

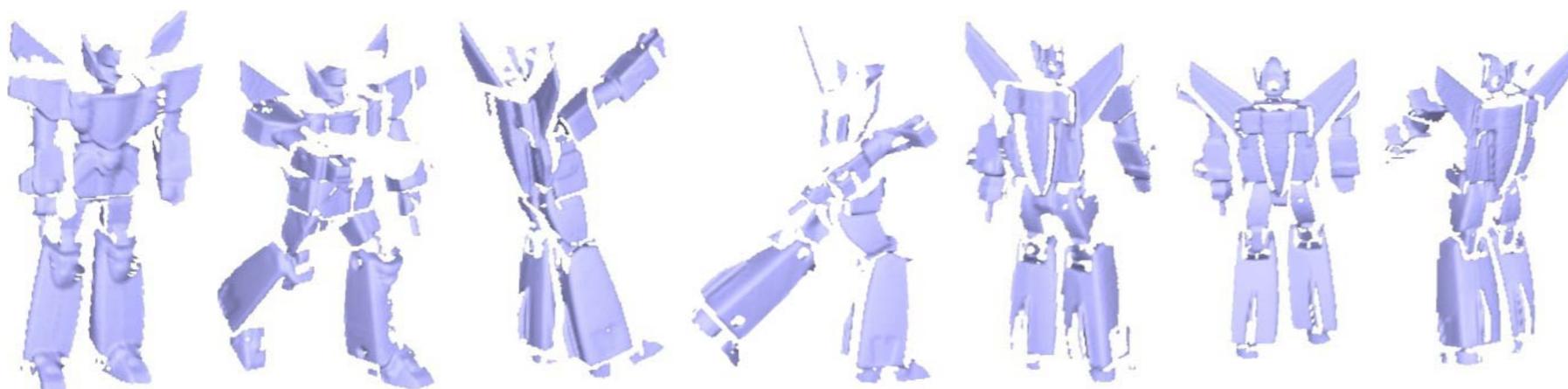


# Articulated Global Registration

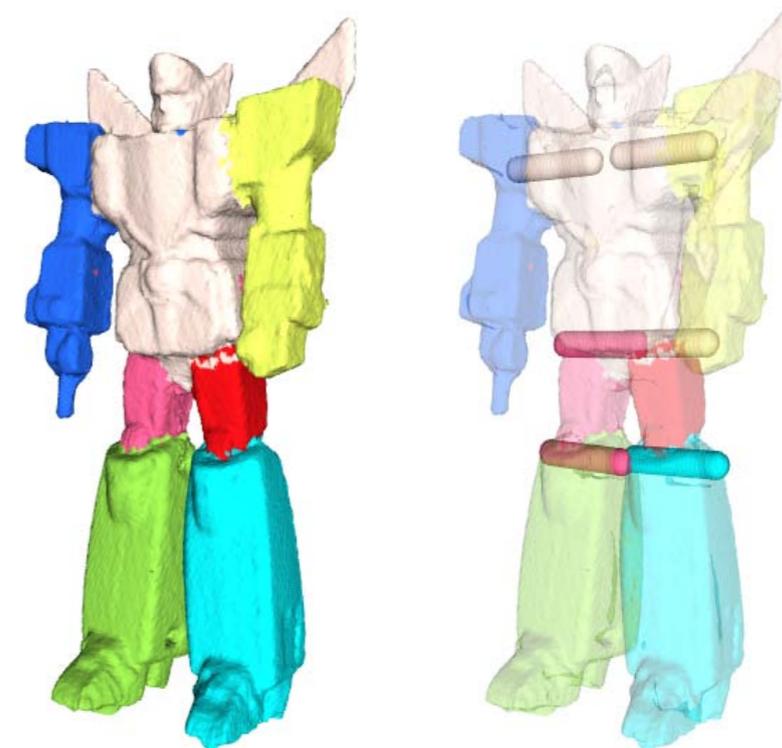
## Introduction and Overview

# Articulated Global Registration

- Complete models from dynamic range scans
- No template, markers, skeleton, segmentation
- Articulated models
  - Movement described by piecewise-rigid components



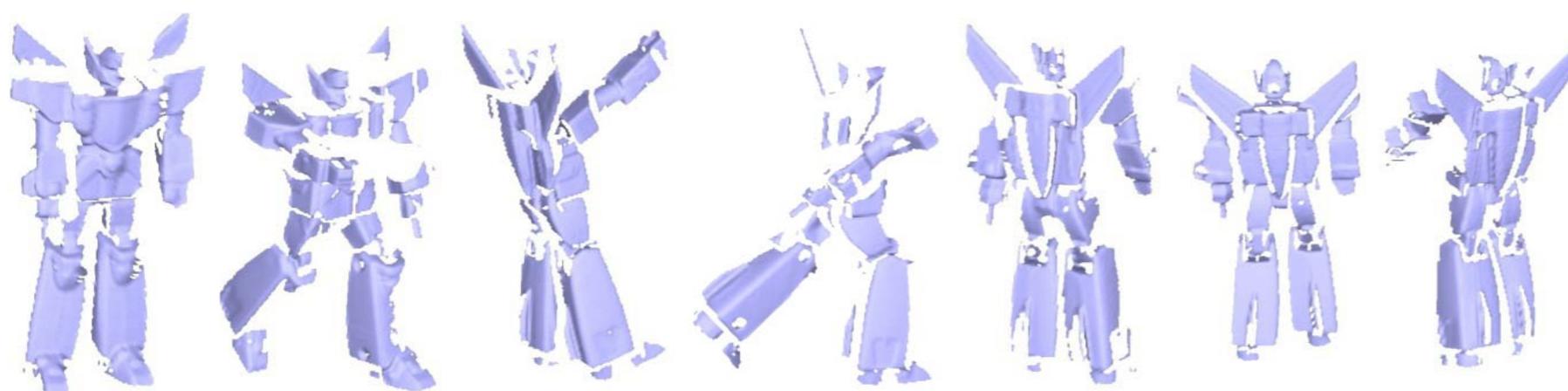
Input Range Scans



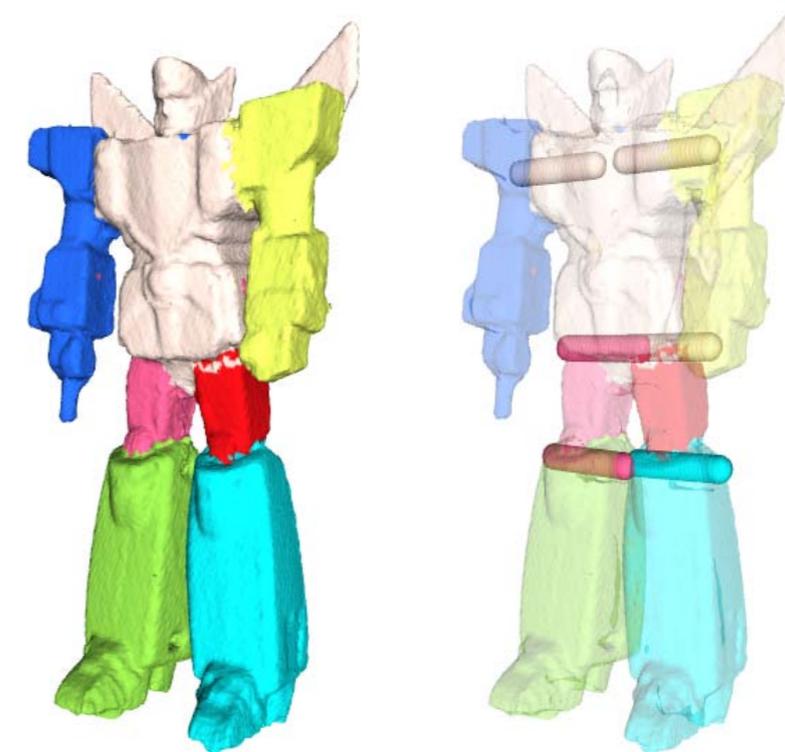
Reconstructed 3D Model

# Features

- Handles large, fast motion
- Incomplete scans (holes, missing data)
- 1 or 2 simultaneous viewpoints
- Optimization is over all scans



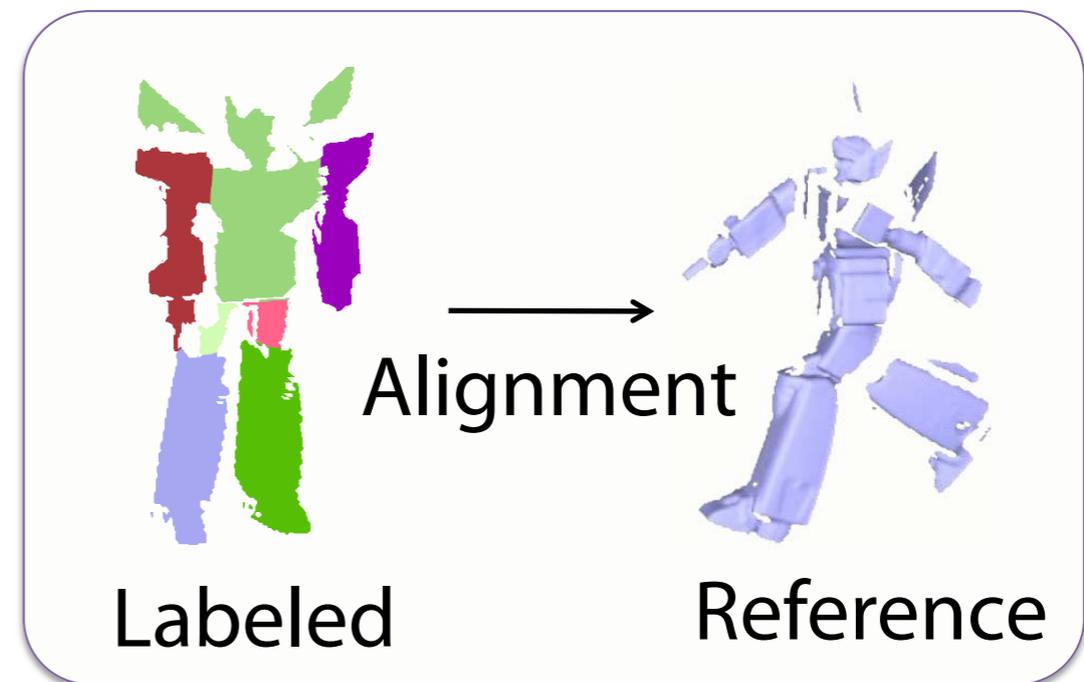
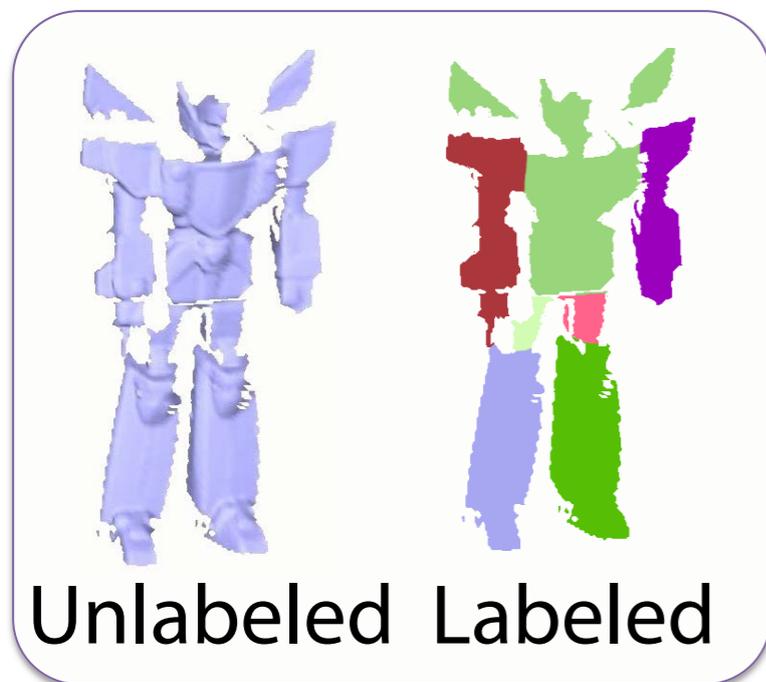
Input Range Scans



Reconstructed 3D Model

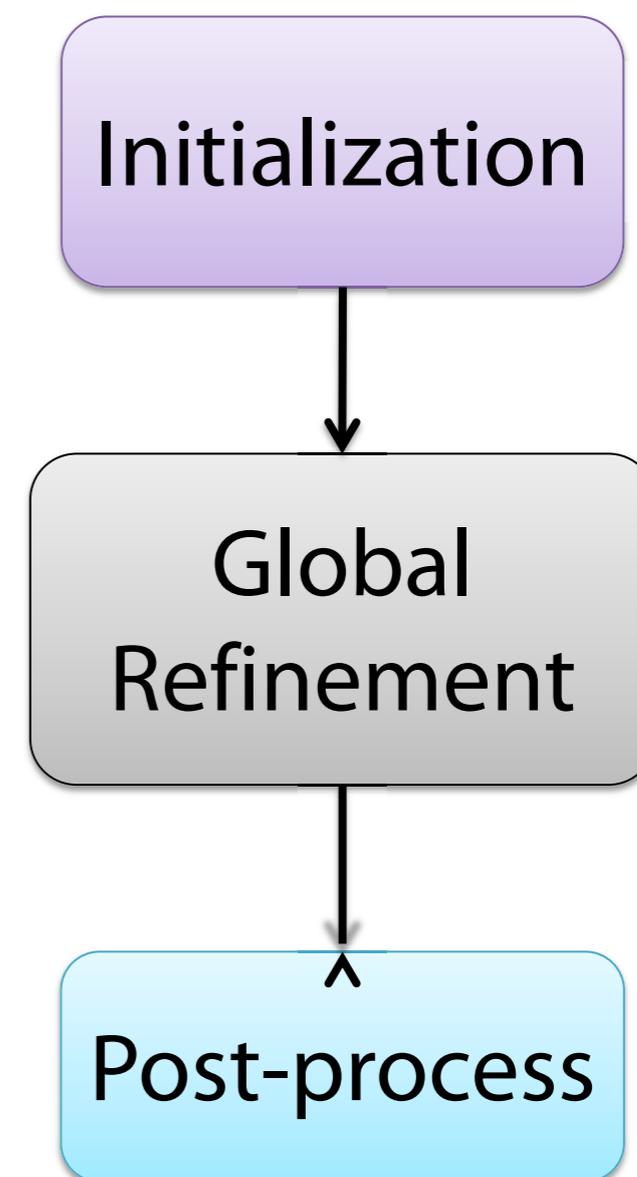
# Reconstructing Articulated Models

- **For every frame, determine**
  - **Labeling** into constituent parts (per-vertex)
  - **Motion** of each part into reference pose (per-label)
- Solve simultaneously for labels, motion, joint constraints



# Algorithm Overview

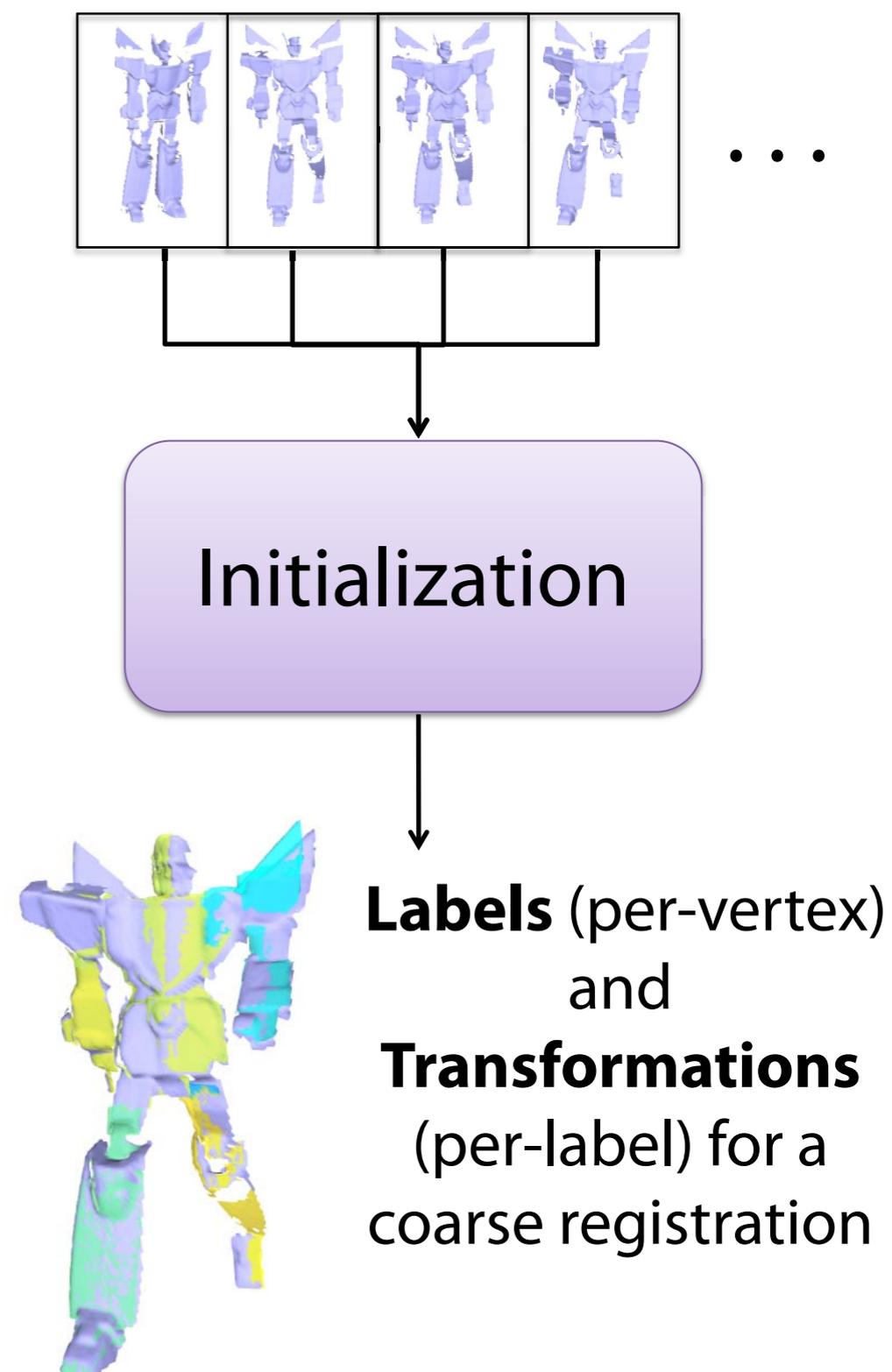
- **Initialization**
- **Global refinement**
- **Post-process**



