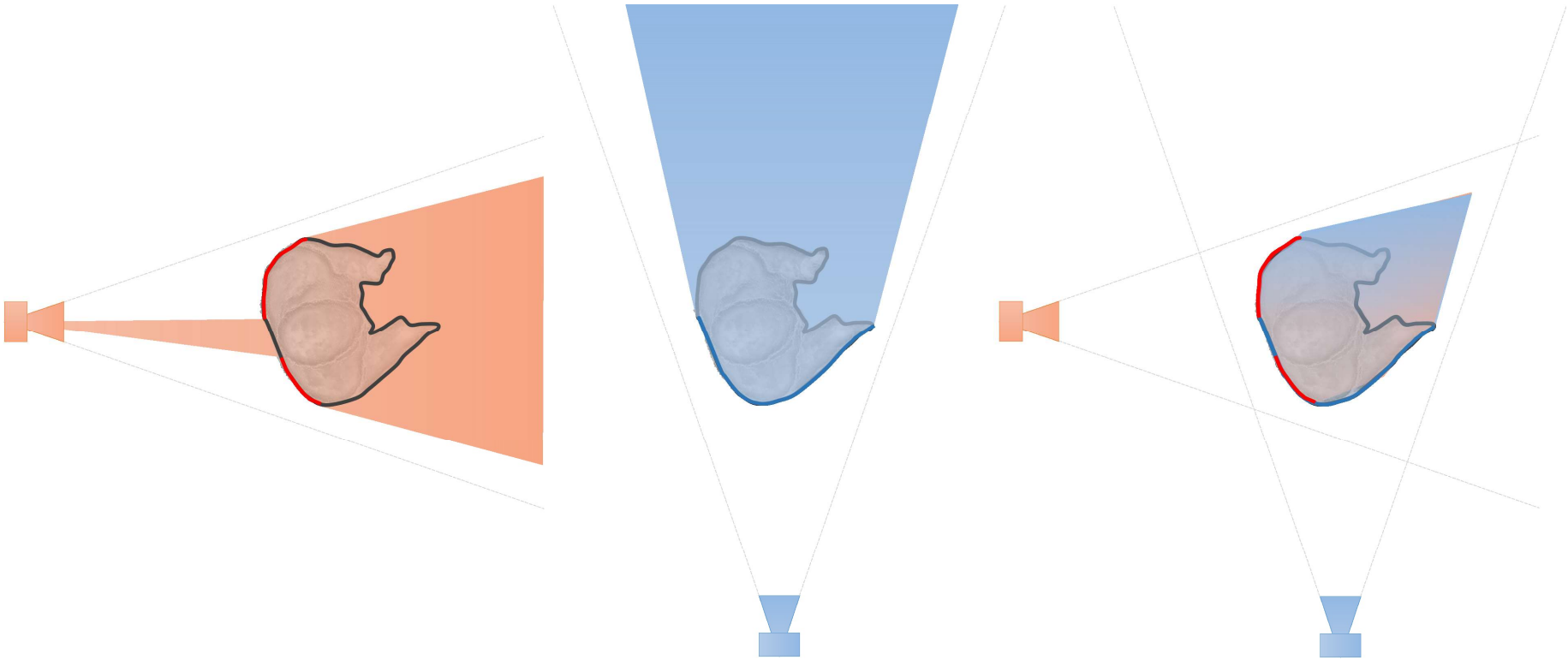
$$E_{rot}(G) = \sum_{k=1}^{K} \left\| A_k^T A_k - \mathrm{I} \right\|_F + \sum_{k=1}^{K} (\det(A_k) - 1)^2$$

Enforce similiar deformation for nearby positions:

$$E_{smooth}(G) = \sum_{k=1}^{K} \sum_{j \in N_k} w_{jk}\, \rho\left(\left\| A_j (g_k - g_j) + g_j + t_j - (g_k + t_k) \right\|^2 \right)$$

Energy Functions – Visual Hull Term

$$E(G) = \lambda_{data}\ E_{data}(G) + \lambda_{hull}E_{hull}(G) + \lambda_{corr}E_{corr}(G) + \lambda_{rot}E_{rot}(G) + \lambda_{smooth}E_{smooth}(G)$$



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Energy Functions – Visual Hull Term

$E(G) = \lambda_{data} E_{data}(G) + \lambda_{hull} E_{hull}(G) + \lambda_{corr} E_{corr}(G) + \lambda_{rot} E_{rot}(G) + \lambda_{smooth} E_{smooth}(G)$

$$E_{hull}(G) = \sum_{m=1}^{M} \mathcal{H}(\mathcal{T}(vm;G))^2$$

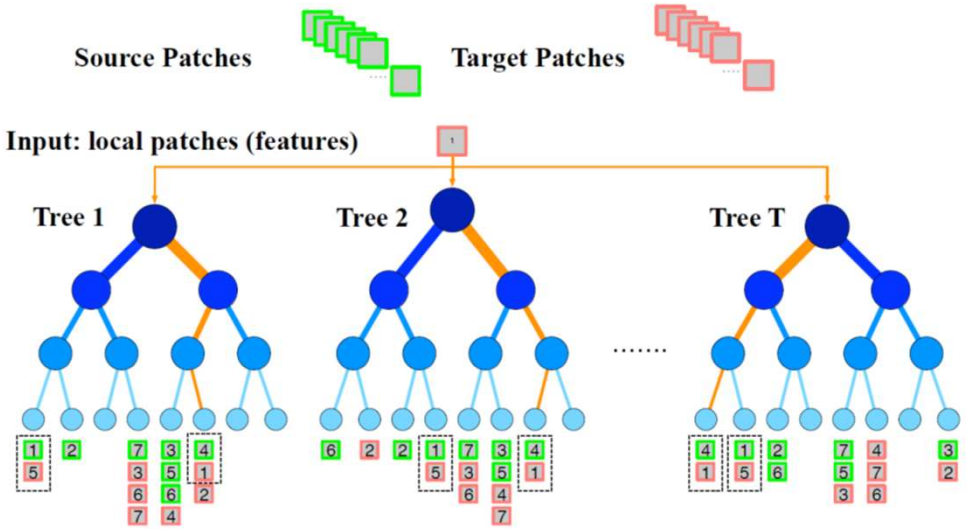
occupancy Volume: $\mathbb{H}(voxel) = \begin{cases} 1 & voxel\ inside\ of\ hull \\ 0 \end{cases}$

$\mathcal{H}(v)$: distance v to $\mathbb{H}$

-> expensive: approximation of $\mathcal{H}$ via Gaussian blur to $\mathbb{H}$

Correspondence Term – Global Patch Collider

- Decision Tree to find matches
  - 5 trees with 15 levels
- Voting Scheme:
  - Vote of all trees with a UNIQUE collision