# Algorithm Overview

## Initialization

–Coarse pairwise registration



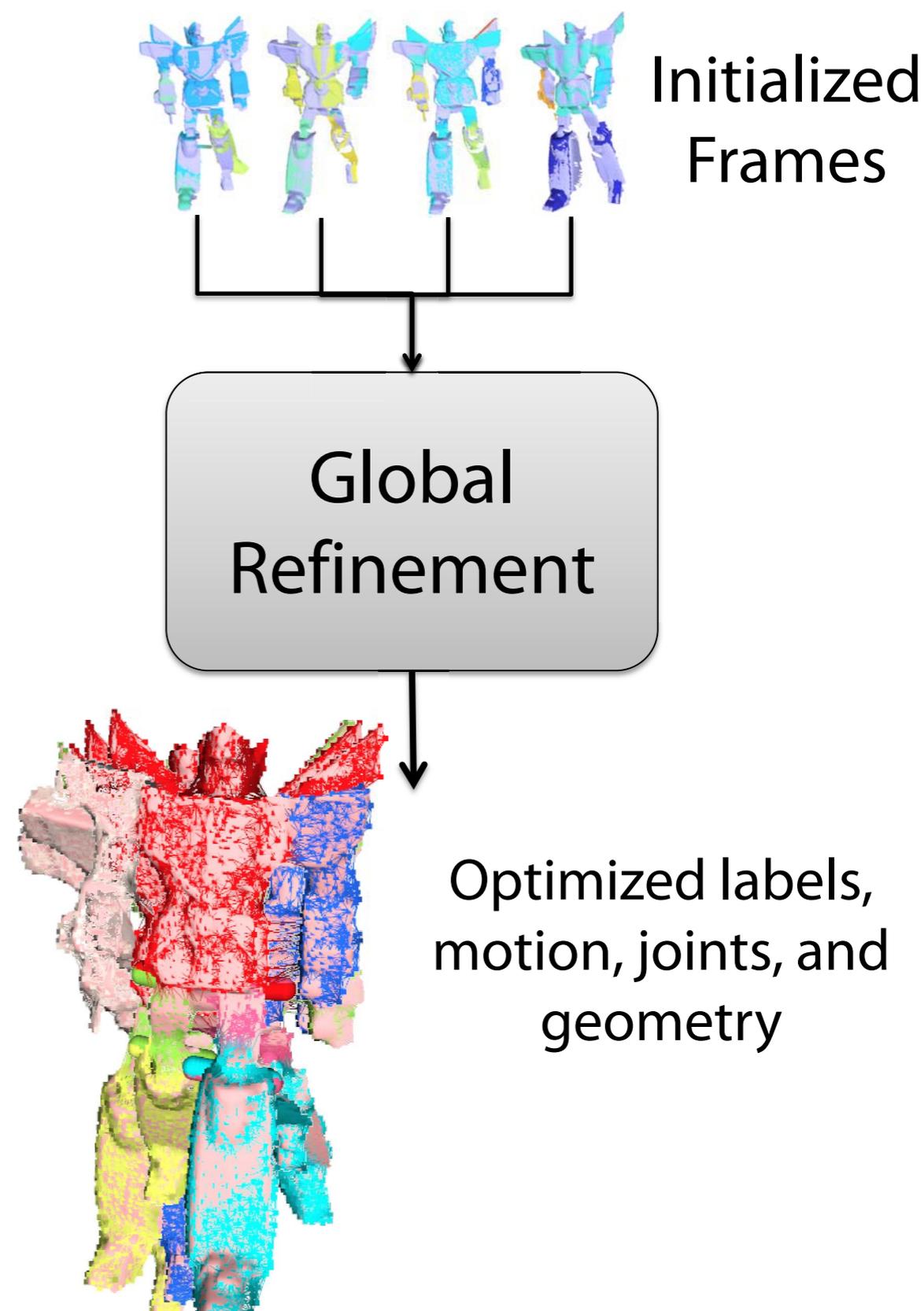
# Algorithm Overview

## Initialization

- Coarse pairwise registration

## Global refinement

- Solve global model incorporating all frames



# Algorithm Overview

## Initialization

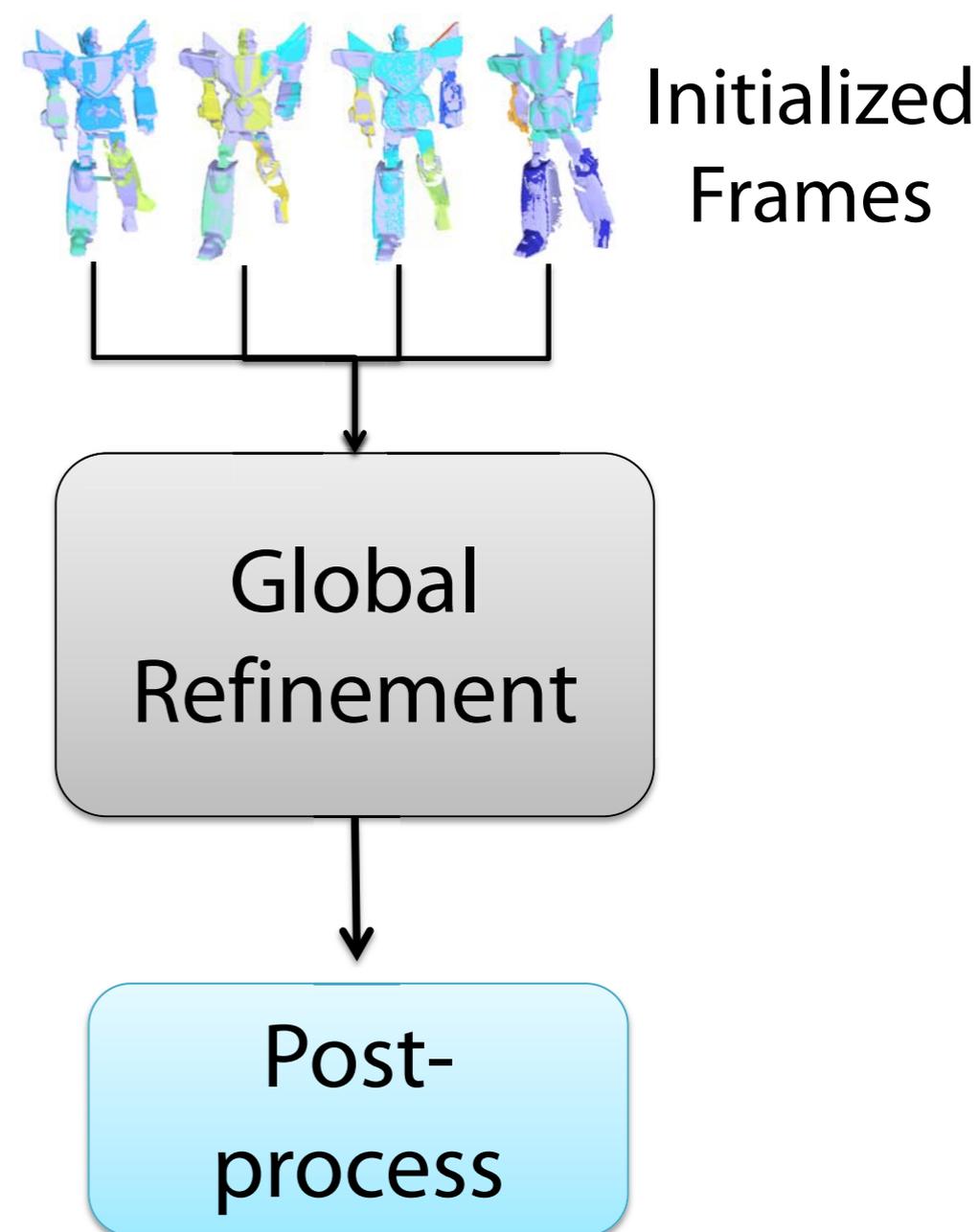
- Coarse pairwise registration

## Global refinement

- Solve global model incorporating all frames

## Post-process

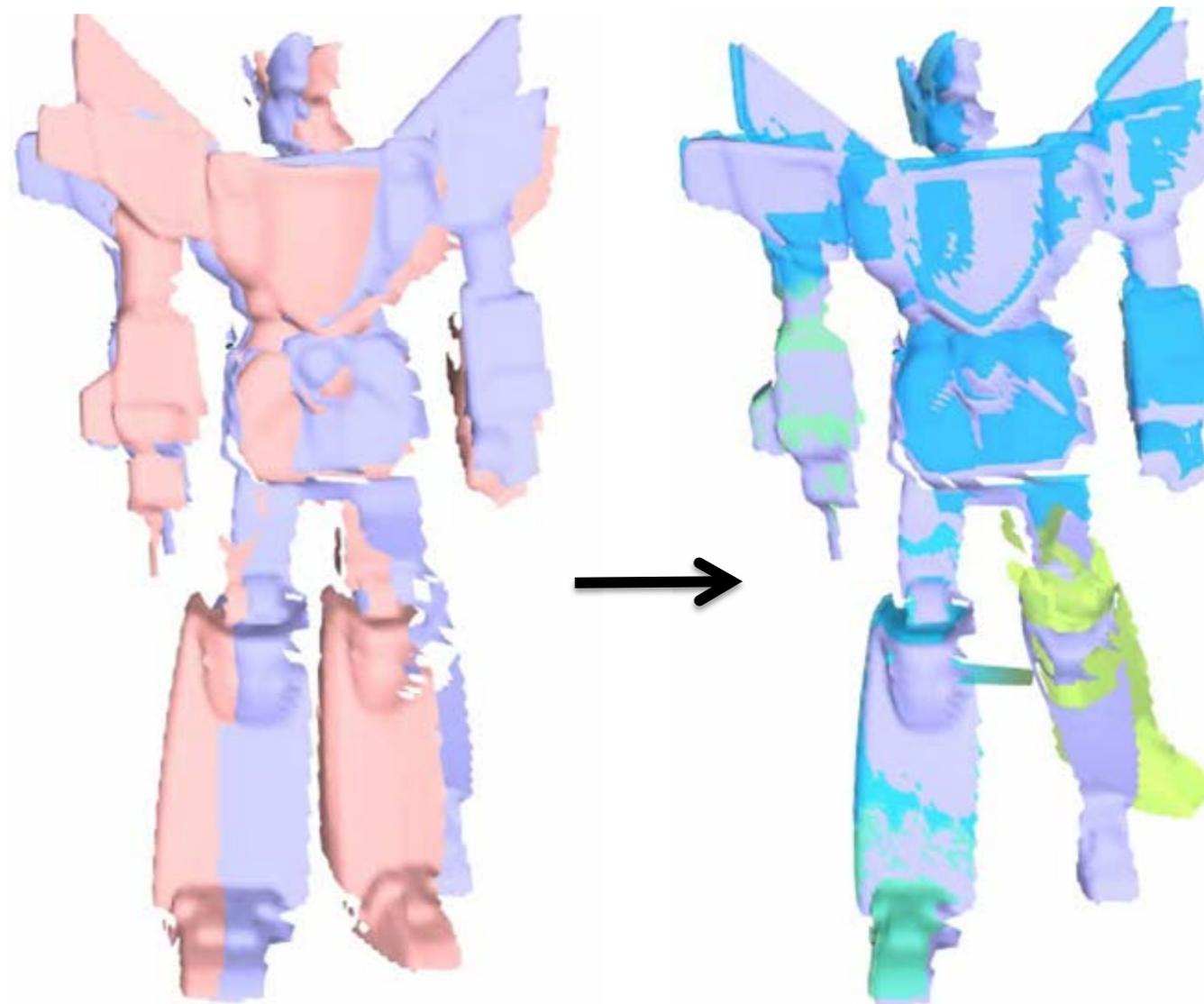
- Gather frames, reconstruct mesh



# Part I: Initialization

# Initialization

Goal: To establish initial correspondence of consecutive frames

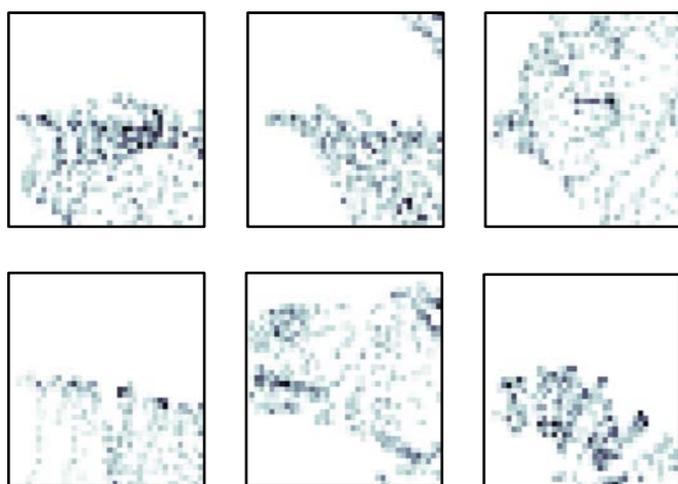


Frame  $i$  and  $i+1$

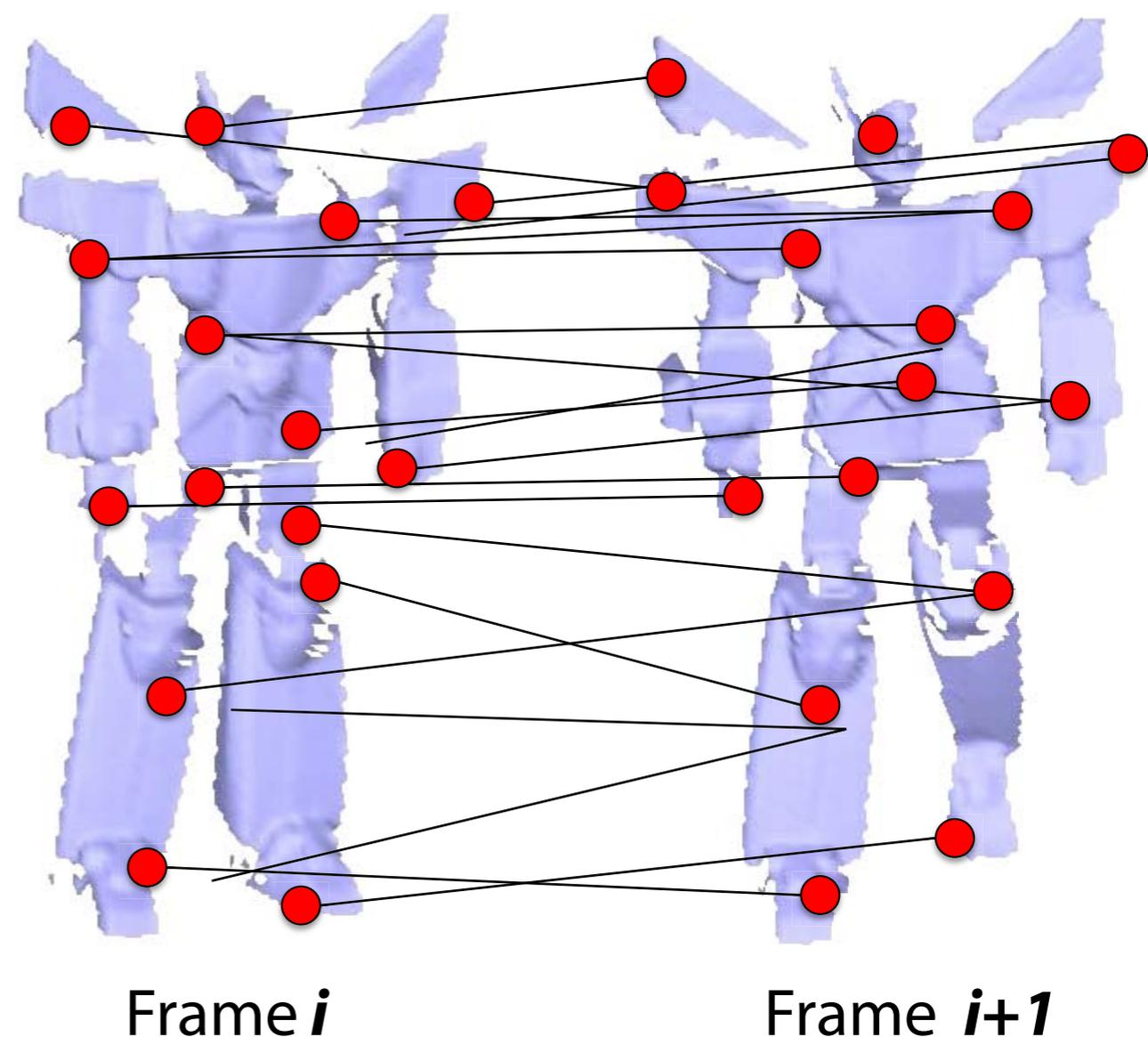
Registered Result

# Initialization

## 1. Point correspondence using feature descriptors

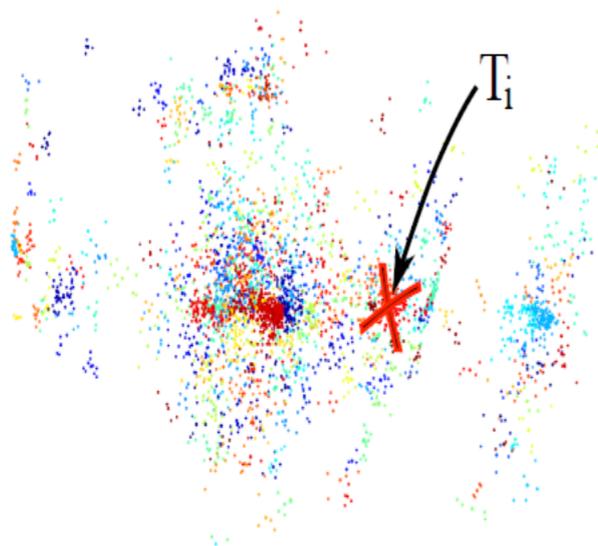


Spin Image examples

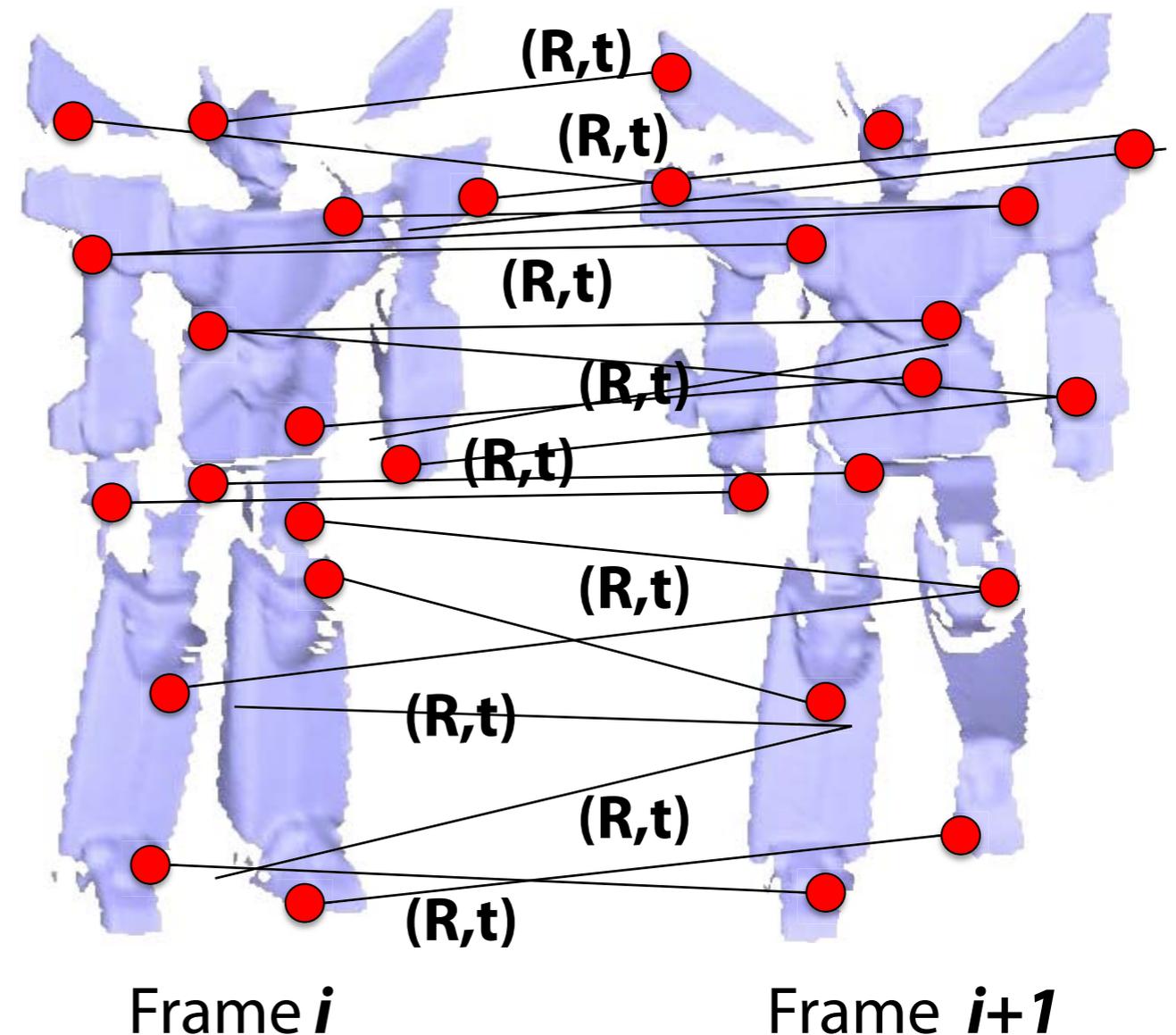


# Initialization

1. Point correspondence using feature descriptors