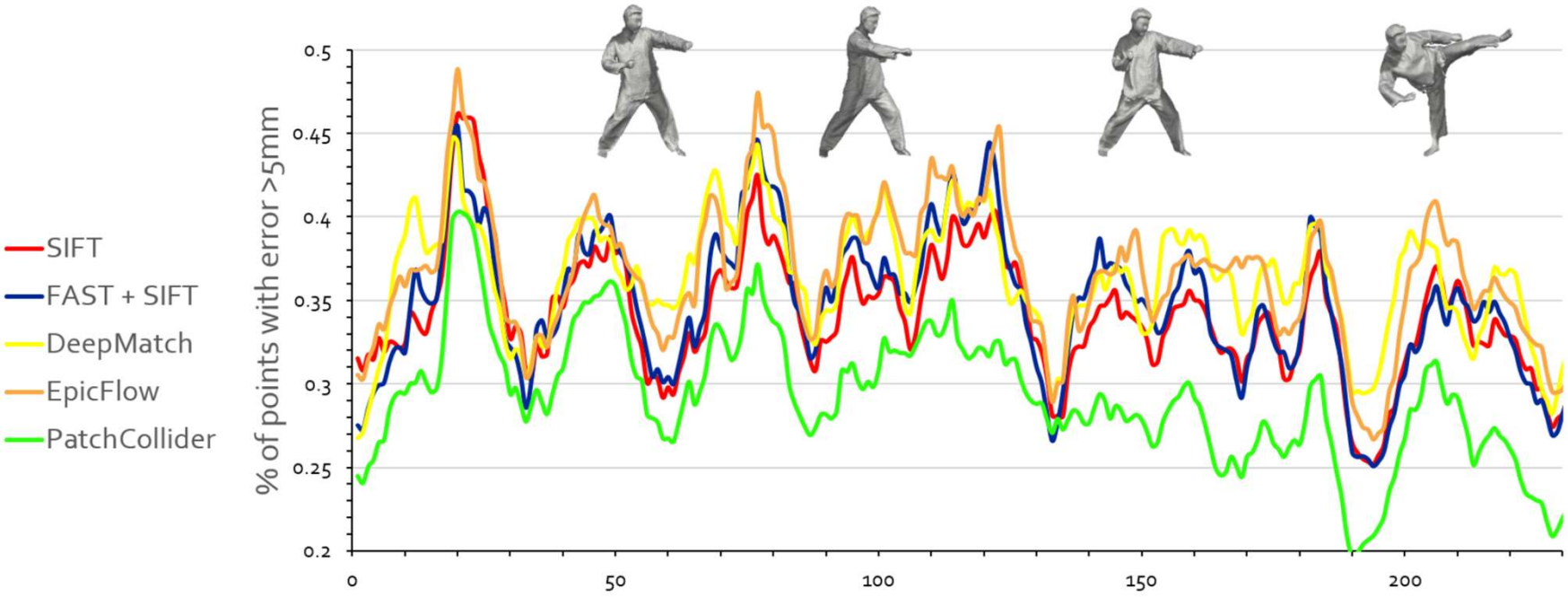
- Splitfunction (5)

$$f(p;\Theta) = \begin{cases} L, & if\ I_s(p + u/D_s(p)) - I_s(p + v/\mathrm{D}_t(p)) < \Theta \\ R, & otherwise \end{cases}$$

- learned: threshold Θ, 2D Pixel offset (u, v)

- Trained OFFLINE to maximize weighted harmonic mean between precision and recall
  - Ground truth: accurate Method of [Dou et al. 2015]

Correspondence Term - Global Patch Collider



(3)

Energy Functions – Correspondence Term

$$E(G) = \lambda_{data}\, E_{data}(G) + \lambda_{hull} E_{hull}(G) + \lambda_{corr} E_{corr}(G) + \lambda_{rot} E_{rot}(G) + \lambda_{smooth} E_{smooth}(G)$$

Set of F_n Matches $\left\{u_{nf}^{prev}, u_{nf}\right\}$

Corresponding point $q_{nf} \in \mathbb{R}^3$ per match:

$$q_{nf} = \underset{v \in V}{\operatorname{argmin}} \left\| \Pi_n(\mathcal{T}(v; G^{prev})) - u_{nf}^{prev} \right\|$$

Correspondence Term:

Deformed point 3D correspondence

$$E_{corr}(G) = \sum_{n=1}^{N} \sum_{f=1}^{F_n} \rho\left(\left\| \mathcal{T}(q_{nf}; G) - P_n\left(u_{nf}\right)\right\|^2\right)$$

robustifier

Optimization of the ED-Model

Every single Energy function was squared, $E(G) = f(X)^T f(X)$ possible

-> standard sparse linear least squares minimization problem

- Initialization:
  - ED-nodebased transformation of the old ED-Model fixed $\{A_k,\ t_k\}_{k=1}^{K}$
  - Iterative closest Points (4 Iterations) for the global translation and rotation $\{T, R\}$

Optimization of the ED-Model

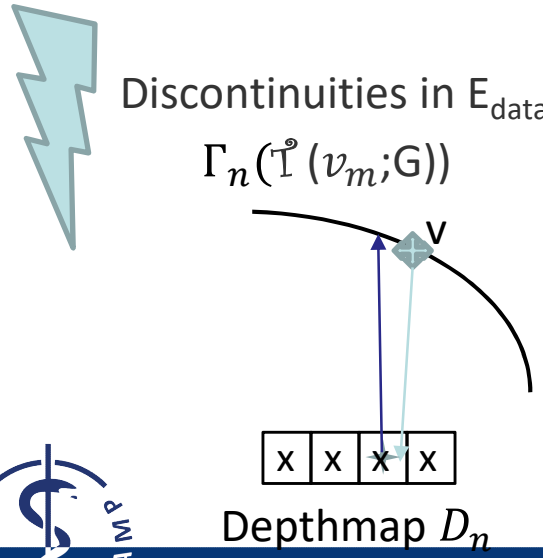
- Levenberg Marquardt Algorithm: damping factor

$$(J^T J + \mu I)h = -J^T f$$

- Stepwise update :
  - Accepted if $\mathrm{E}\big(f(X+h)\big) < E(X)$, μ lowered -> more aggressive
  - Otherwise μ increased and solved again

Discontinuities in $E_{data}(G)$:

$\Gamma_n(\mathbb{T}(v_m;G))$



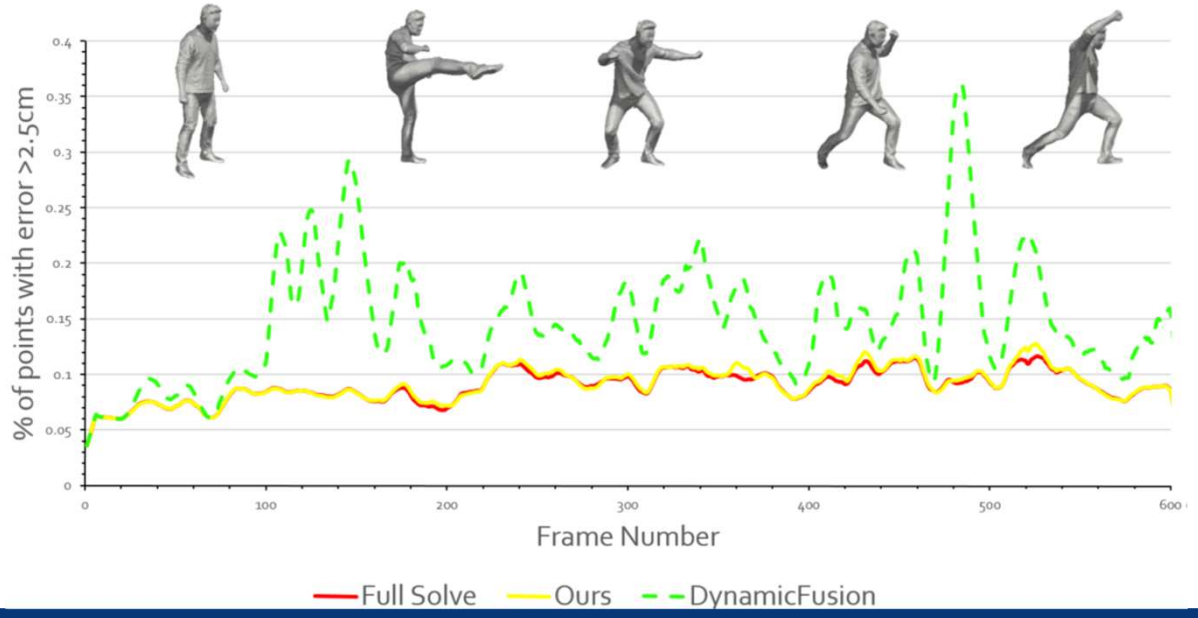
differentiable Approximation:

$$\sum_{n=1}^{N} \sum_{m \in V_n(G_0)} (\widetilde{n_m}((G_0)^T (\widetilde{v_m}((G) - \Gamma_n(\widetilde{v_m}((G_0)))^2$$

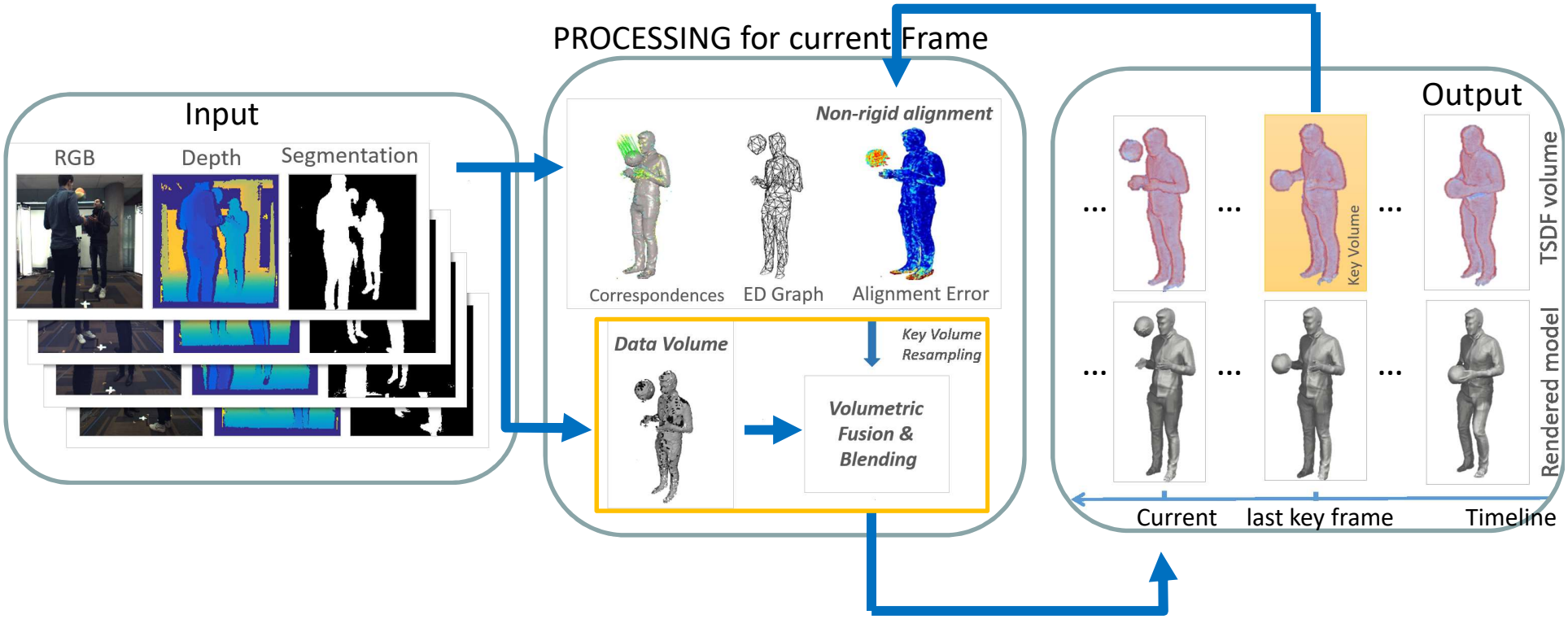
current Parameters

Linear Solving

- Store $J^T J$ and $J^T f$ instead of J, since it is magnitudes larger
  - Lower memory footprint -> time efficience
  - $E_{data}(G)$ Approximation -> independent of the number of cameras
  - $J^T J$ is a sparse matrix -> consists of nonzero blocks
    - » Blockwise calculation via CUDA blocks
- iterative solve of $J^T J$ via preconditioned conjugat gradient (PCG)
  - Preconditioner: diagonal Blocks of $J^T J$
- DynamicFusion 2015 uses direct sparse Cholesky decomposition:
  - Approximation of $J^T J$



Overview - Pipeline



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Fusion

- Fusion at Data Frame
  - Warping
  - Selective Fusion
  - Blending
- Fusion at Reference Frame
- Key Volume

Volume Warping

- Warp key Volume to align the data via ED-model
  - Voxel $\in \mathbb{R}^3$ containing $\langle d, w \rangle$ in the key Volume

- Fusion into fused TSDF: x^d weighted average of warped neighboring reference-voxels $\langle \bar{d}^r, w^r \rangle$

warped Gradient of key Vol.

Correction of the depthvalue: $\bar{d}^r = \mathrm{d}^r + (\tilde{x}^r - x^d)^T \tilde{\Delta}$

Fusion at Data frame – Selective Fusion

- Voxel Collision
  - $|x - \dot{x}^R| > \eta$
  - $\dot{x}^R$ closest reference voxel

(3) reference volume, without and with voxelcolldetect.

- Voxel Misalignment
  - Discard voxel if alignment error > threshold

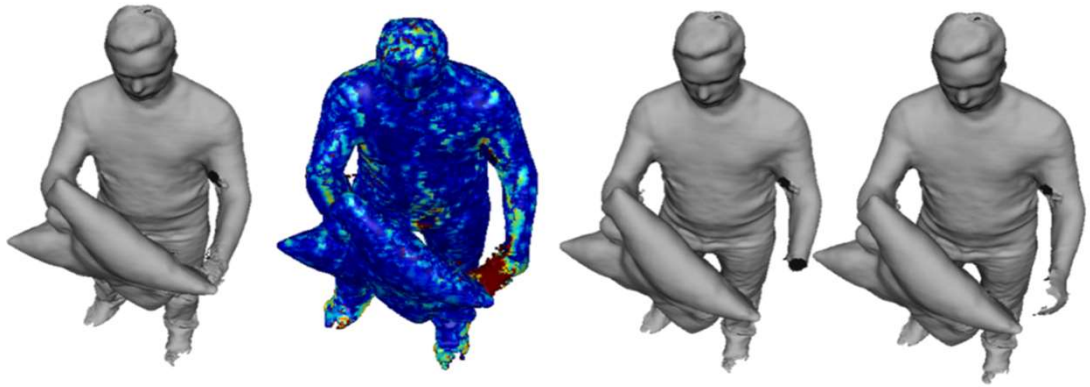
fused TSDF Hull

$$e_{\tilde{x}^r} = \begin{cases} \left|D^d(\tilde{x}^r)\right|, & if\ \mathcal{H}^d(\tilde{x}^r) = 0 \\ \min\left(\left|D^d(\tilde{x}^r)\right|, \mathcal{H}^d(\tilde{x}^r)\right), & otherwise \end{cases}$$

Fusion at Data frame - Blending

- Fuse dataVolume and warped reference Volume
  - No naive blending (boundary-voxels)

$$\bar{d}^d = \frac{\tilde{d}^r \tilde{w}^r (1.0 - e_{voxel}) + d^d w^d}{\tilde{w}^r (1.0 - e_{voxel}) + w^d}$$



e_{voxel}: aggregated average of e_{pixel} of every depthmap

$$e_{pixel} = \begin{cases} \min\left(1.0, \frac{|d - d_{proj}|}{d_{max}}\right), & if\ d_{proj}\ is\ valid \\ 1.0, & otherwise \end{cases}$$

Fusion at the Reference Frame

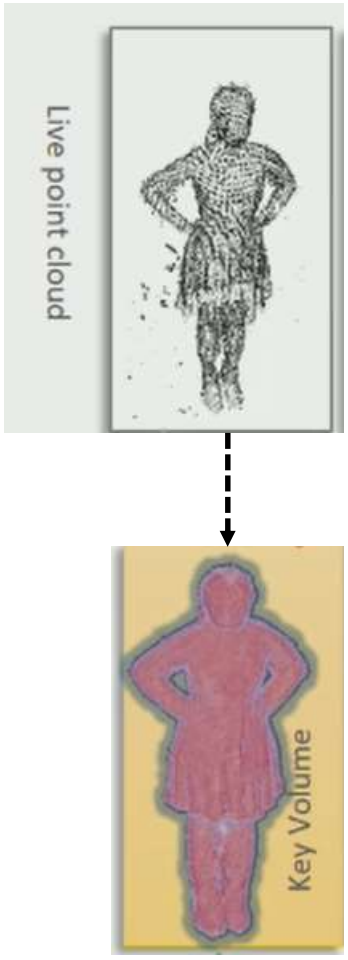
Just like DynamicFusion:

- Discarding Voxels not aligned well to the Data, and refreshing them
  - $alignmenterror\ e_{\tilde{x}^r}$
- Update depth and weight by projecting it to the depthmaps

BUT: Key Volumes

- Complete Reset periodically (here 10 frames)

Key Volumes



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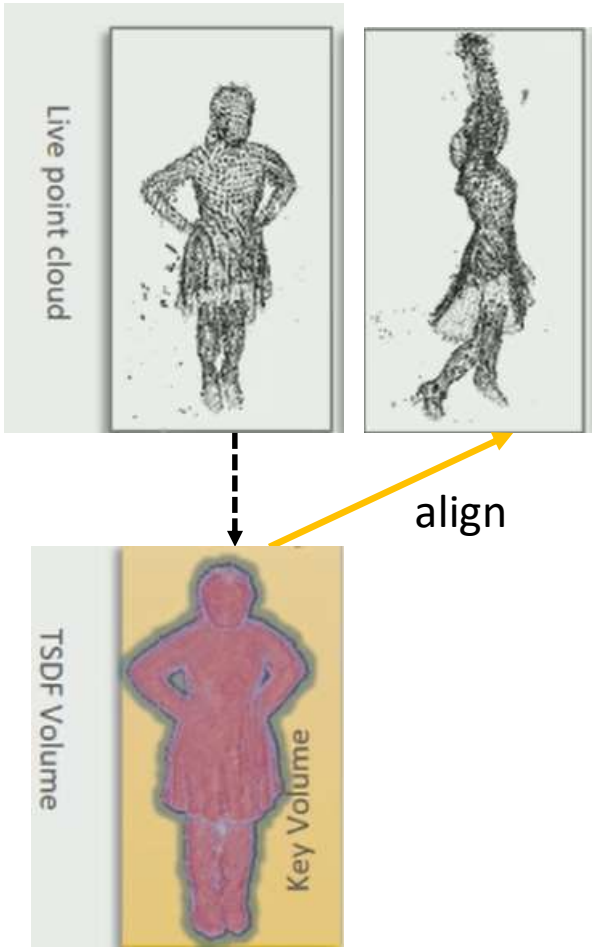
Key Volumes



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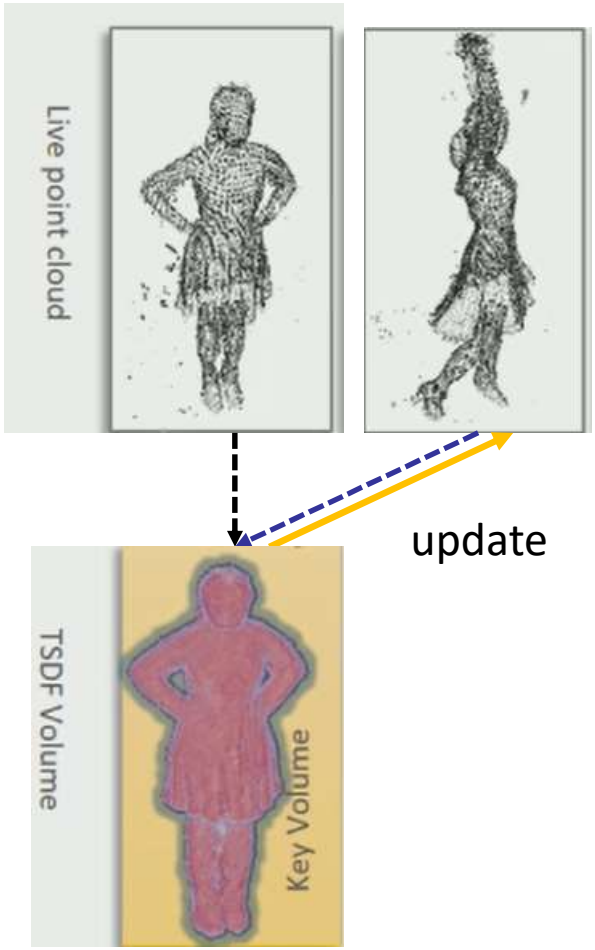
Key Volumes