2. Transformation  $(R,t)$  per correspondence
3. Cluster  $(R,t)$



Transformation Space  $se(3)$

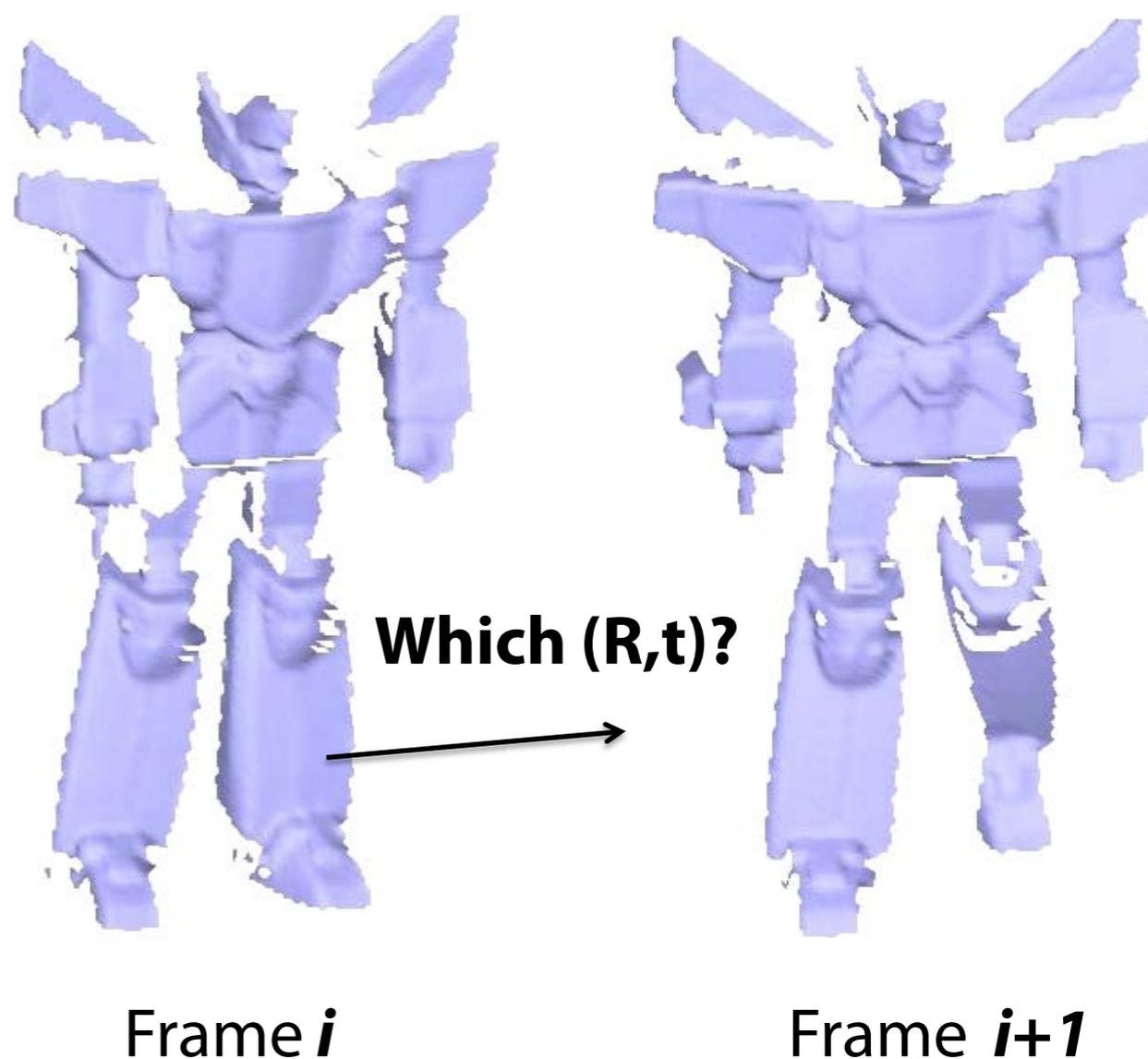


Frame  $i$

Frame  $i+1$

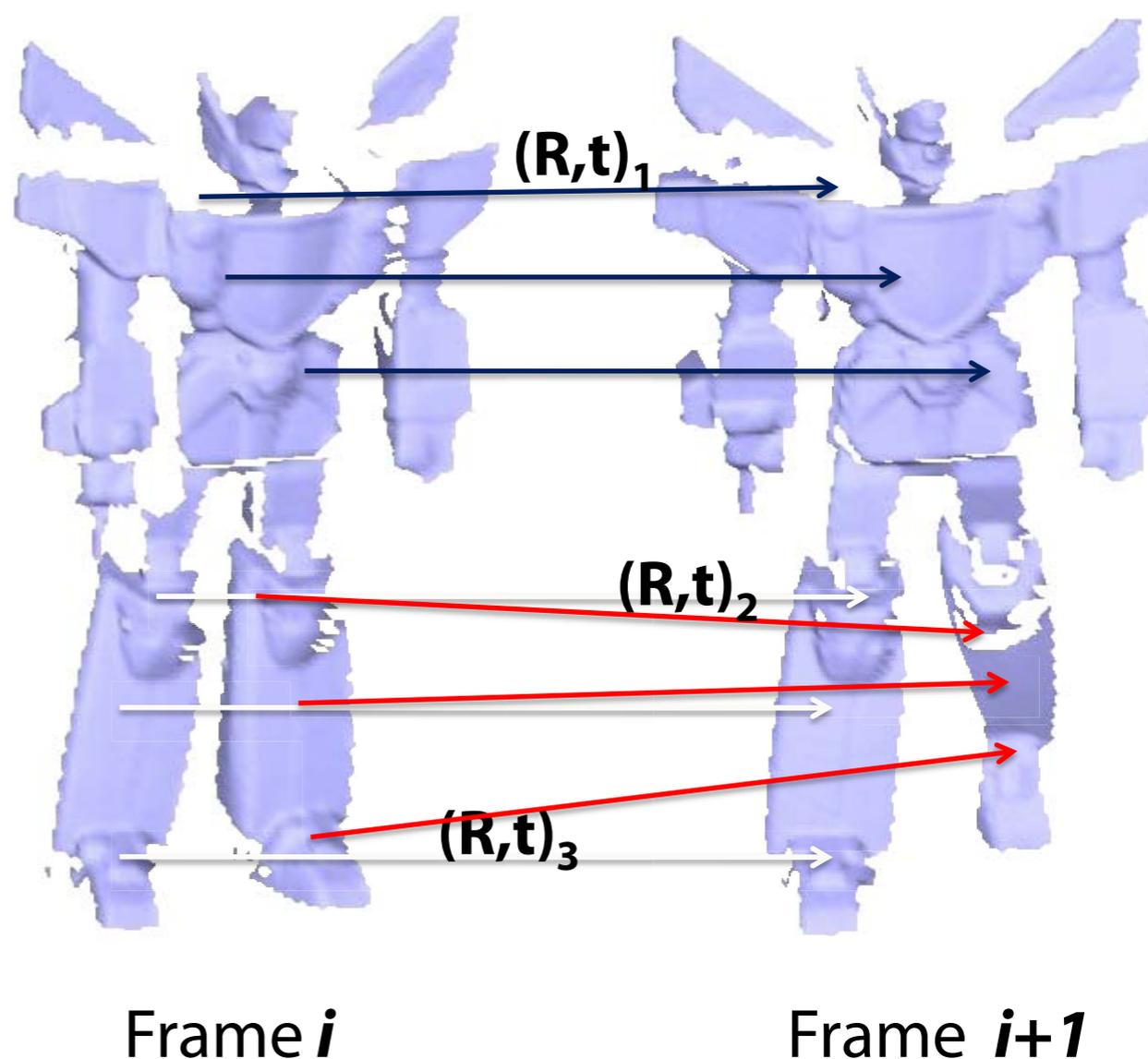
# Initialization

1. Point correspondence using feature descriptors
2. Transformation  $(R,t)$  per correspondence
3. Cluster  $(R,t)$
4. Optimize using "Graph Cuts" [Boykov et al. 2001]



# Initialization

1. Point correspondence using feature descriptors
2. Transformation  $(R,t)$  per correspondence
3. Cluster  $(R,t)$
4. Optimize using "Graph Cuts" [Boykov et al. 2001]



Frame  $i$

Frame  $i+1$

# Initialization Result



Both Frames



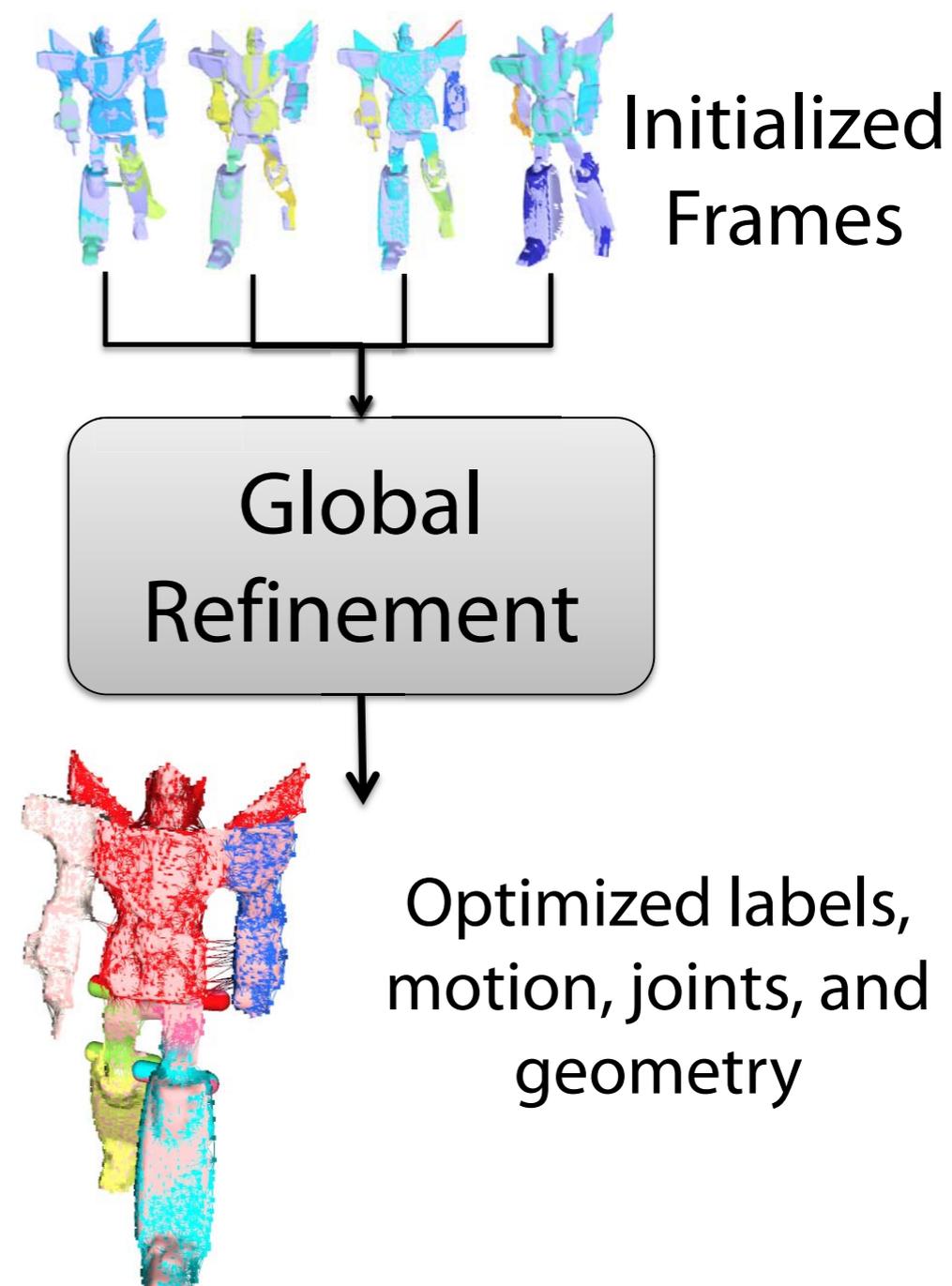
Registered Result

# Part II: Global Refinement

# Global Refinement

## Global refinement

- Solve global model incorporating all frames



# Dynamic Sample Graph (DSG)

## Sparse representation

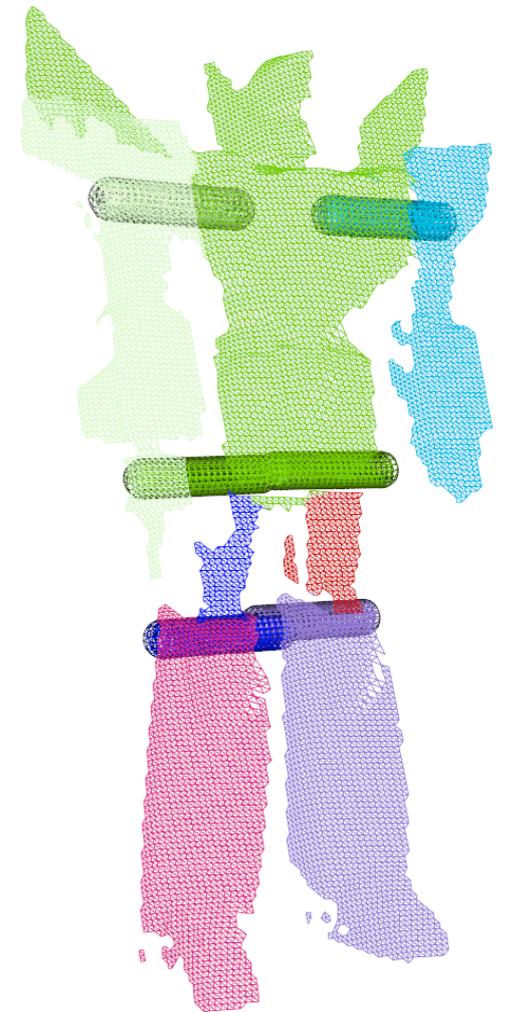
- Increases efficiency
- Joints: part connectivity