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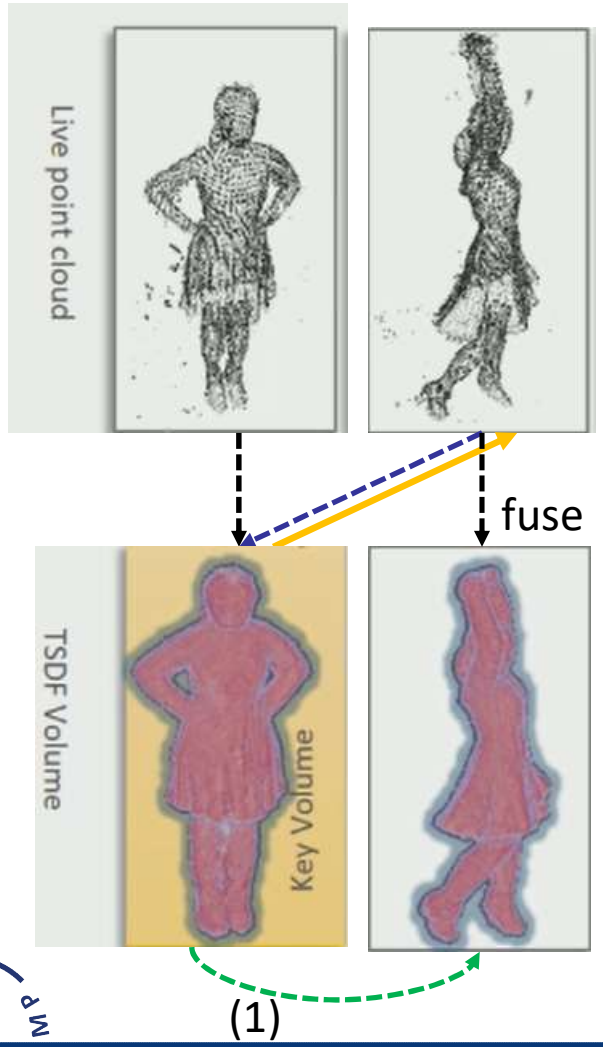
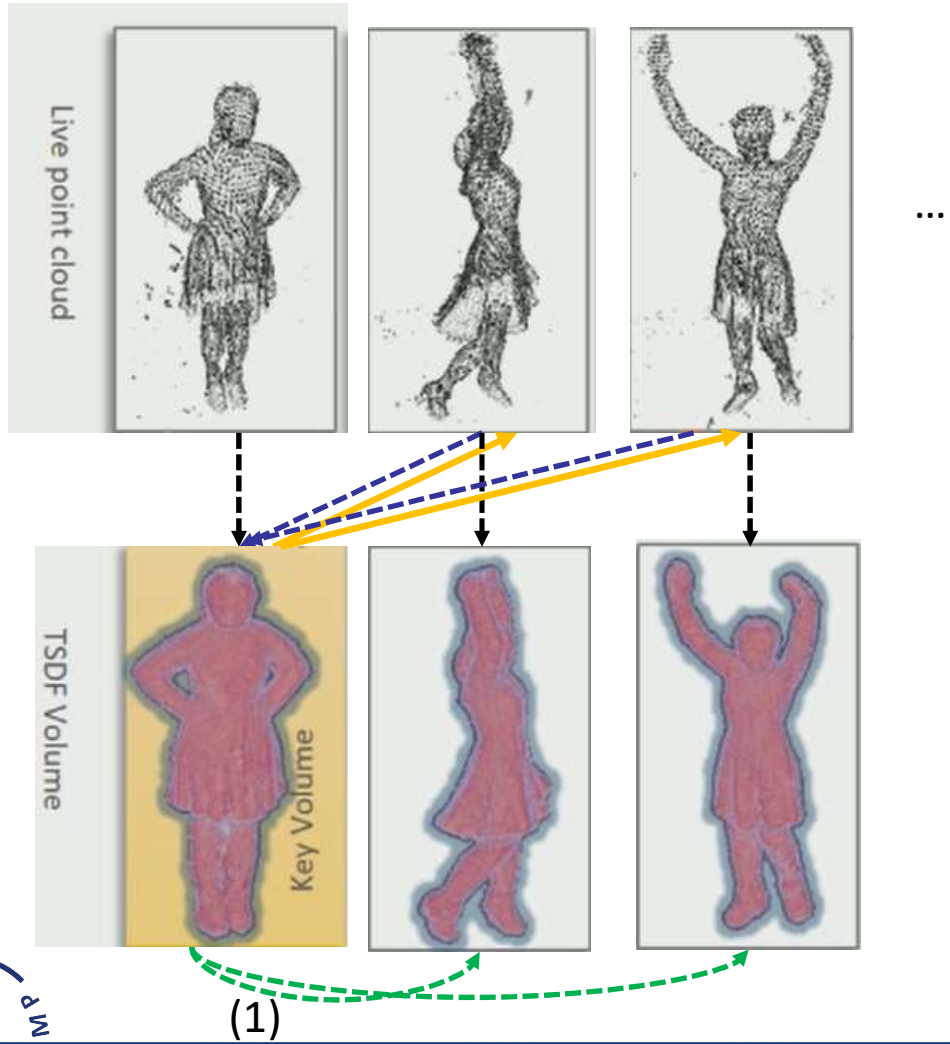
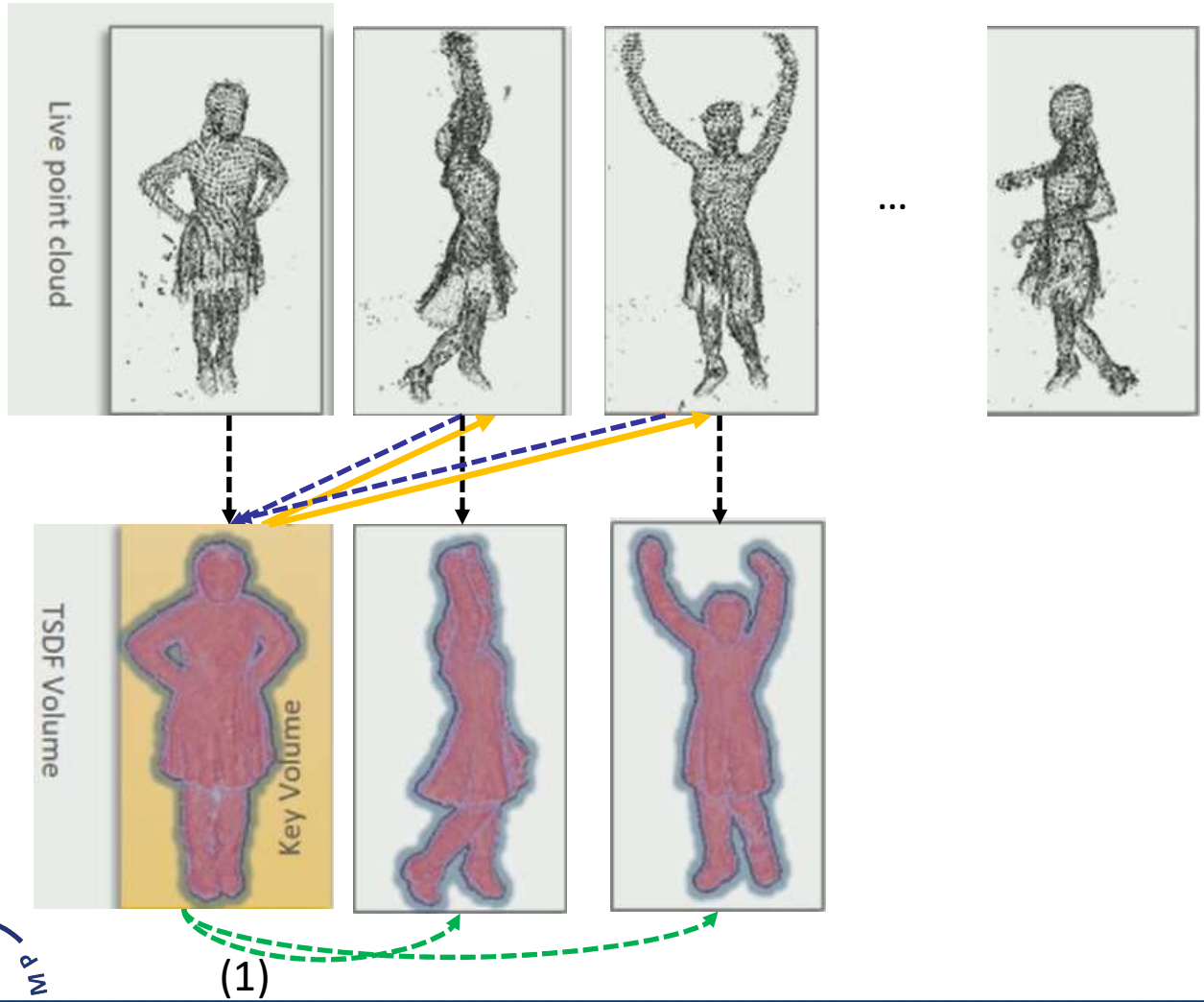
Key Volumes



Key Volumes



Key Volumes



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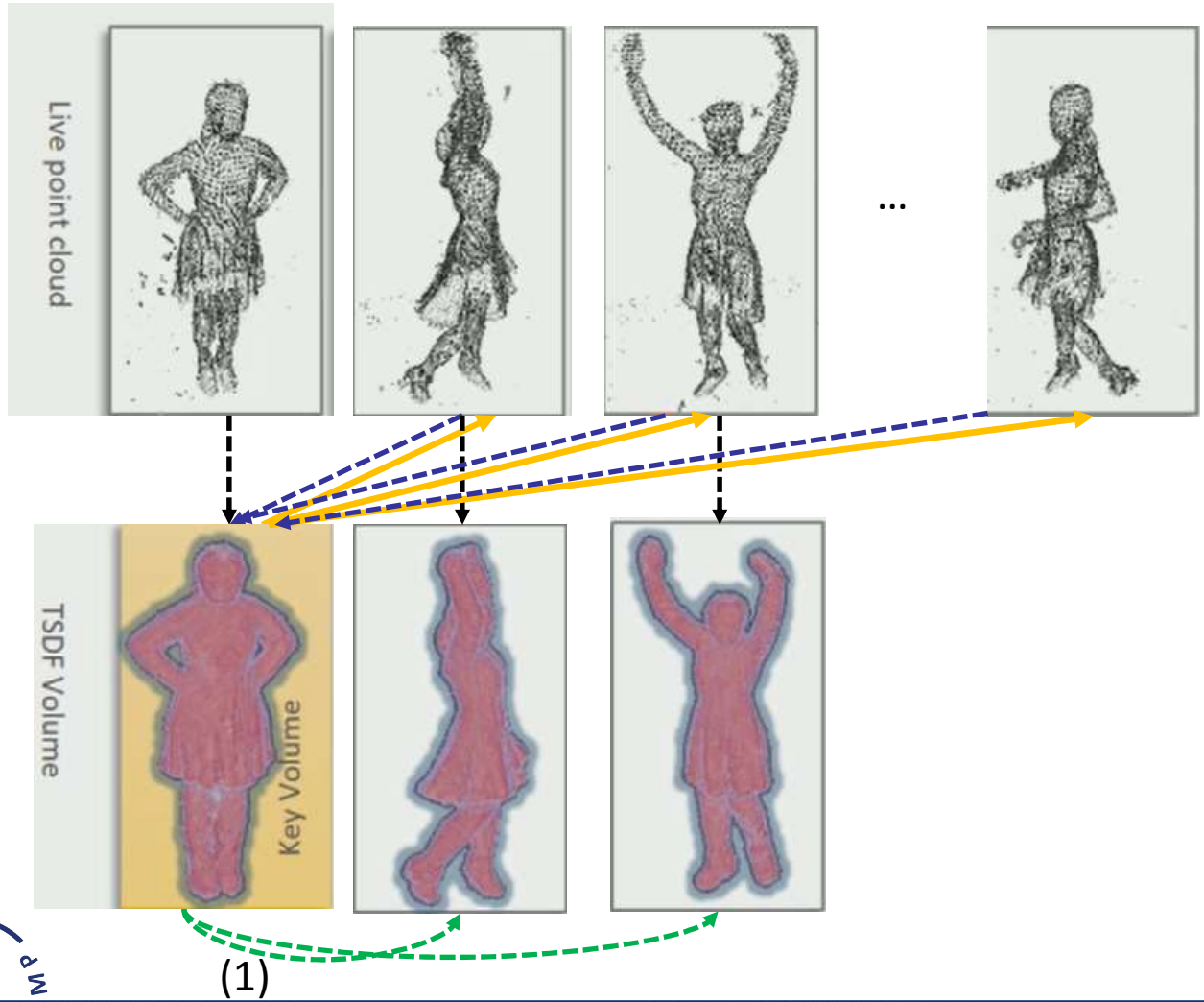