## Continuously updating

- Update samples from new surface data



Dynamic Sample Graph (DSG)



Extracted Joints

# Global Refinement

**Fit the DSG to all scans simultaneously (Global Fit)**

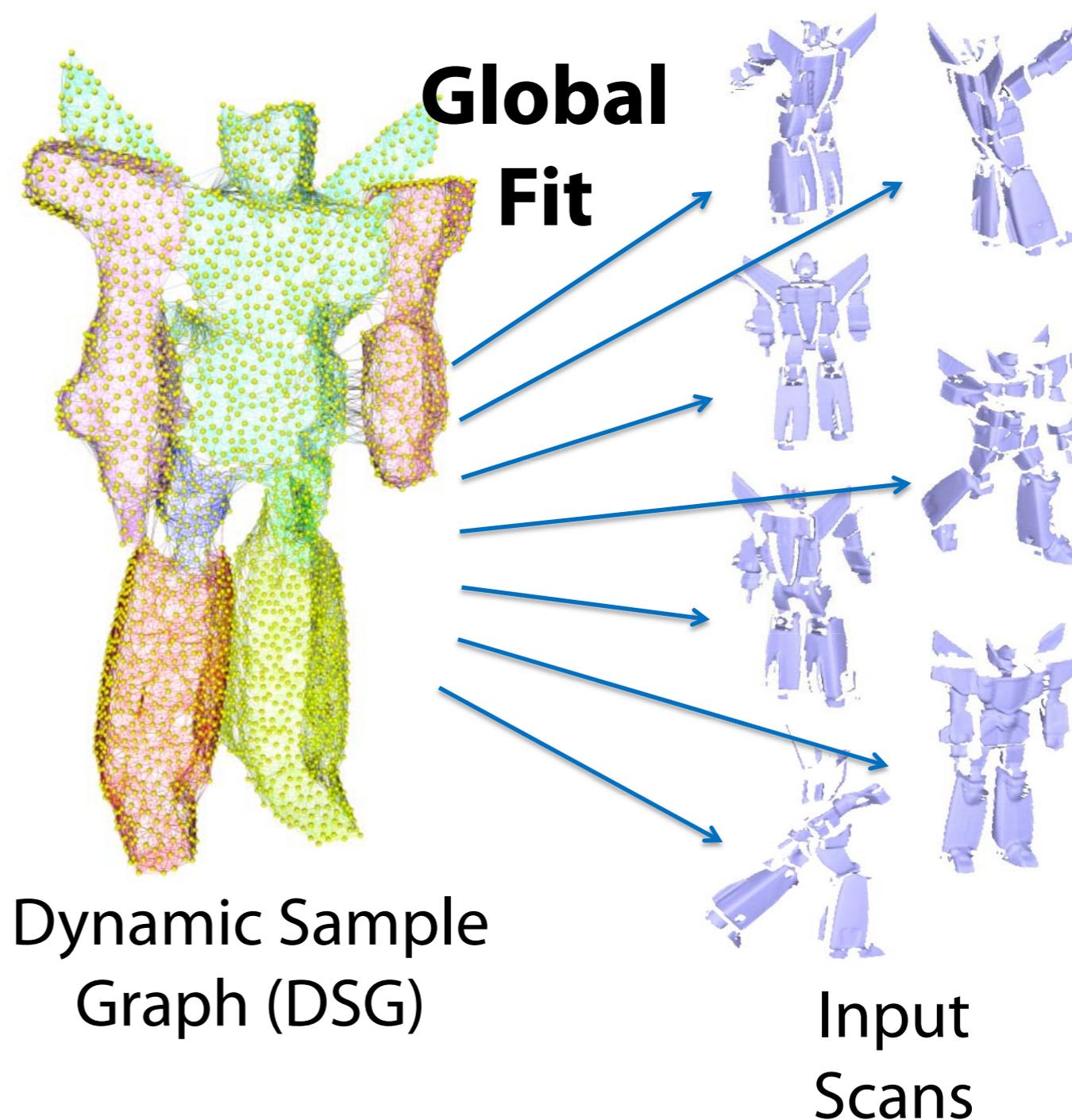
**Alternating Optimization**

1. Optimize Transformations
2. Optimize Labels
3. Update joint locations

**Repeat until convergence**

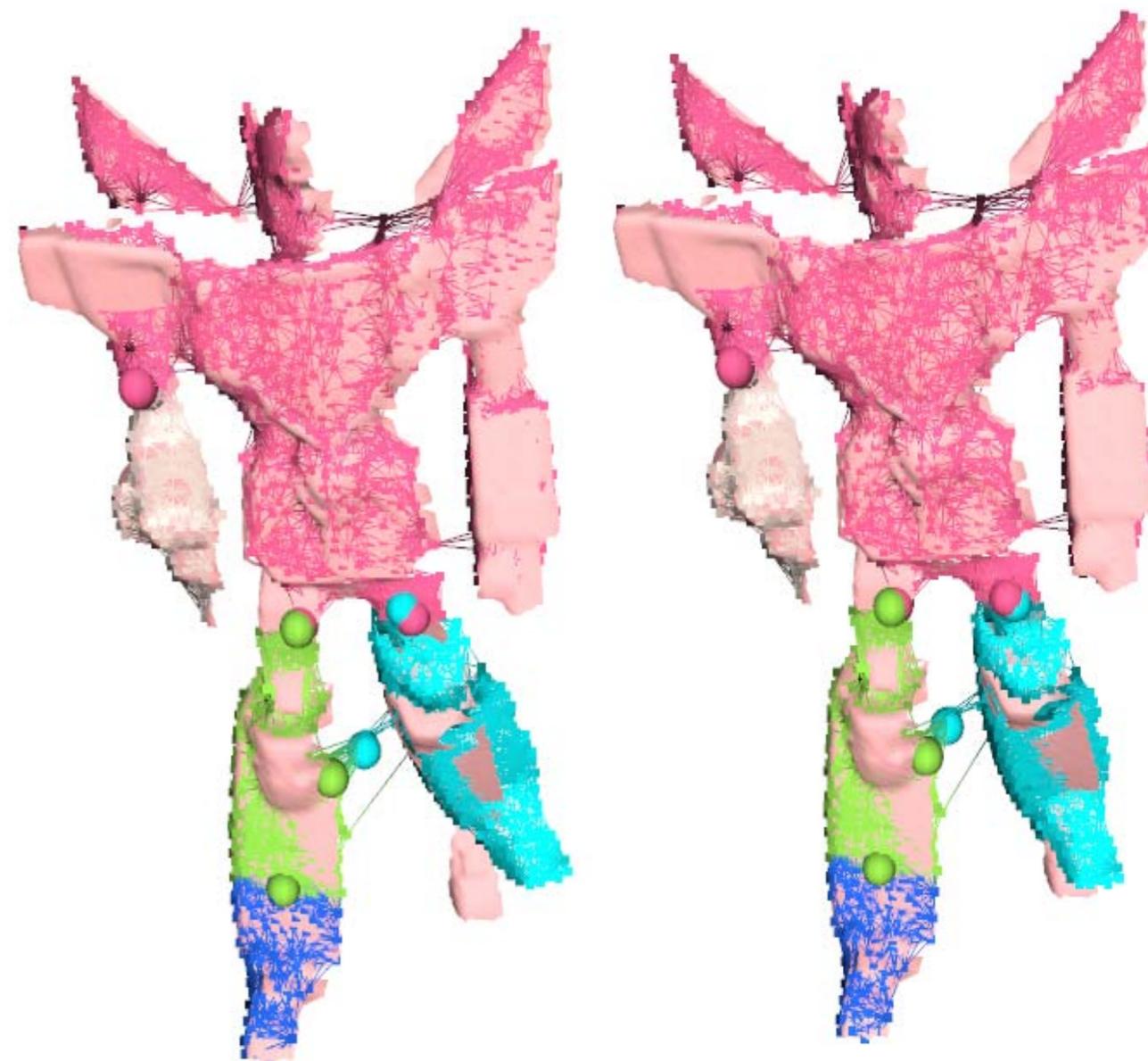
- 3-5 iterations/frame

**Update samples**



# Transformation Optimization

- Align DSG as closely as possible to all scans
- Labels fixed
- Measure alignment using closest point distance



Before

After

# Transformation Optimization

- Multi-part, multi-frame articulated Iterative Closest Point (ICP)
  - Update closest point
  - Solve for transformation
  - Repeat until convergence
- Gauss-Newton for non-linear least squares



(Converged)

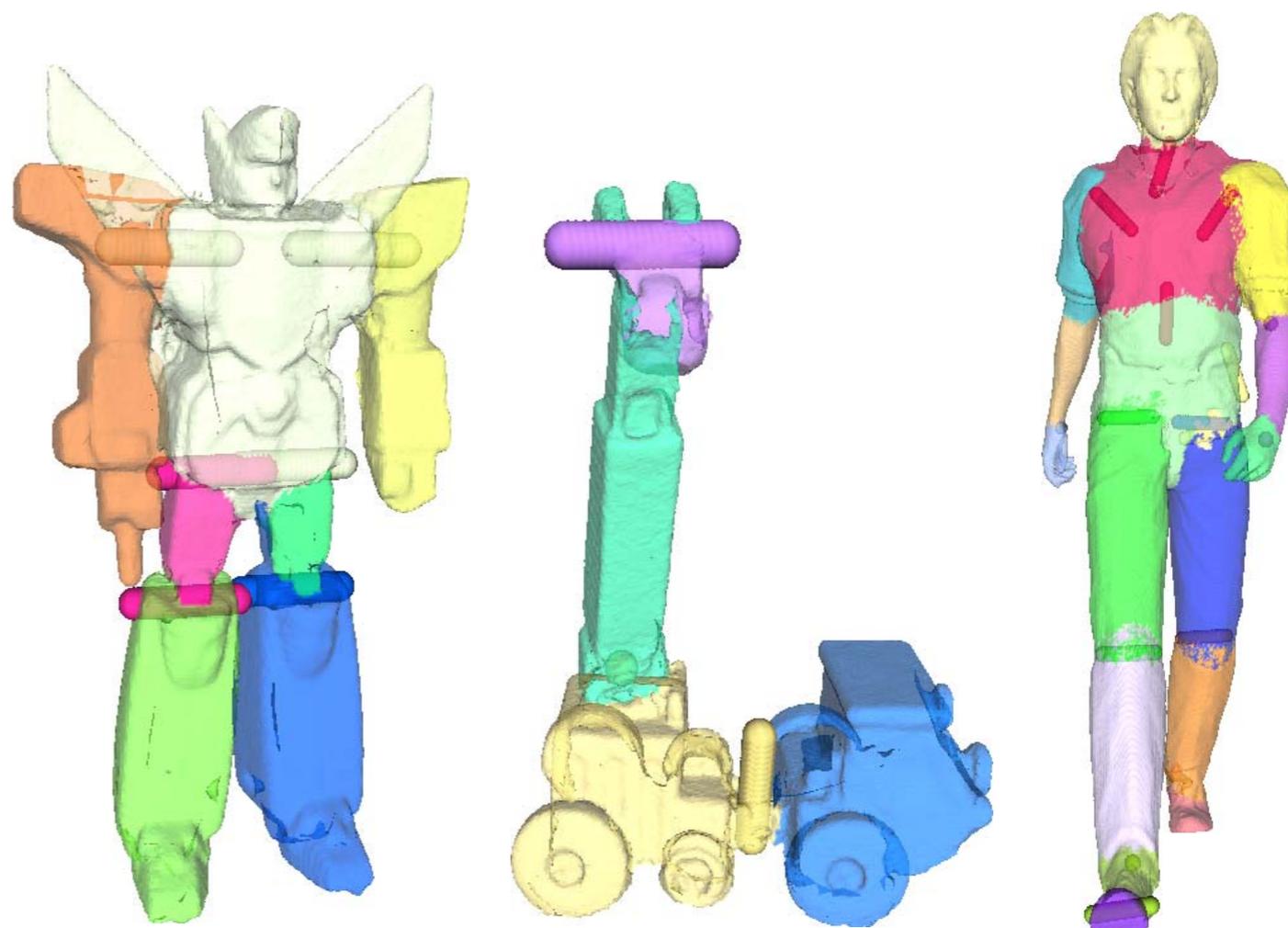
# Joint Constraint

**Prevents parts from separating**

**Two types of joints**

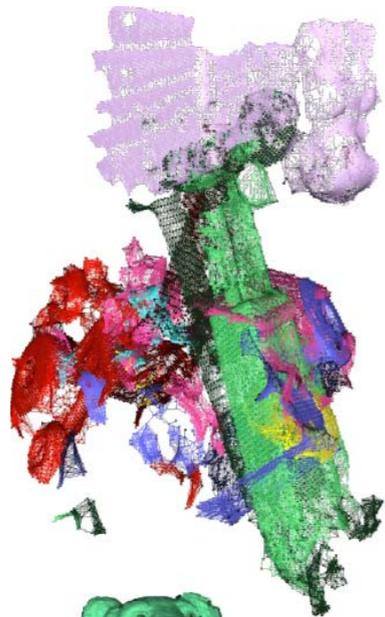
- Ball Joints (3 DOF)
- Hinge Joints (1 DOF)

**Derived from part boundaries & transformations solved so far**

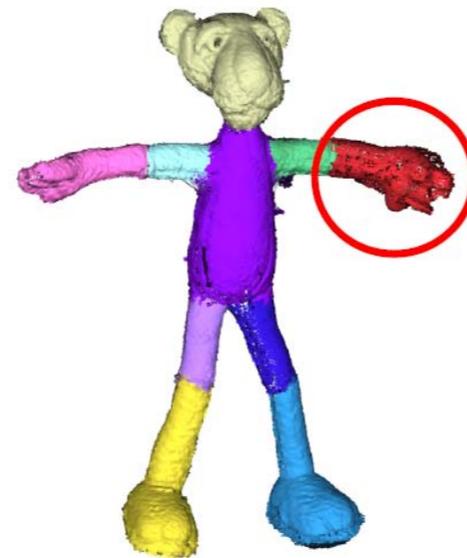
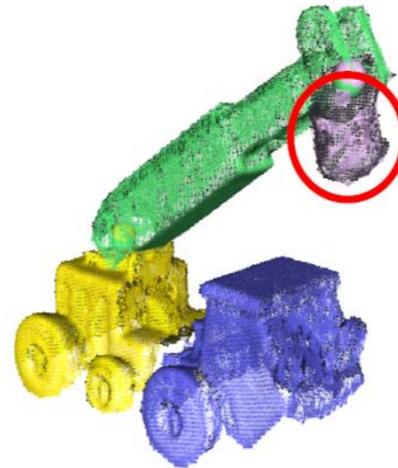


Reconstructed  
Joints

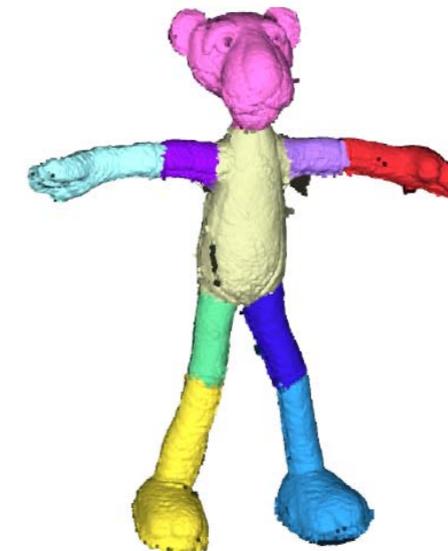
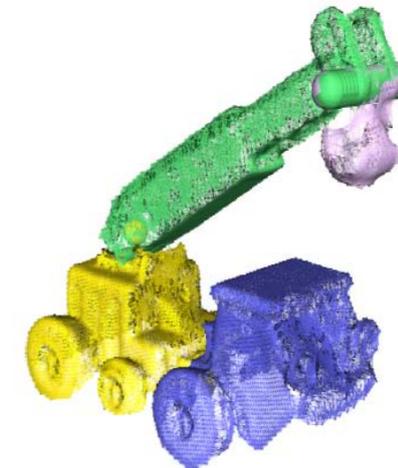
# Joint Constraint



No Joints



Ball Joints  
Only



Ball and  
Hinge Joints

# Label Optimization

- Change the labels to produce better alignment
- Transformations fixed
- Measure alignment using closest point distance

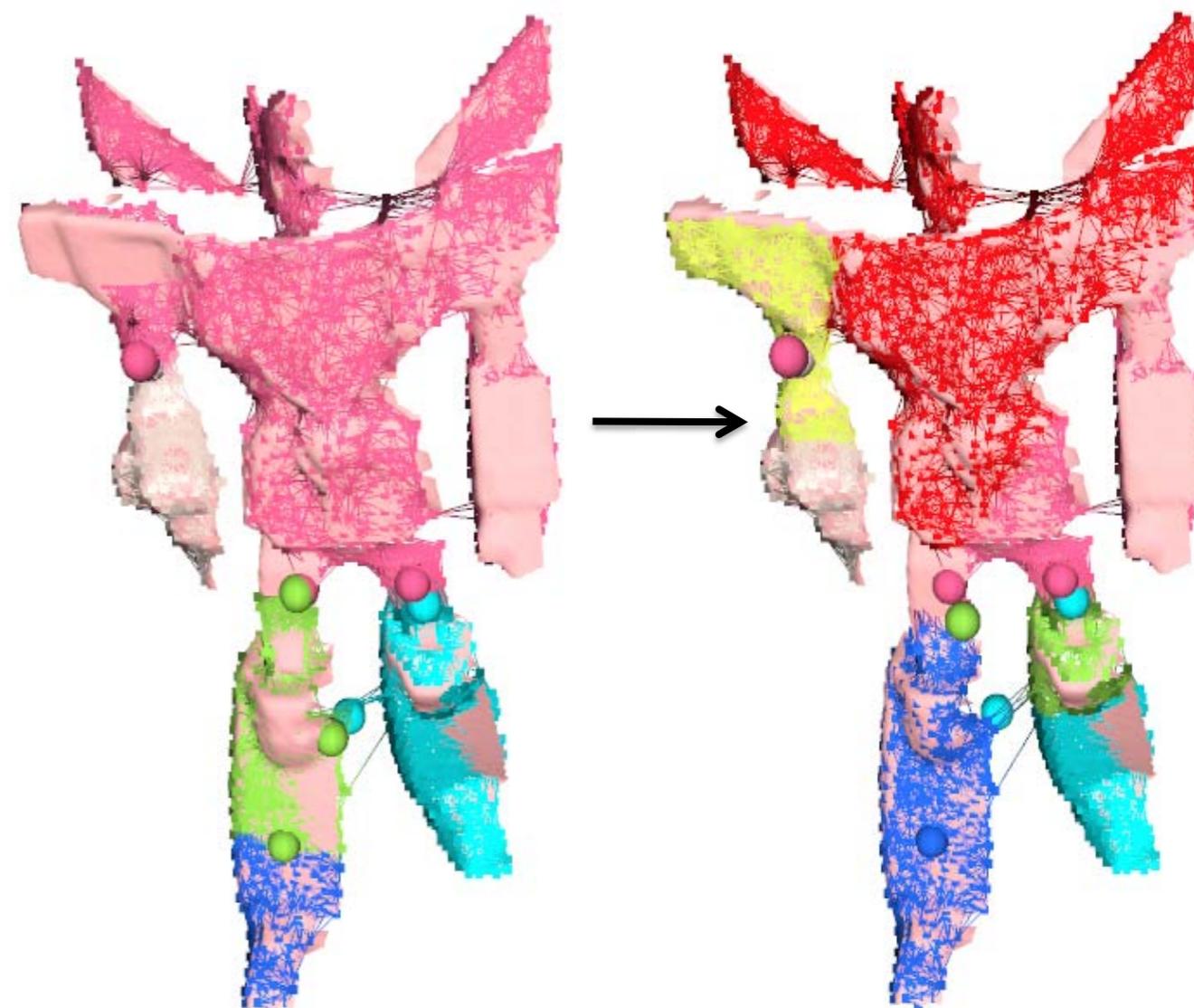


Before

After

# Label Optimization

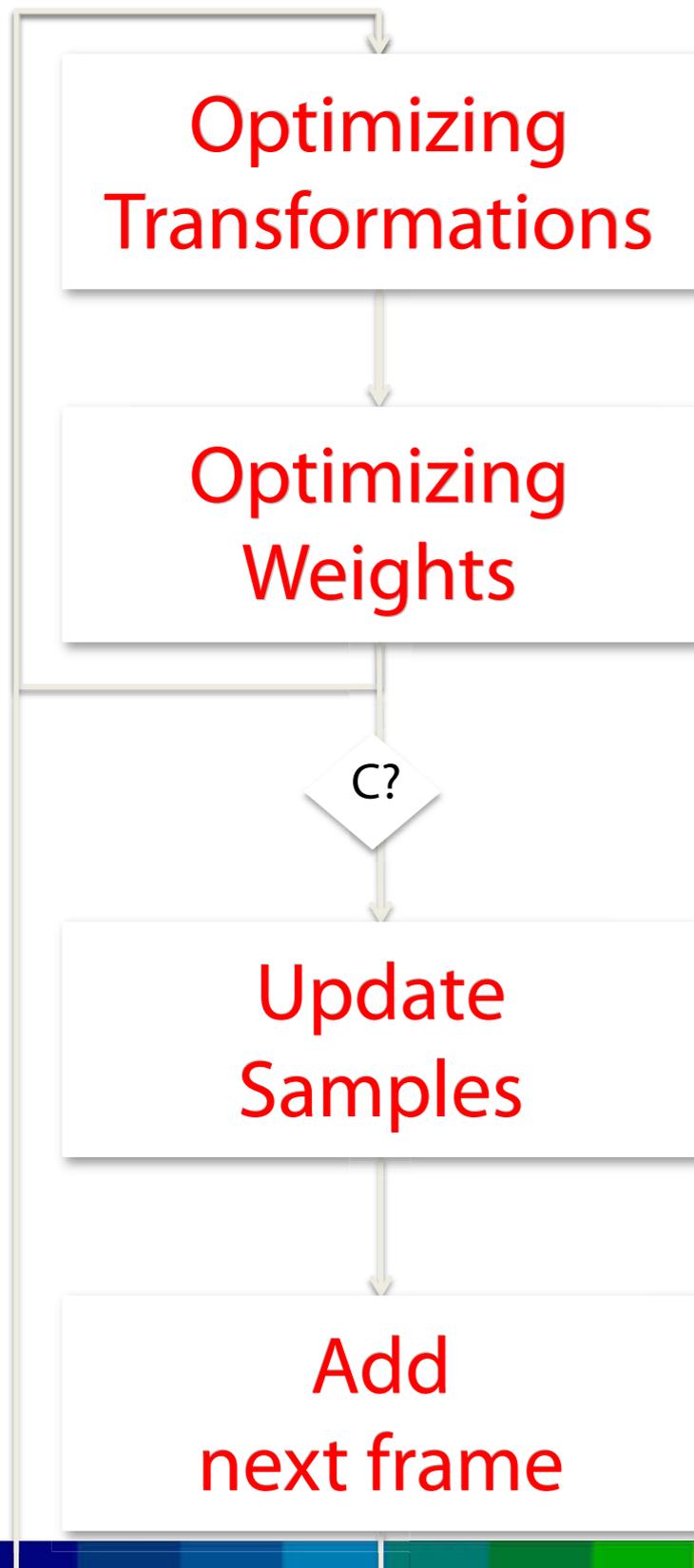
- **Graph Cuts [Boykov et al. 2002]**
  - Data constraint: minimize distance
  - Smoothness constraint: consolidate labels



Before

After

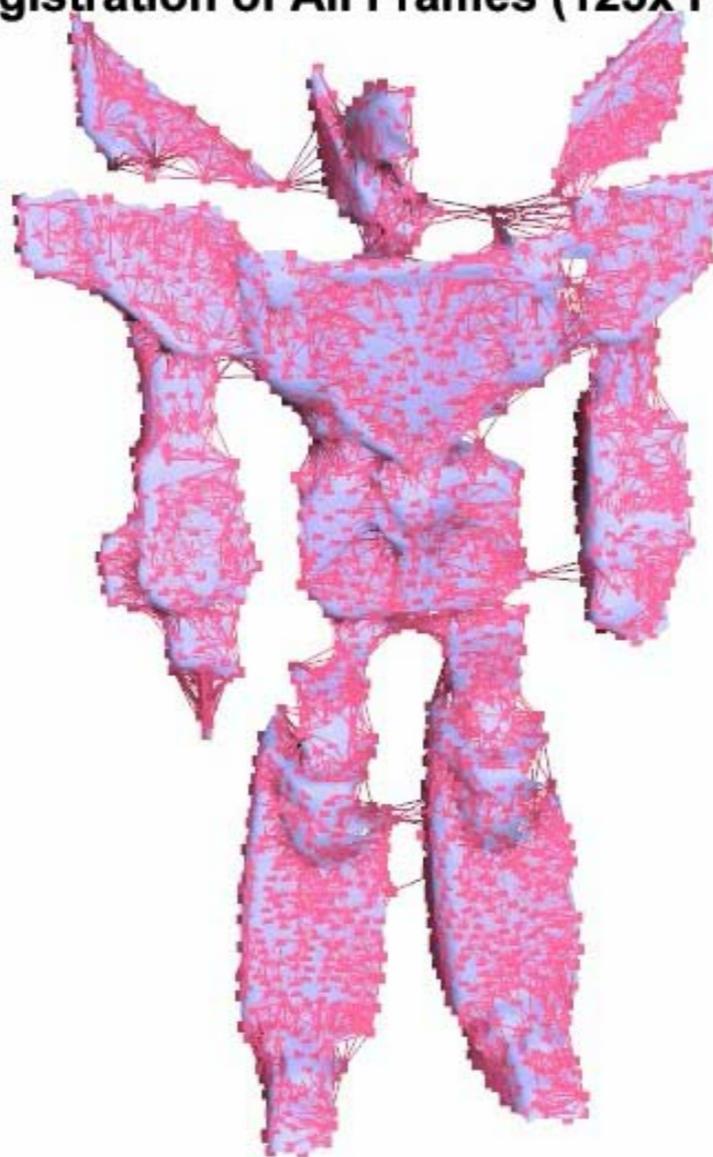
# Global Refinement: Step Through



(Converged)

# Global Refinement: Fast Forward

Simultaneous Registration of All Frames (125x Fast Forward)



Idle

# Post-processing

- Gather all frames into reference pose
- Resample surface, reconstruct mesh



# Results

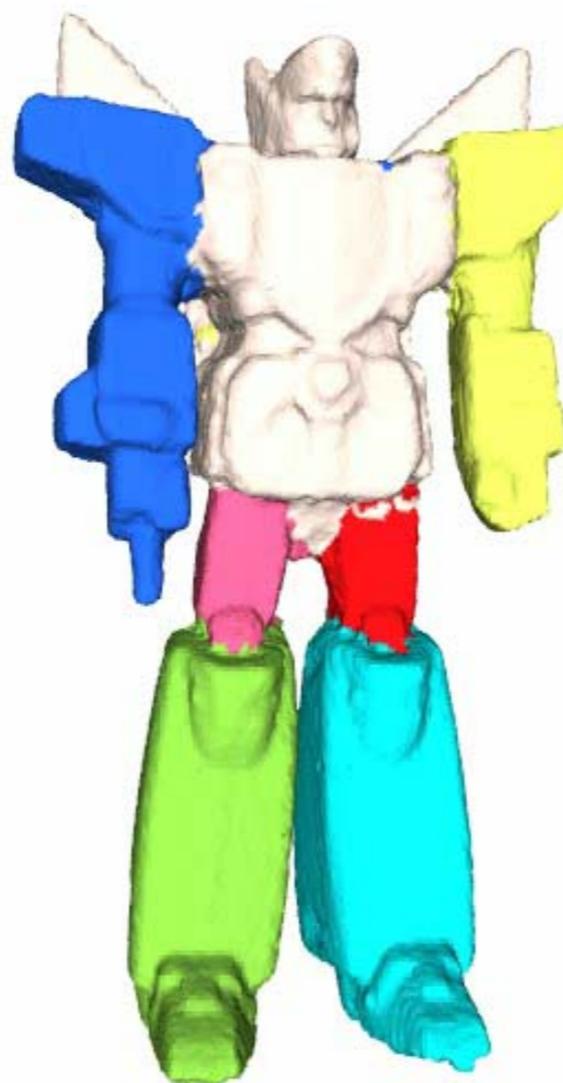
# Results: Registration

Frame 0

Robot Model



Input Range Scans



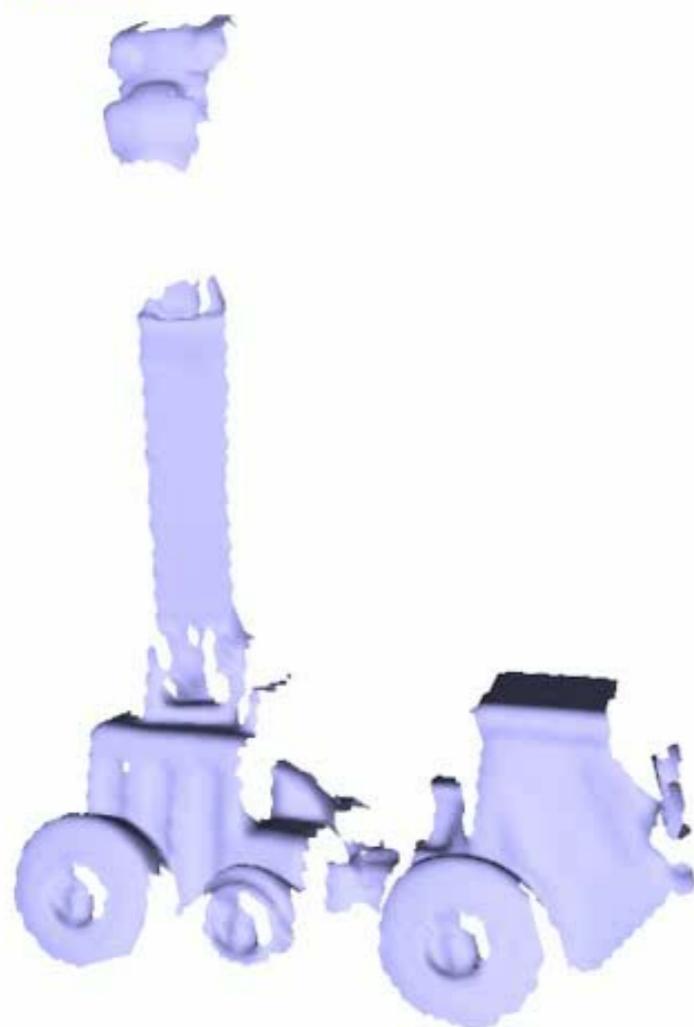
Reconstructed Model

- Intel Xeon 2.5 GHz
- 90 Frames
- 7 Parts
- 0.84 million points
- 5000 DSG samples
- Total 165 mins
- 110 sec/frame

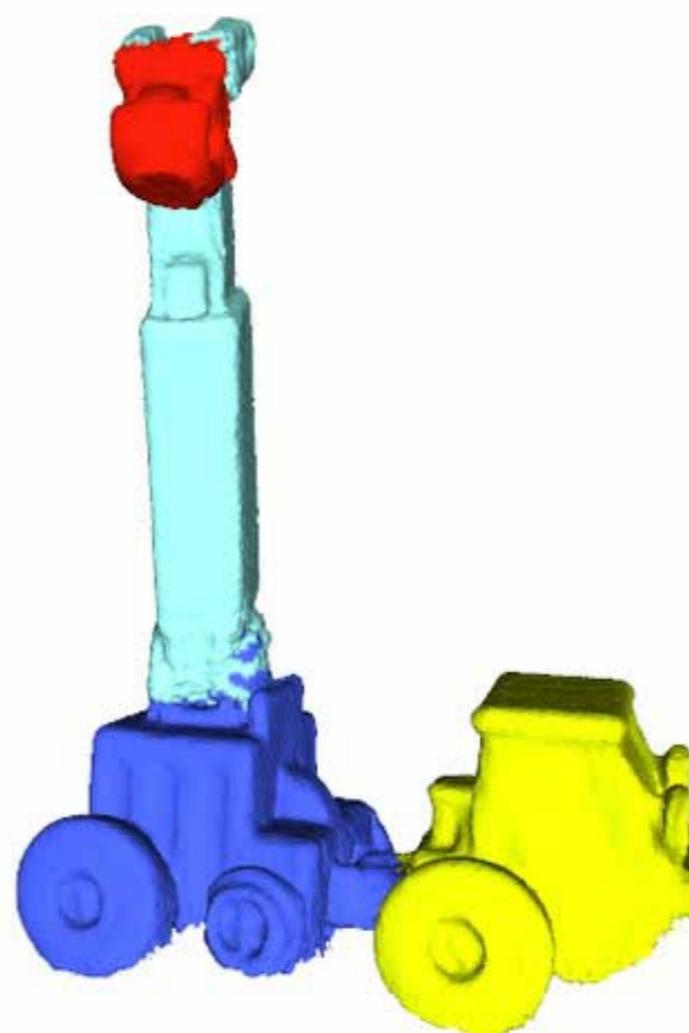
# Results: Registration

## Car Dataset

Frame 0



Input Range Scans



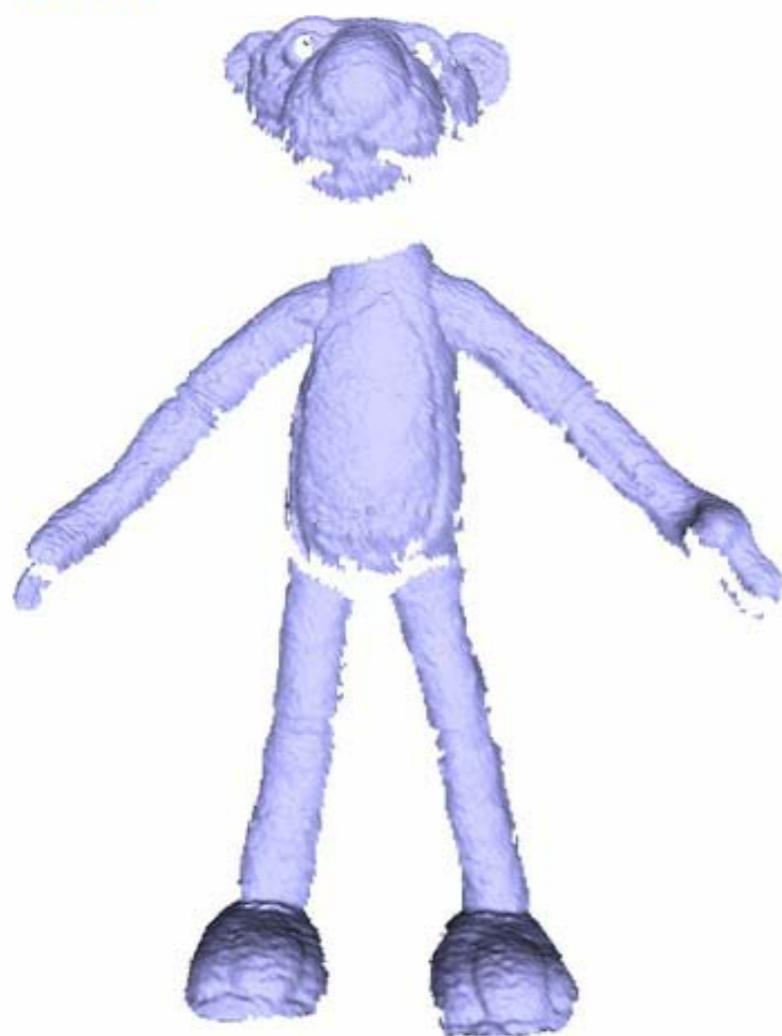
Reconstructed Model

- Intel Xeon 2.5 GHz
- 90 Frames
- 4 Parts
- 0.48 million points
- 2700 DSG samples
- Total 66 mins
- 44 sec/frame