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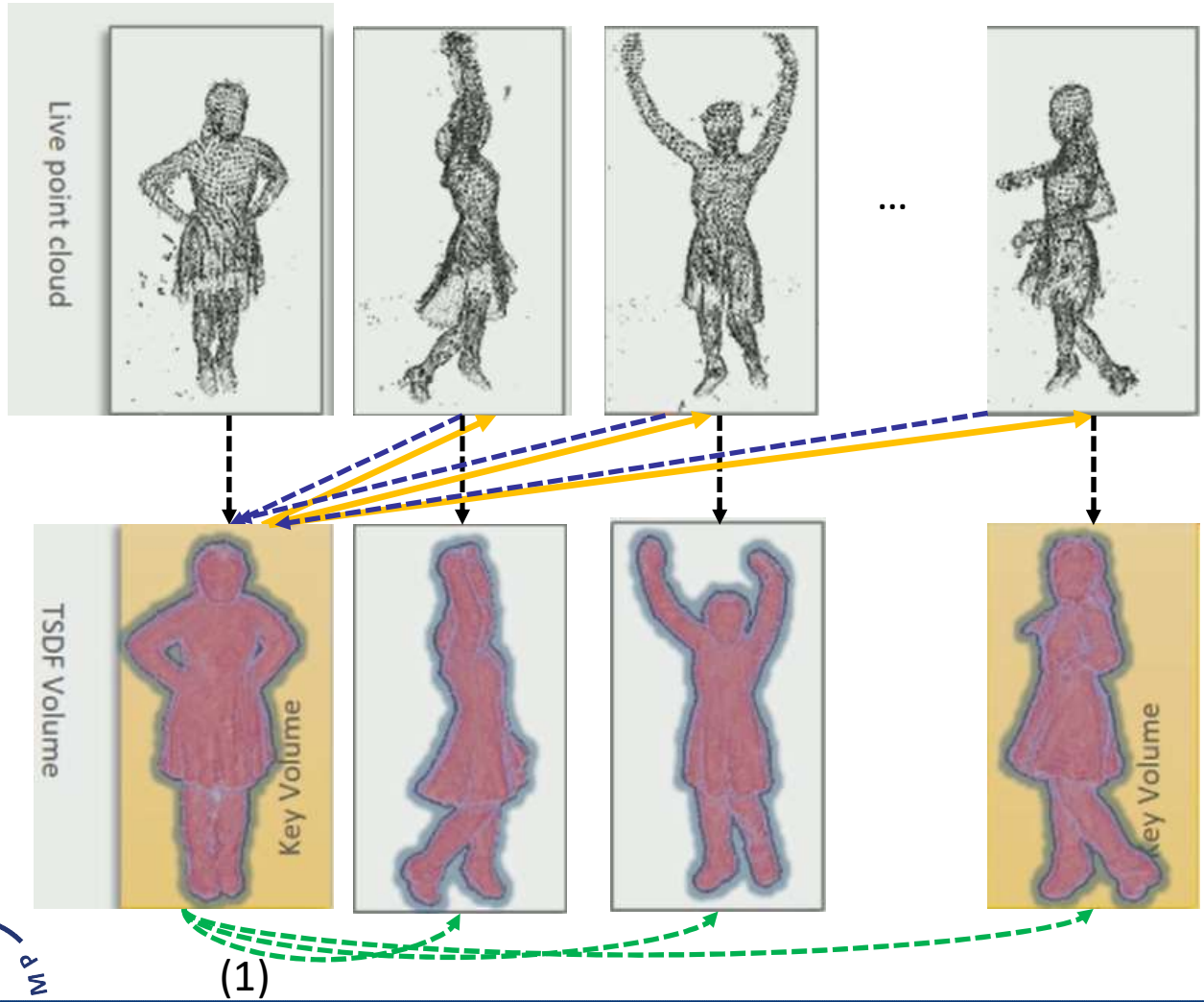
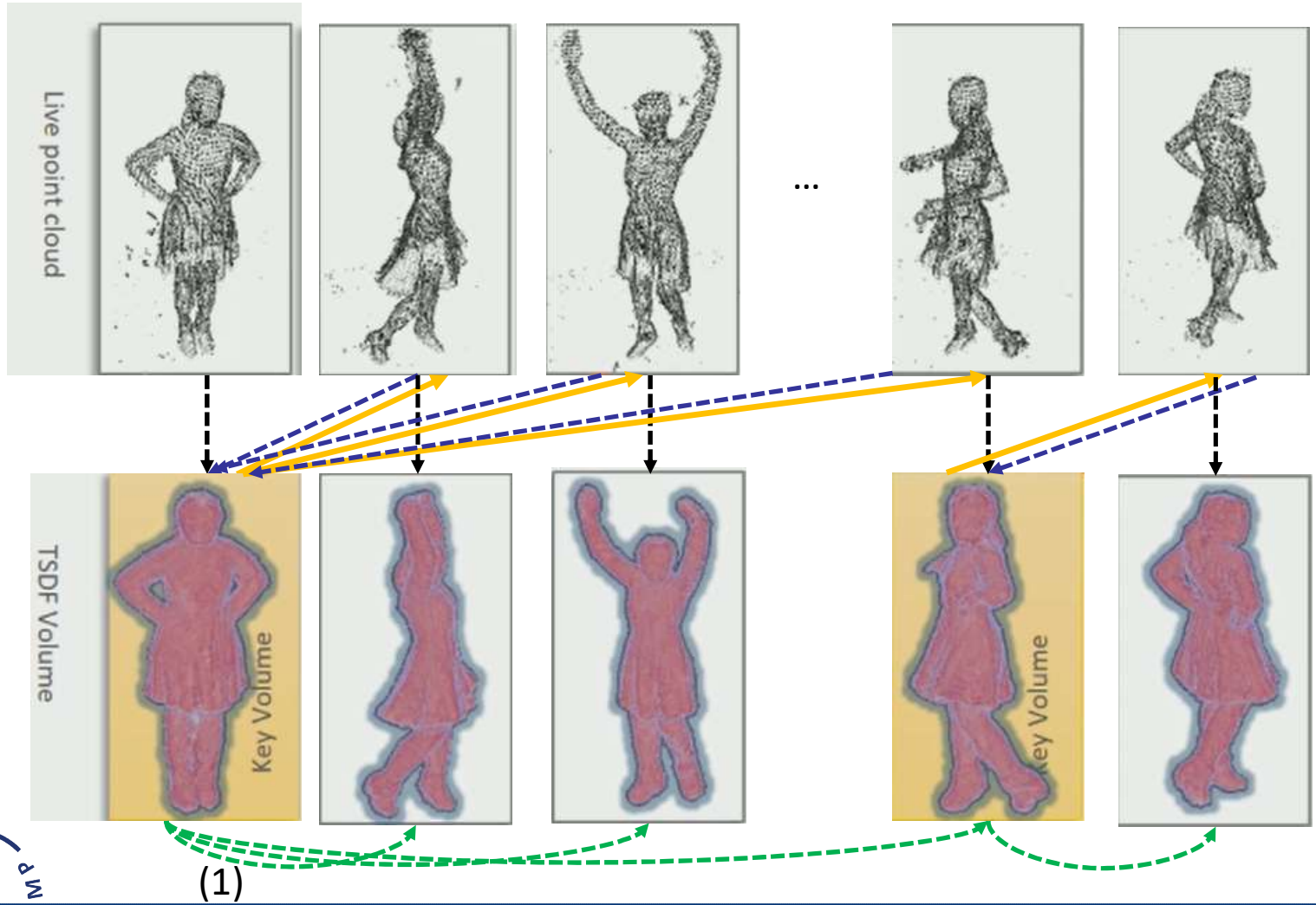
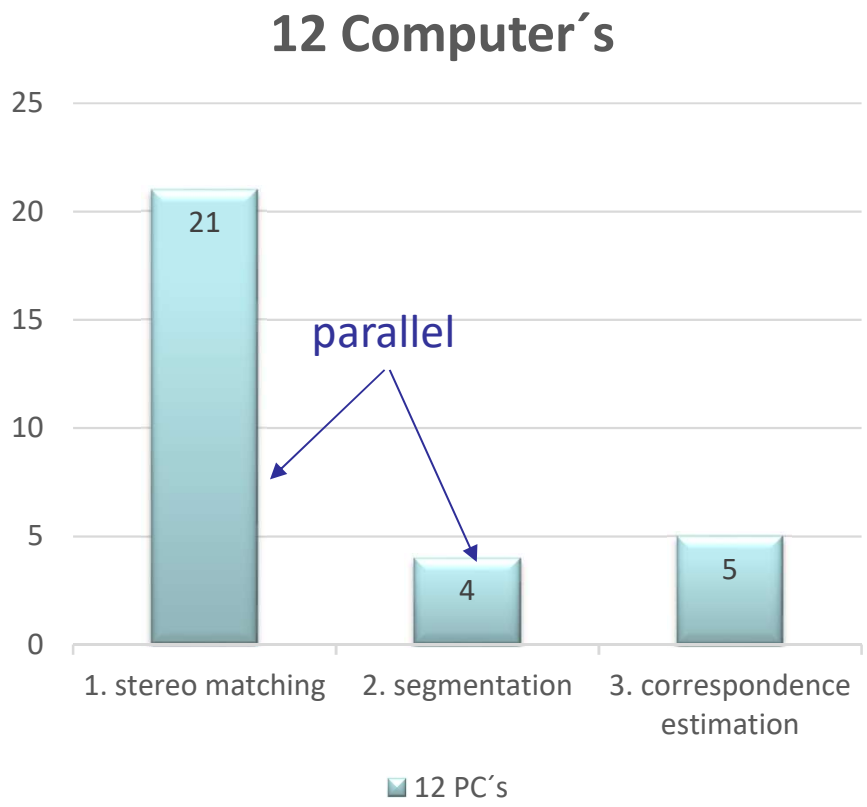