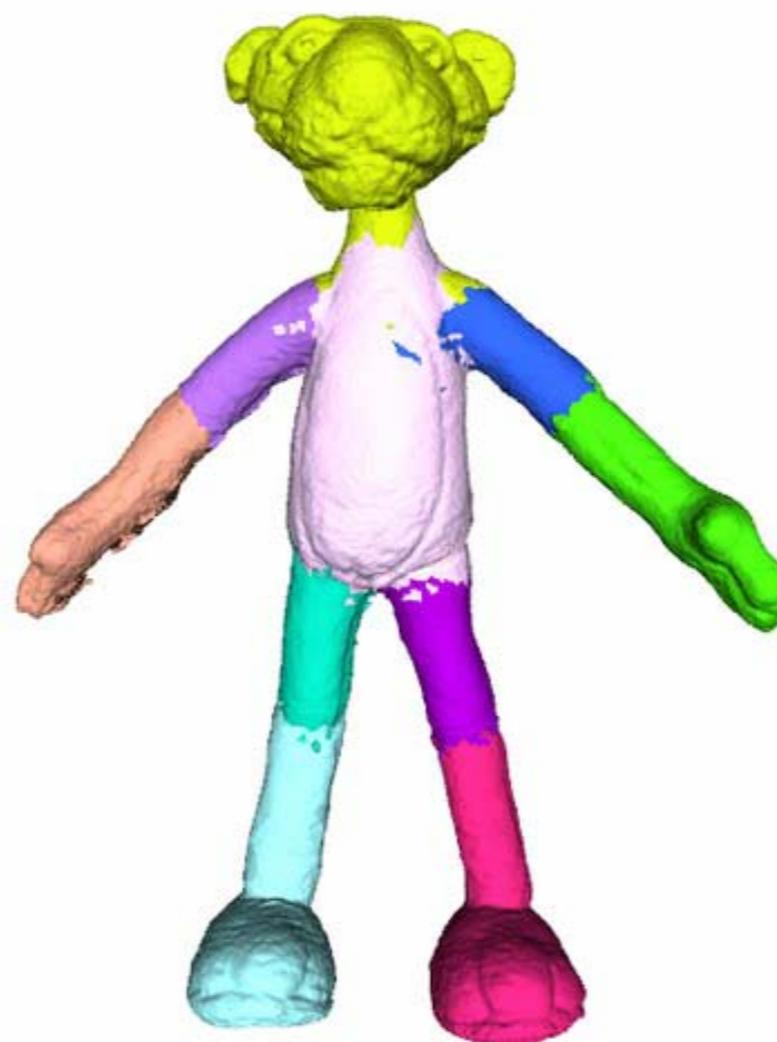
# Results: Registration

Frame 0

Pink Panther (Faster Input Motion)



Input Range Scans



Reconstructed Model

- Intel Xeon 2.5 GHz
- 40 Frames
- 10 Parts
- 2.4 million points
- 4000 DSG samples
- Total 75 mins
- 113 sec/frame

# Ground truth comparison

Walking Man (Synthetic, 2 Cameras)

Frame 0

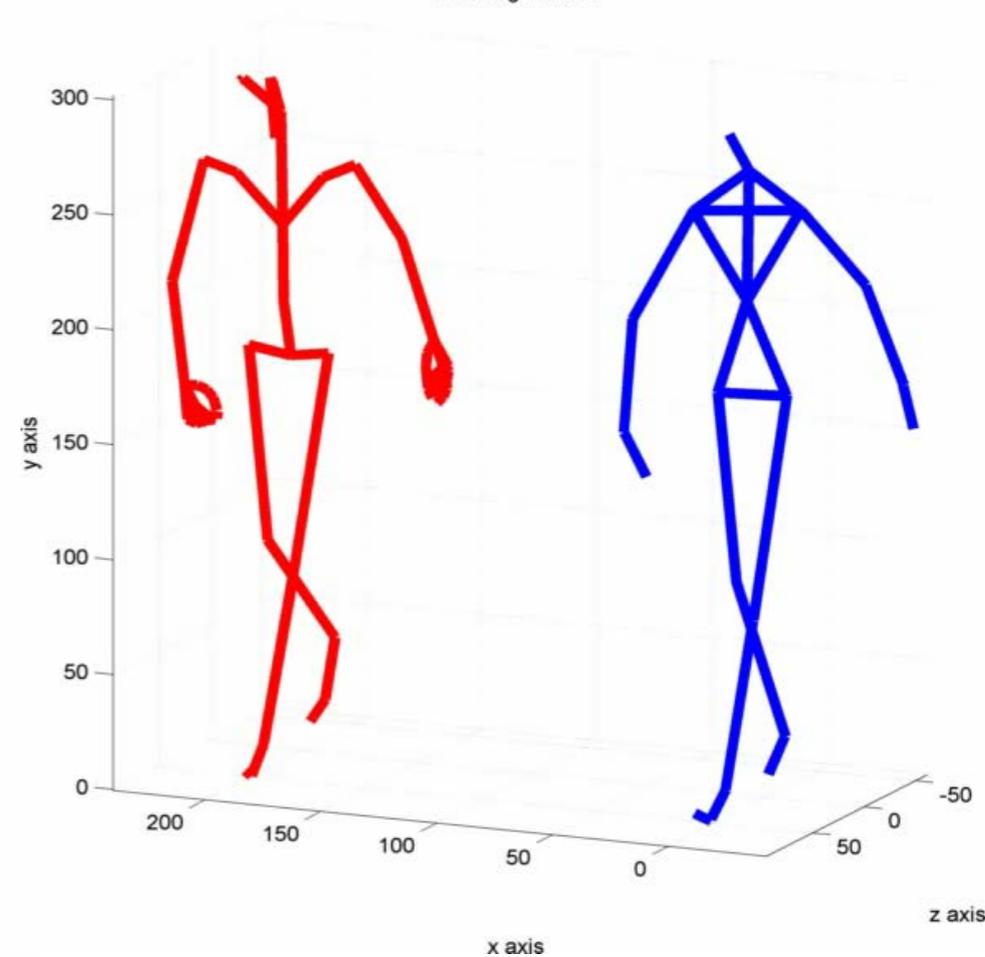


Input Range Scans



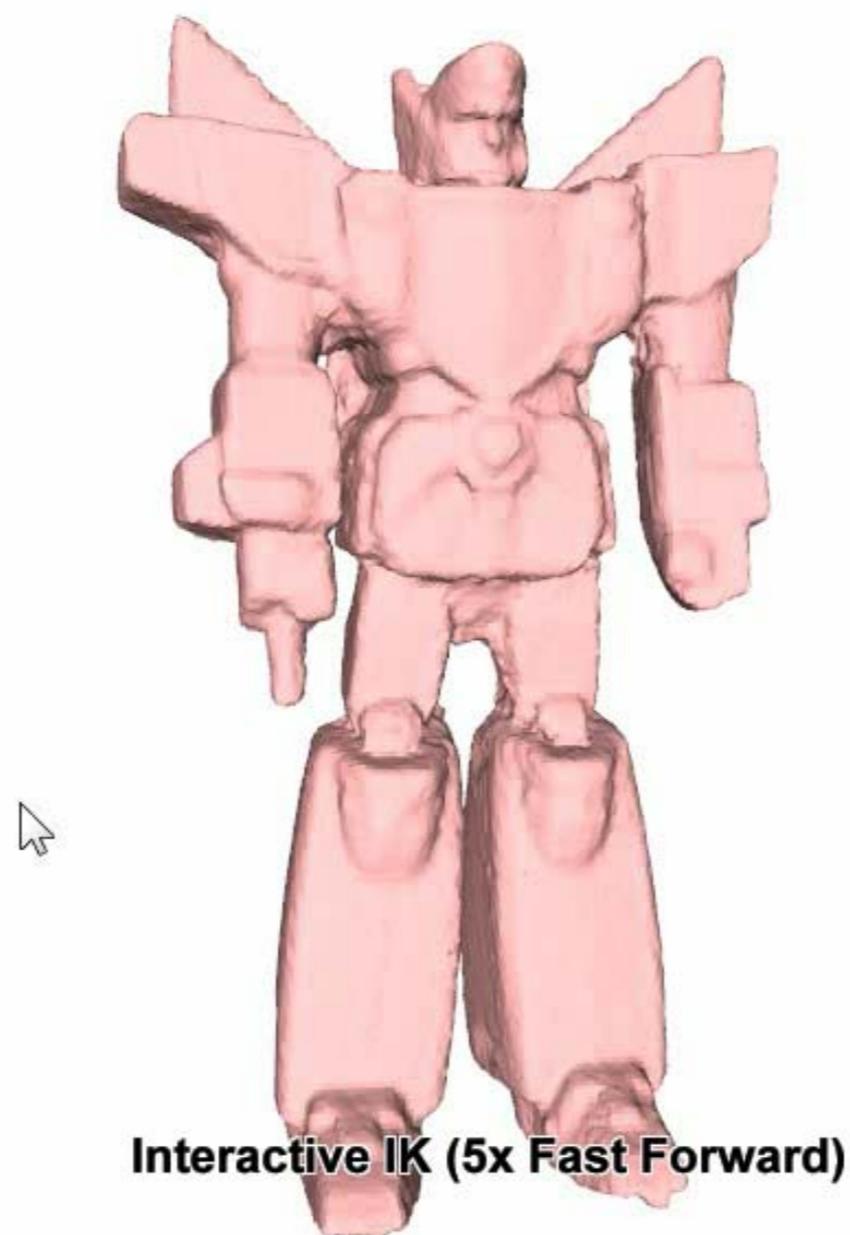
Reconstructed Model

Drawing frame 1



Red: Ground-truth  
Blue: Reconstructed

# Results: Inverse Kinematics

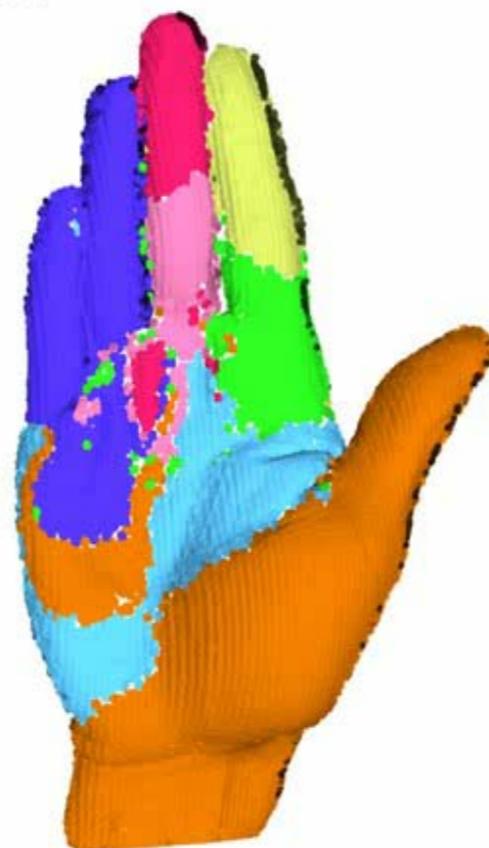


# Limitations

## Piecewise rigid approximation

Non-Rigid Datasets from Wand et al. [2009]

Frame 0



Hand-2

Frame 0



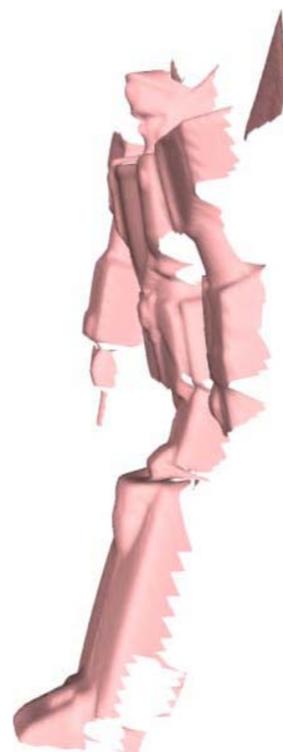
Popcorn Tin

# Limitations

Needs sufficient overlap



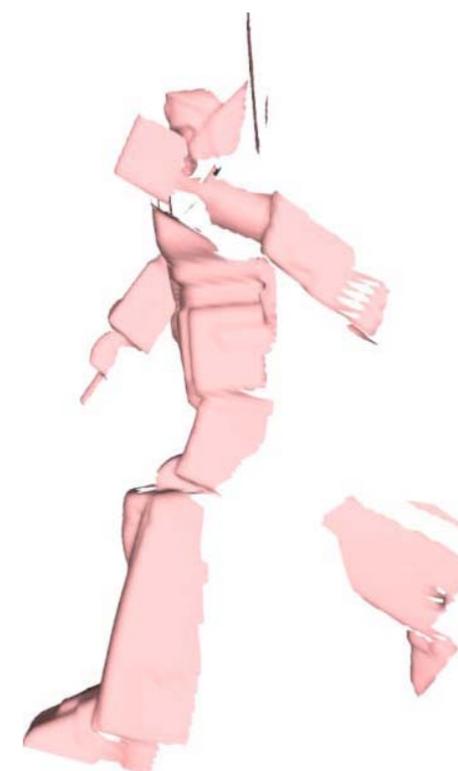
Frame  $i$



Frame  $i+1$



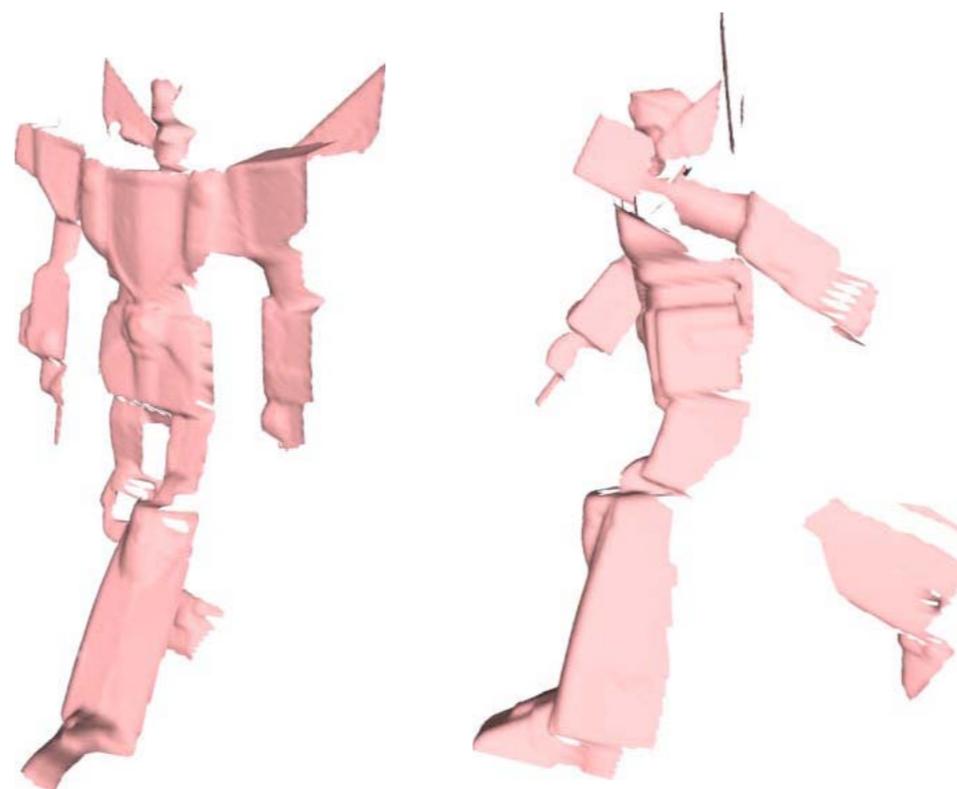
Frame  $i+2$



Frame  
 $i+3$

# Limitations

Needs sufficient overlap



Frame  $i$

Frame  $i+1$

# Articulated Global Registration

## Implementation Details

# Major Implementation Issues

## Global registration T-step

Simple outline of the essential steps

Setting up the non-linear system for optimization

## Global registration W-step

Setting up the graph-cut optimization

# The algorithm in essence

**At the end of the day:** we have a huge “database” of closest-point correspondences.

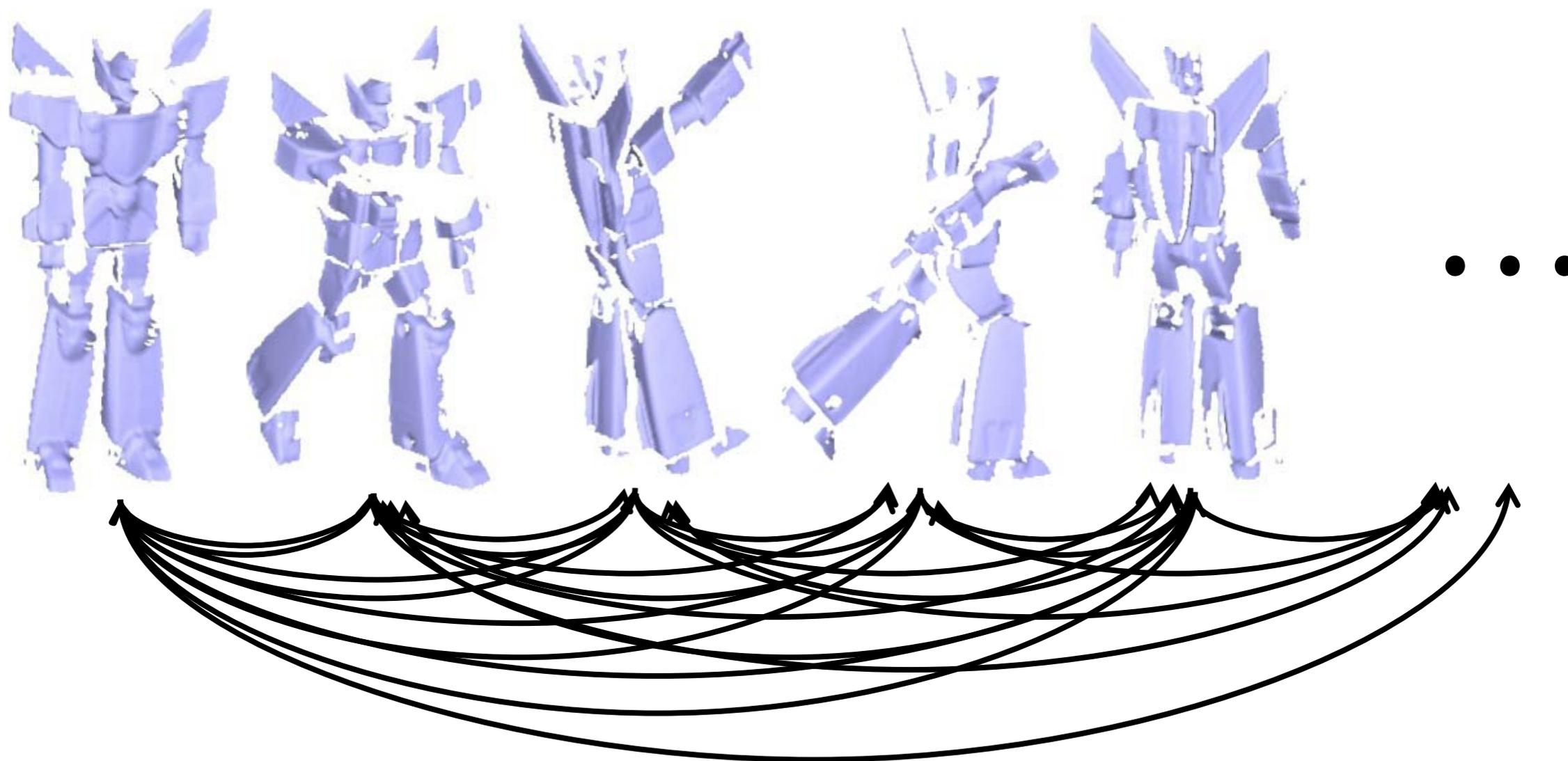
## Each correspondence has the following info:

- Source point info, including
  - Frame of origin ( $f$ )
  - Original vertex position & normal in scan ( $x, n_x$ )
  - Weight ( $w$ )
- Target point info, including
  - Frame of origin ( $g$ )
  - Original vertex position & normal in scan ( $y, n_y$ )

Always a sample from the DSG!

# Naïve method vs. DSG

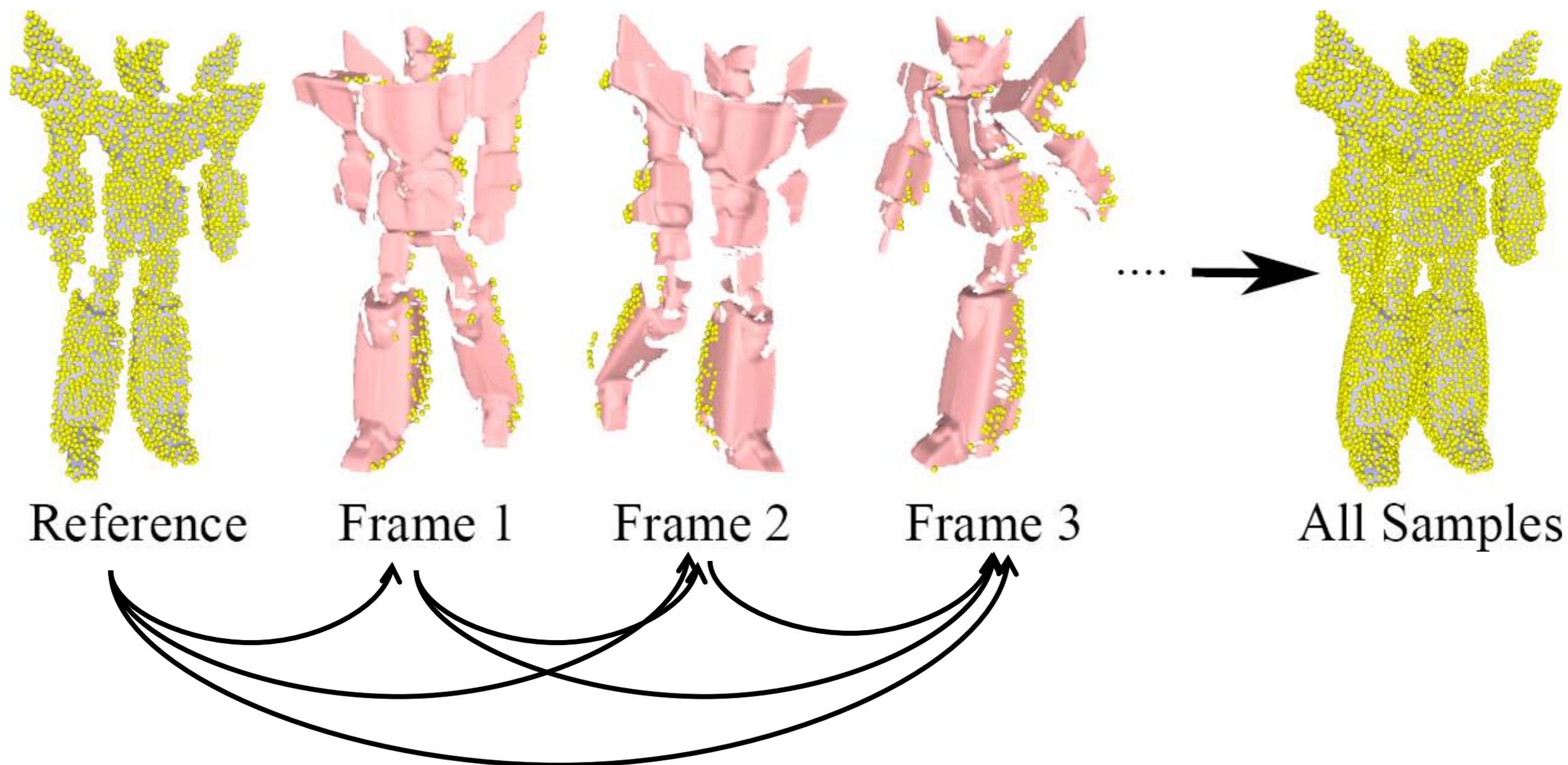
A simple way to setup the optimization:



$O(n^2)$  combinations!!!

# Naïve method vs. DSG

## Using the DSG:



# Life of a “sample point”

A sample point has multiple target points

- A target for each frame and for each transformation

*Example*

- A sample point from frame  $f$  has
  - a target point to frame  $f+1$
  - a target point to frame  $f+2$
  - a target point to frame  $f+3$  (etc...)

How to find the target points?

- Transform from frame  $f \rightarrow g$  (using current weight)
- The closest point is the target!

# How to setup the optimization?

$$\operatorname{argmin}_{\mathcal{T}, \mathcal{W}} \quad \alpha \mathcal{E}_{\text{fit}}(\mathcal{T}, \mathcal{W}) + \beta \mathcal{E}_{\text{joint}}(\mathcal{T}) + \gamma \mathcal{E}_{\text{weight}}(\mathcal{W})$$

$$\mathcal{E}_{\text{fit}}(\mathcal{T}, \mathcal{W}) = \sum_{\mathbf{x} \in \mathcal{S}} \sum_{\text{Valid } \mathbf{y}_{j^*}^{(g)}} d \left( T_{j^*}^{(f \rightarrow \text{Ref})}(\mathbf{x}), T_{j^*}^{(g \rightarrow \text{Ref})}(\mathbf{y}_{j^*}^{(g)}) \right)$$

$$\mathcal{E}_{\text{joint}}(\mathcal{T}) = \sum_{\text{All } F_f} \sum_{\text{Valid Joints } (\mathbf{u}_{ij}, \vec{\mathbf{v}}_{ij})} \sum_{t \in \mathbb{R}^3}$$

$$\left\| T_i^{(f \rightarrow \text{Ref})^{-1}}(\mathbf{u}_{ij} + t\vec{\mathbf{v}}_{ij}) - T_j^{(f \rightarrow \text{Ref})^{-1}}(\mathbf{u}_{ij} + t\vec{\mathbf{v}}_{ij}) \right\|^2$$

$$\mathcal{E}_{\text{weight}}(\mathcal{W}) = \sum_{(\mathbf{x}, \mathbf{y}) \in E} I(\mathbf{w}_{\mathbf{x}} \neq \mathbf{w}_{\mathbf{y}})$$

# Non-linear optimization by linearization

## We solve it by repeatedly linearizing the objective

How to linearize a rigid transformation  $T = (R, t)$ ?

- $T(\mathbf{x}) = R\mathbf{x} + t$  ( $R$  = rotation matrix,  $t$  = translation)
- $T(\mathbf{x}) \sim (I + W^\wedge) \mathbf{x} + v$ 
  - $W^\wedge$  is a skew-symmetric matrix,  $v$  is a translation
  - This approximates the rotation about the identity
- To linearize about an arbitrary rigid transformation?
  - Apply the approximation as a “correction”
  - $T(\mathbf{x})' = T^{corr} * T(\mathbf{x}) = (I + W^\wedge) T(\mathbf{x}) + v$

How about an inverse  $T^{-1} = (R^T, -R^T t)$  ?

- Note  $R^T \sim (I + W^\wedge)^T = (I - W^\wedge)$
- Eventually  $T^{-1}(\mathbf{x})' = T^{-1} * T^{corr}^{-1}(\mathbf{x}) = T^{-1} [(\mathbf{x} - v) - W^\wedge(\mathbf{x} - v)]$   
 $\sim T^{-1} [(\mathbf{x} - v) - W^\wedge \mathbf{x}]$

# $E_{\text{fit}}$ boils down to:

$$\begin{bmatrix} -\widehat{(\mathbf{x}')} & I & \widehat{(\mathbf{y}_j^{(g)'})} & -I \\ -(\vec{\mathbf{n}}_y' \times \mathbf{x}')^\top & \vec{\mathbf{n}}_y'^\top & (\vec{\mathbf{n}}_y' \times \mathbf{y}_j^{(g)'})^\top & -\vec{\mathbf{n}}_y'^\top \end{bmatrix} \begin{bmatrix} \omega_j^{(f)} \\ \nu_j^{(f)} \\ \omega_j^{(g)} \\ \nu_j^{(g)} \end{bmatrix} = \begin{bmatrix} \mathbf{x}' - \mathbf{y}_j^{(g)'} \\ \vec{\mathbf{n}}_y'^\top (\mathbf{x}' - \mathbf{y}_j^{(g)'}) \end{bmatrix}$$

First three rows: point-to-point constraint

Fourth row: point-to-plane constraint

- Hat operator  $\wedge \rightarrow$  “skew-symmetrizes” a vector
- $\mathbf{x}'$  (or  $\mathbf{y}'$ ) = current transformation applied to  $\mathbf{x}$  (or  $\mathbf{y}$ )
- Note: this constraint relates different frames  $f$  and  $g$

## $E_{\text{joint}}$ boils down to:

$$\begin{bmatrix} R_i^{(f \rightarrow \text{Ref})\top} \hat{\mathbf{u}} & -R_i^{(f \rightarrow \text{Ref})\top} & -R_j^{(f \rightarrow \text{Ref})\top} \hat{\mathbf{u}} & R_j^{(f \rightarrow \text{Ref})\top} \end{bmatrix} \begin{bmatrix} \omega_i^{(f)} \\ v_i^{(f)} \\ \omega_j^{(f)} \\ v_j^{(f)} \end{bmatrix} = \begin{bmatrix} \mathbf{u}'_i - \mathbf{u}'_j \end{bmatrix}$$

Three rows for each joint constraint (in each frame)

- $R_i$  and  $R_j$  are the current tfs (before correction)
- $\mathbf{u}' =$  current transformation applied to  $\mathbf{u}$
- Note: this constraint doesn't relate different frames

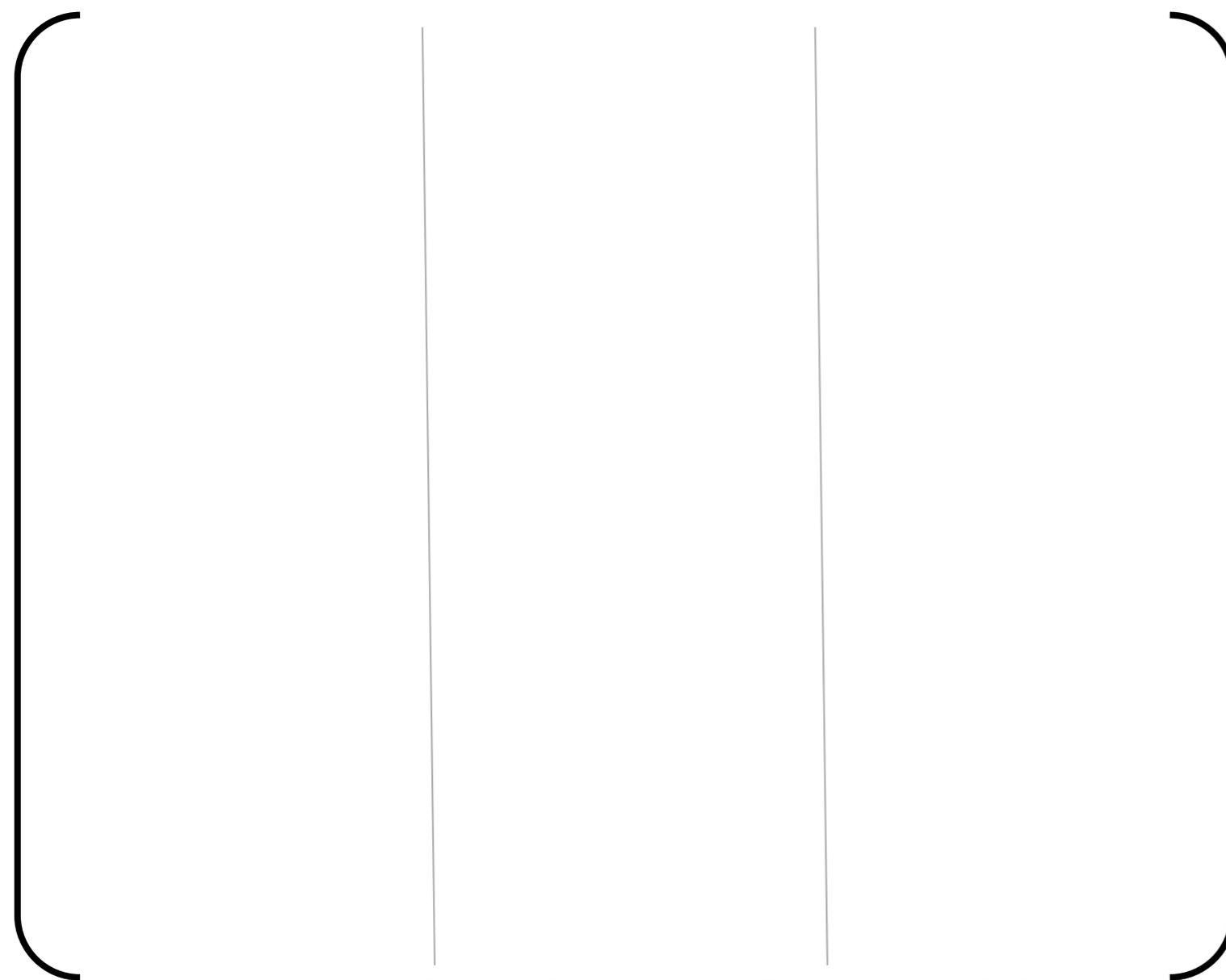
# Populating the linear system

- 1. Simply plug in these formulas**
- 2. Put numbers in the right location in the matrix**

Example: Suppose we have 3 frames and 2 bones.