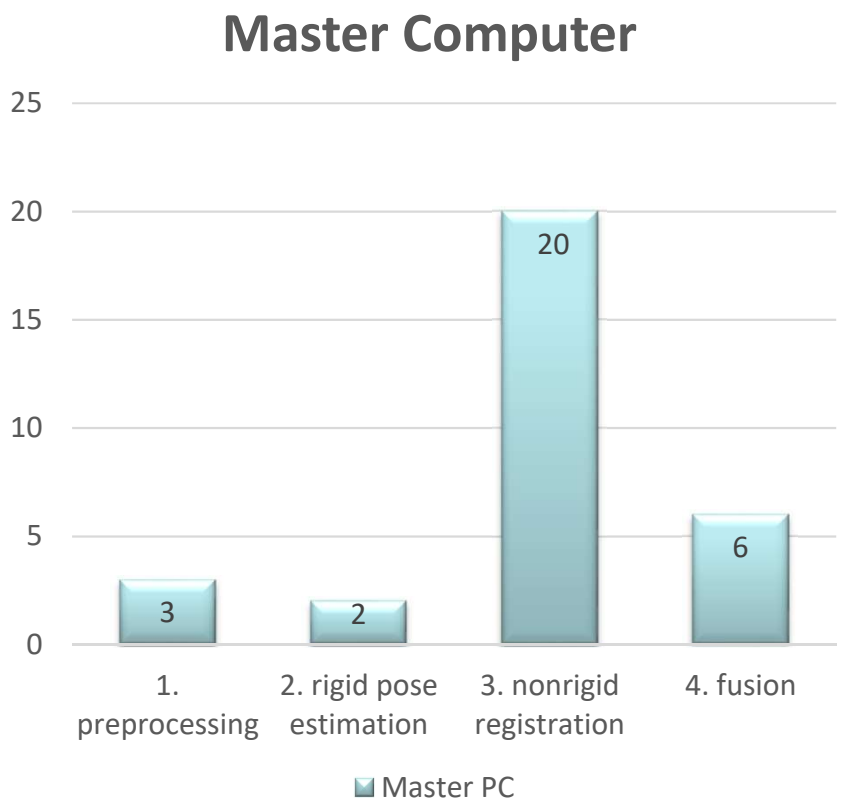
Key Volumes



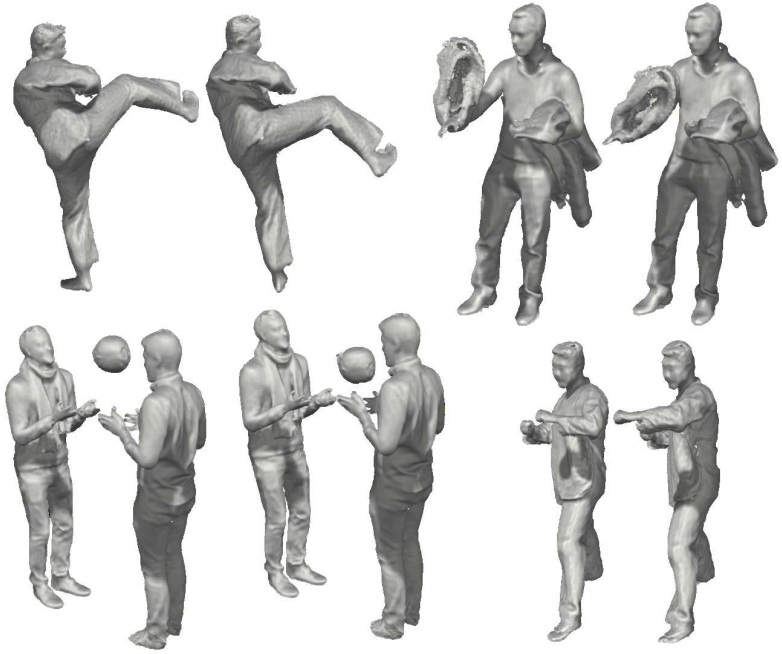
Conclusion

- Time Consumption:





Results

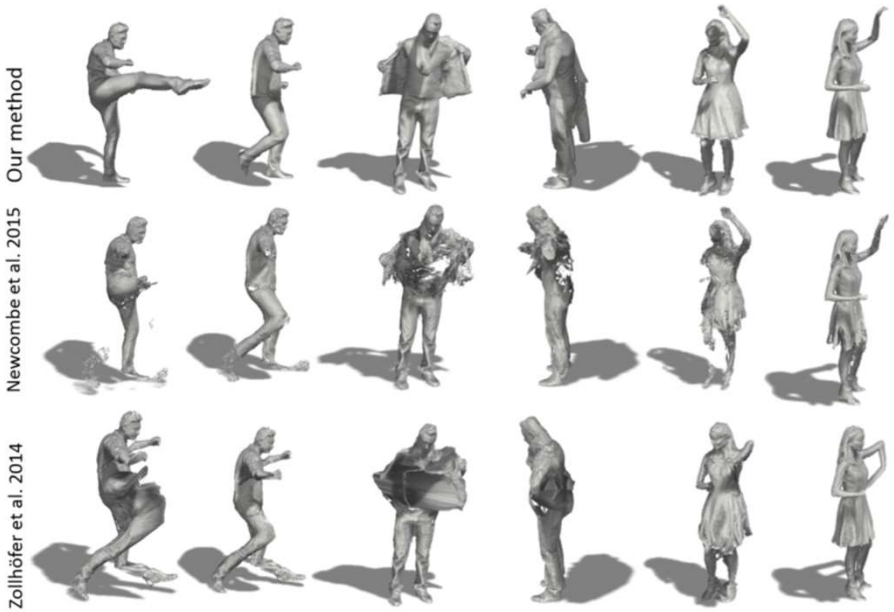


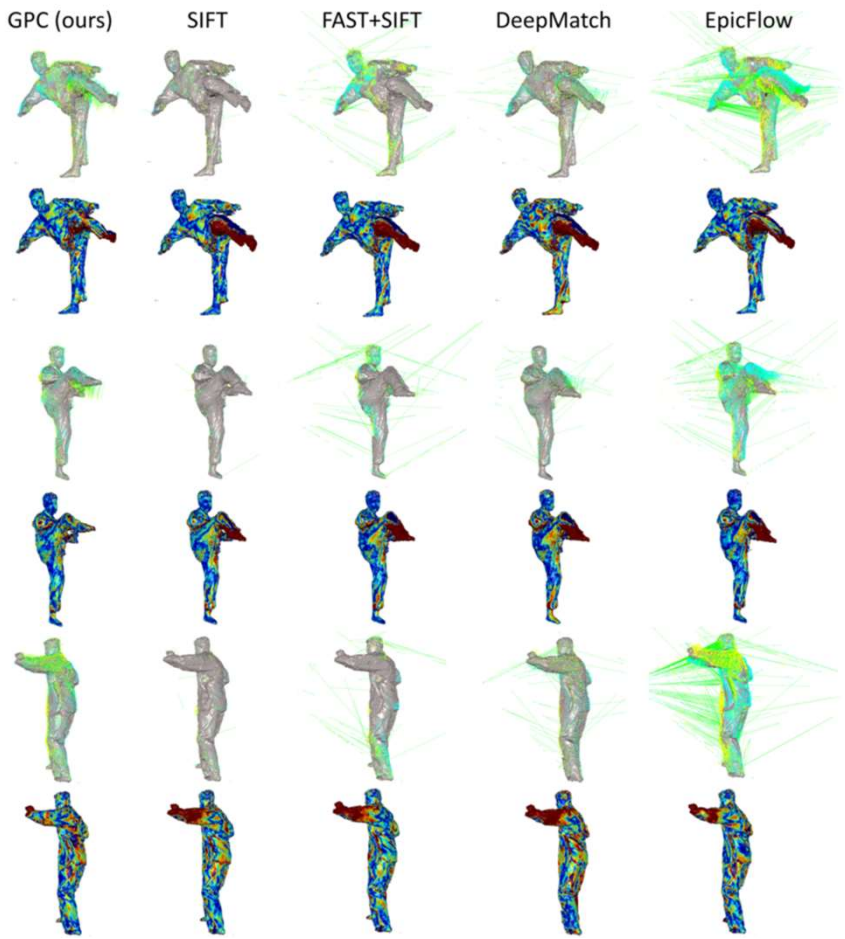
- robustness to fast motion

- complex topology changes

(3)

Comparison


Our method
Newcombe et al. 2015
Zollhöfer et al. 2014

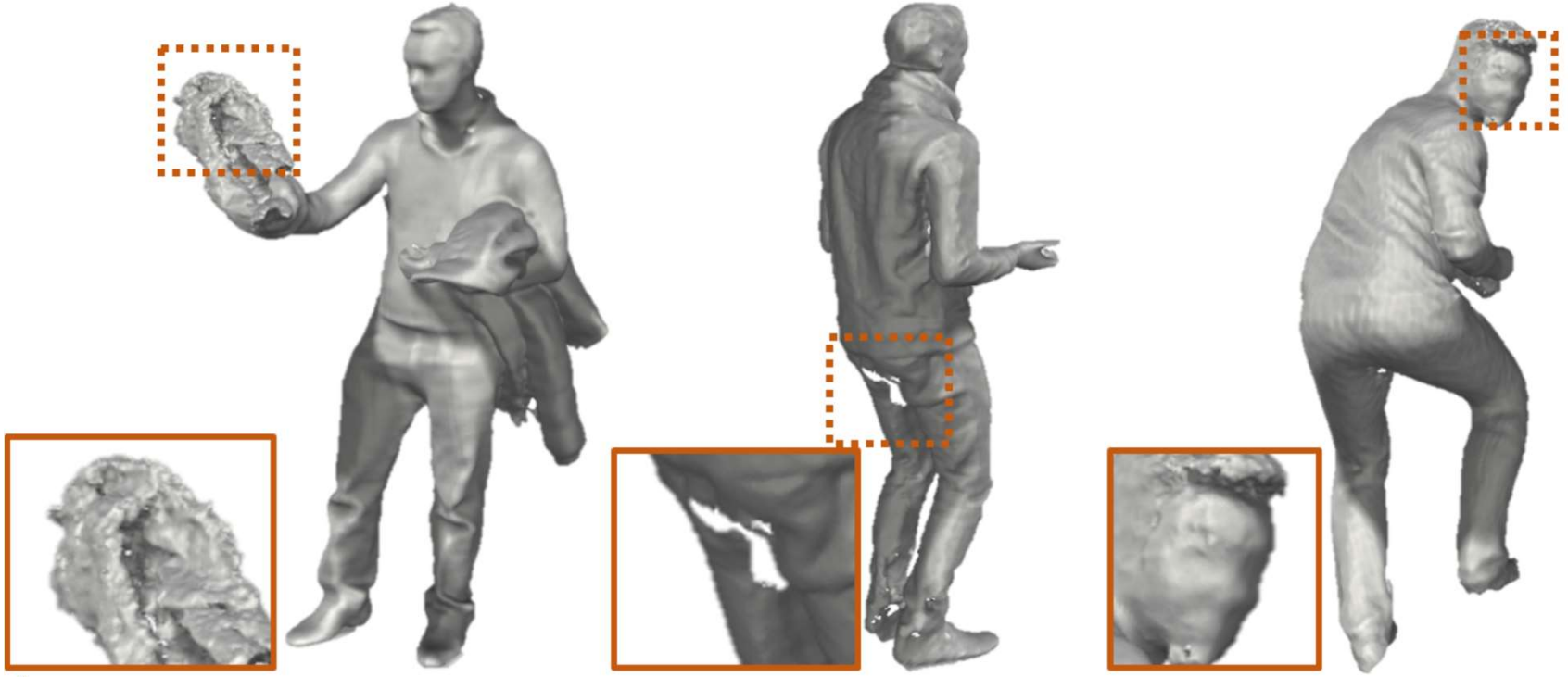

GPC (ours)
SIFT
FAST+SIFT
DeepMatch
EpicFlow

Limitations

Lost tracking

segmentation error

alignment error



(3)

Sources

- (1): http://dl.acm.org/citation.cfm?id=2925969 05.12.2016 Source Materials „Mp4“
- (2): http://dl.acm.org/citation.cfm?id=2925969 05.12.2016
  Source Materials „Supplemental files“
- (3): **Fusion4D: Real-time Performance Capture of Challenging Scenes**
  in SIGGRAPH2016
- (4): **Linear Least-Squares Optimization for Point-to-Plane ICP Surface Registration**
  - https://www-new.comp.nus.edu.sg/~lowkl/publications/lowk_point-to-plane_icp_techrep.pdf
    07.12.2016

- (5): **The Global Patch Collider** in CVPR

Questions?