- 2 corresp between  $f_0$  &  $f_1$  (one for  $b_0$ , one for  $b_1$ )
- 1 corresp between  $f_0$  &  $f_2$  (for  $b_0$ )
- 1 corresp between  $f_1$  &  $f_2$  (for  $b_1$ )
- 1 joint between  $b_0$  and  $b_1$  (applies to all frames)

# Populating the linear system



2 joints between  $b_0$  and  $b_1$   
 (expressed as  $b_0$  and  $b_1$ )

$$\begin{bmatrix}
 w_0^0 \\
 v_0^0 \\
 w_1^0 \\
 v_1^0 \\
 \hline
 w_0^1 \\
 v_0^1 \\
 w_1^1 \\
 v_1^1 \\
 \hline
 w_0^2 \\
 v_0^2 \\
 w_1^2 \\
 v_1^2
 \end{bmatrix}
 =
 \begin{bmatrix}
 \phantom{w_0^0} \\
 \phantom{v_0^0} \\
 \phantom{w_1^0} \\
 \phantom{v_1^0} \\
 \phantom{w_0^1} \\
 \phantom{v_0^1} \\
 \phantom{w_1^1} \\
 \phantom{v_1^1} \\
 \phantom{w_0^2} \\
 \phantom{v_0^2} \\
 \phantom{w_1^2} \\
 \phantom{v_1^2}
 \end{bmatrix}$$

Frame number  
Bone number

# Solving the system

## After constructing the matrix:

- (1) Solve for the values of  $w, v$
- (2) Convert them to a rigid tf (exponential map)
- (3) Apply correction
- (4) Repeat until convergence ( $\delta$  error  $<$  threshold)

A number of sparse linear solvers exist

-- We used TAUCS

# Setting up the graph-cut optimization

## We need to *solve* for the weights

- Evaluate distance to closest point for **all transformations** and **all frames**
  - This is different in the previous step, where we found the closest point only for the **current** transformation

*Example* ( $B = \text{number of bones}$ )

- Each sample point from frame  $f$  has
  - $B$  targets to frame  $f+1$  (*one per transformation*)
  - $B$  targets to frame  $f+2$
  - $B$  targets to frame  $f+3$  (etc...)

# Setting up the graph-cut optimization

## Use the same error term as before

- Data term for assigning bone “b” to a sample point x
  - Sum up the error for all frames, and average using the number of valid correspondences used in the sum
  - Special case: (a) rules for “invalidating” closest points exist. (b) If the closest point using the **current** weight is invalid, exclude all target points for that sample (in that frame). (c) Error in units of distance, not distance<sup>2</sup>
- Smoothness term for assigning similar labels nearby
  - Use the “graph” part of the DSG, with constant error
- Can easily use existing graph-cut minimization code

# Conclusions

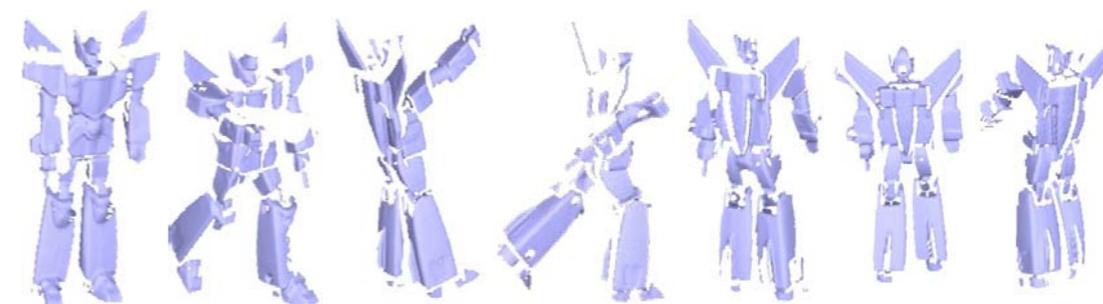
## Articulated Global Registration

### Contributions

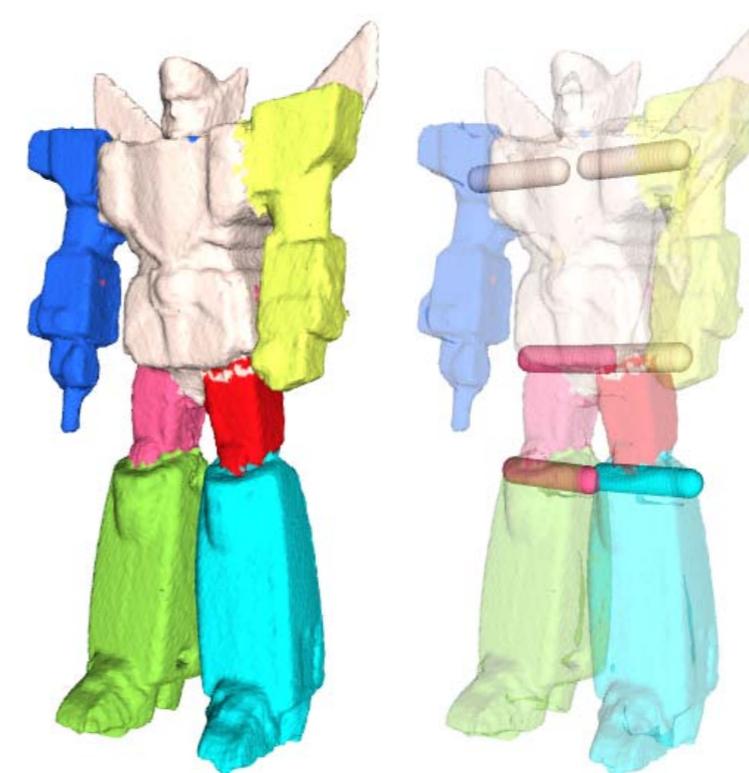
- Automatic registration algorithm for dynamic subjects
- No template, markers, skeleton, or segmentation needed
- Final result used directly to produce new animations

### In the future

- Add non-rigid motion
- Reduce parameters
- Real-time



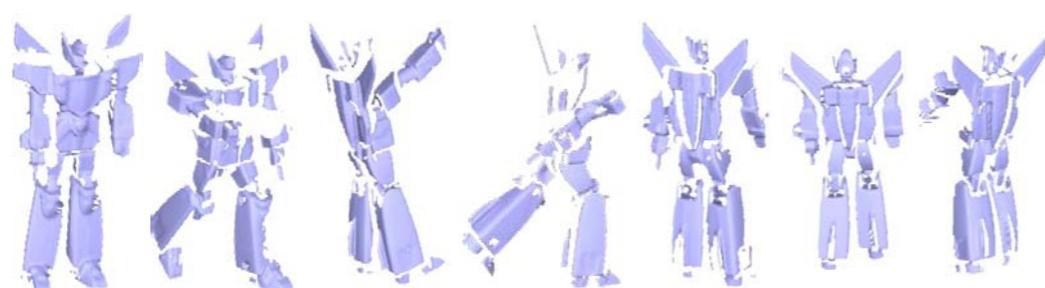
Input Range Scans



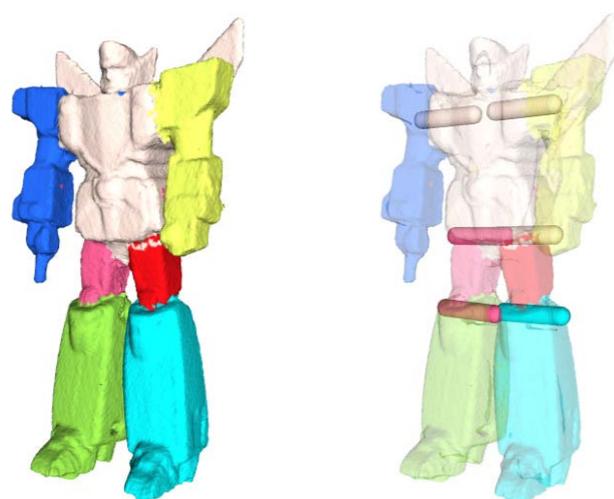
Reconstructed Poseable 3D Model

# Thank you for your attention!!

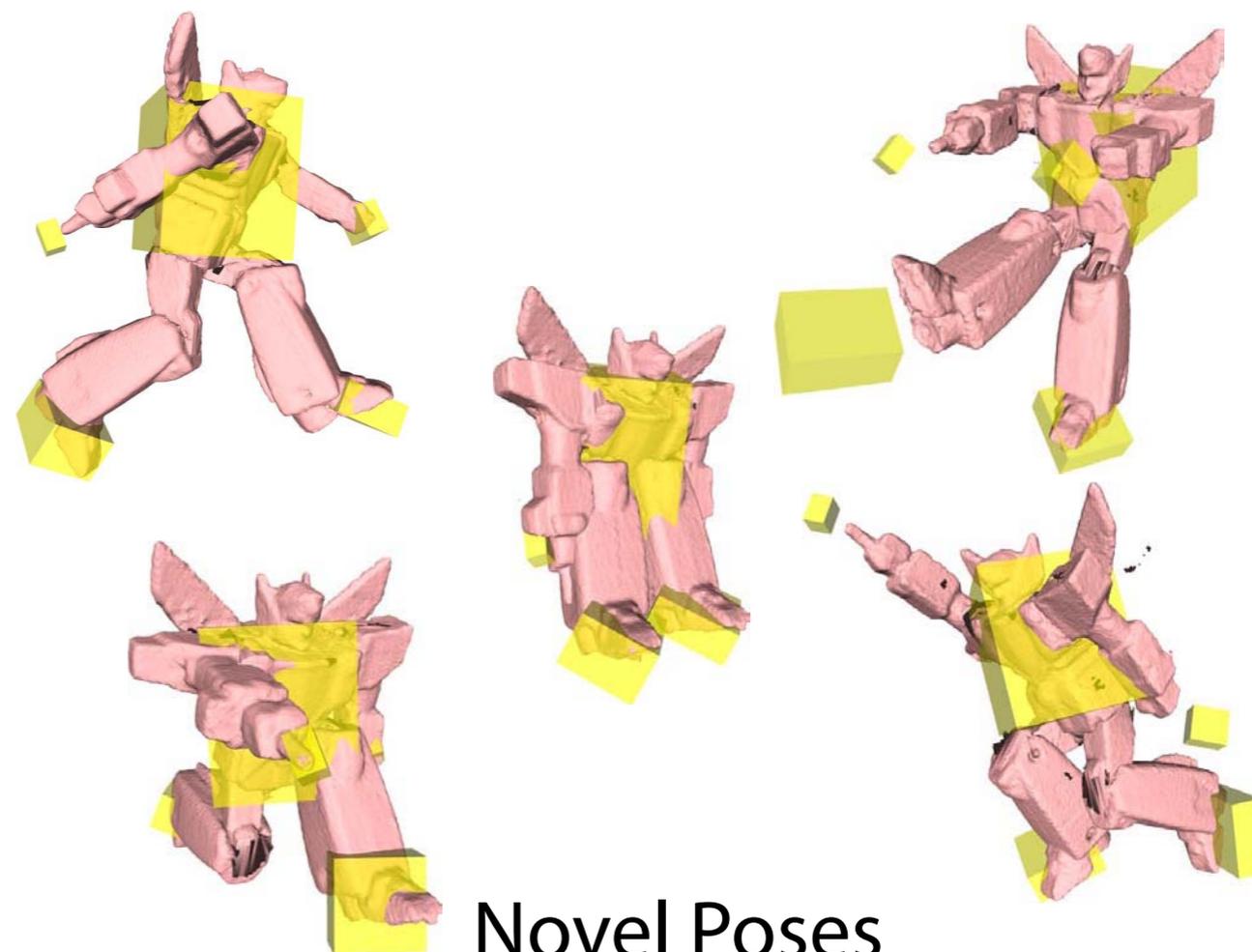
## Questions?



Input Range Scans



Reconstructed Poseable 3D Model



Novel Poses

# Additional Comparisons

# Sliding window comparison

Pink Panther (40 frames)

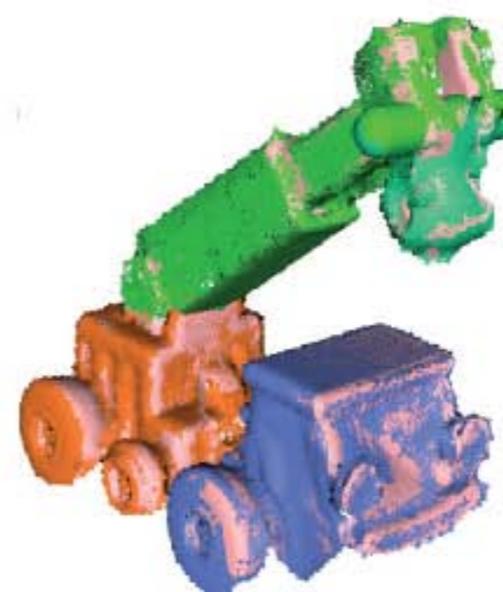


Sliding Window  
58.5 min

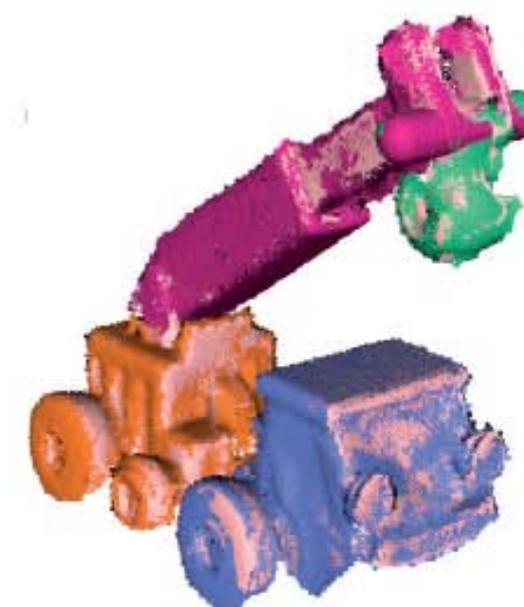


Full Global Reg  
5.64 hrs

Car (90 frames)

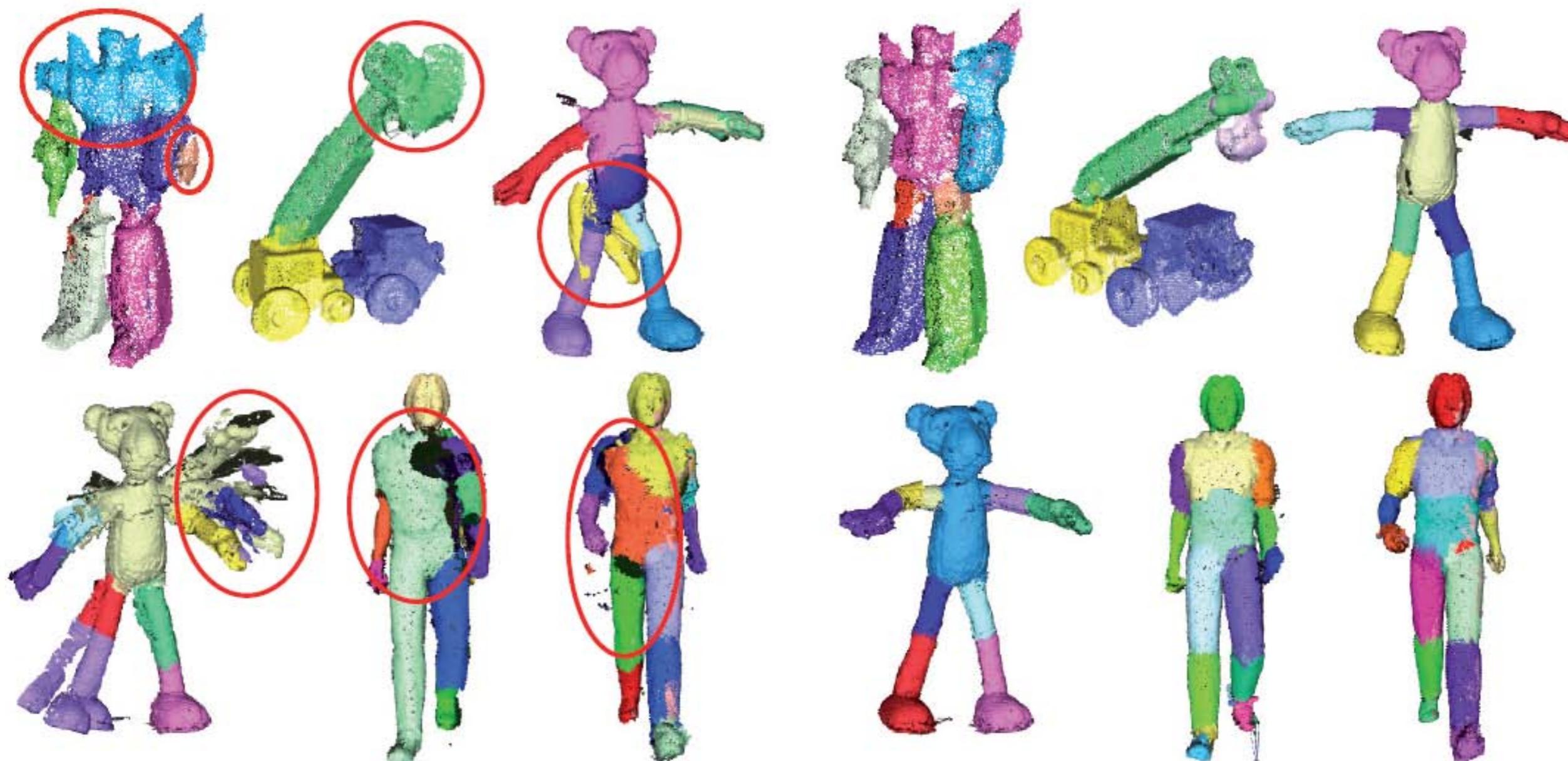


Sliding Window  
34.4 min



Full Global Reg  
11.2 hrs

# Local vs. global comparison



(a) Using sequential registration

(b) Using simultaneous registration