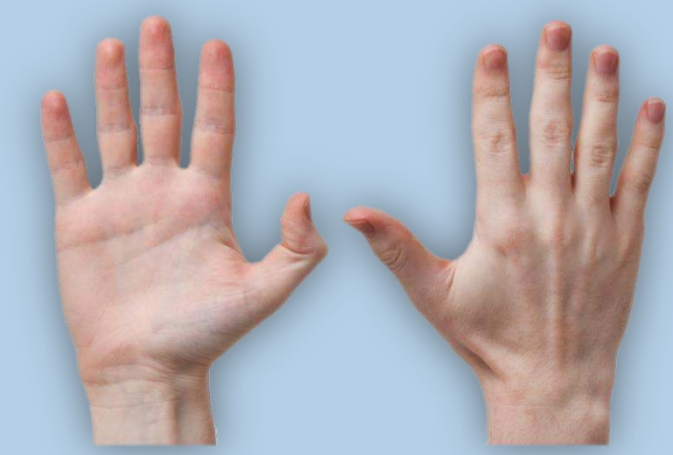
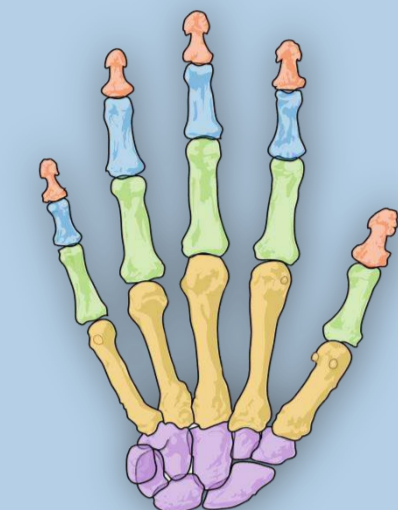


Interactive Markerless Articulated Hand Motion Tracking Using RGB and Depth Data

PROBLEM



Markerless tracking of hand motion



Model the hand as a skeleton

CHALLENGES

- Many DoFs
- **Fast finger motion**
- **Self-occlusions**
- **Homogeneous skin color distribution**

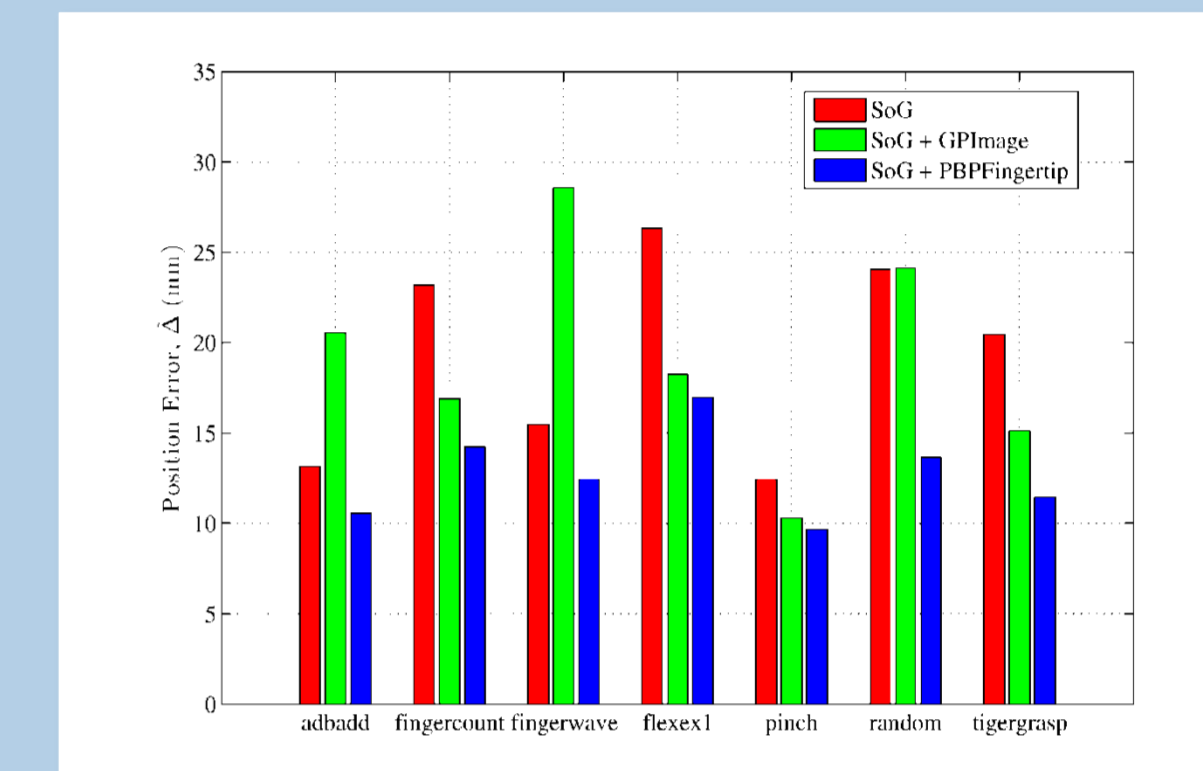
CONTRIBUTIONS

1. **Part-based Hybrid Approach:** We combine generative and discriminative methods using a part-based pose retrieval strategy.
2. **Interactive:** Our method captures hand motions with a level of precision and speed necessary for interactive applications.
3. **Annotated Dataset:** We provide an extensive, annotated benchmark dataset consisting of general hand motion sequences.

4

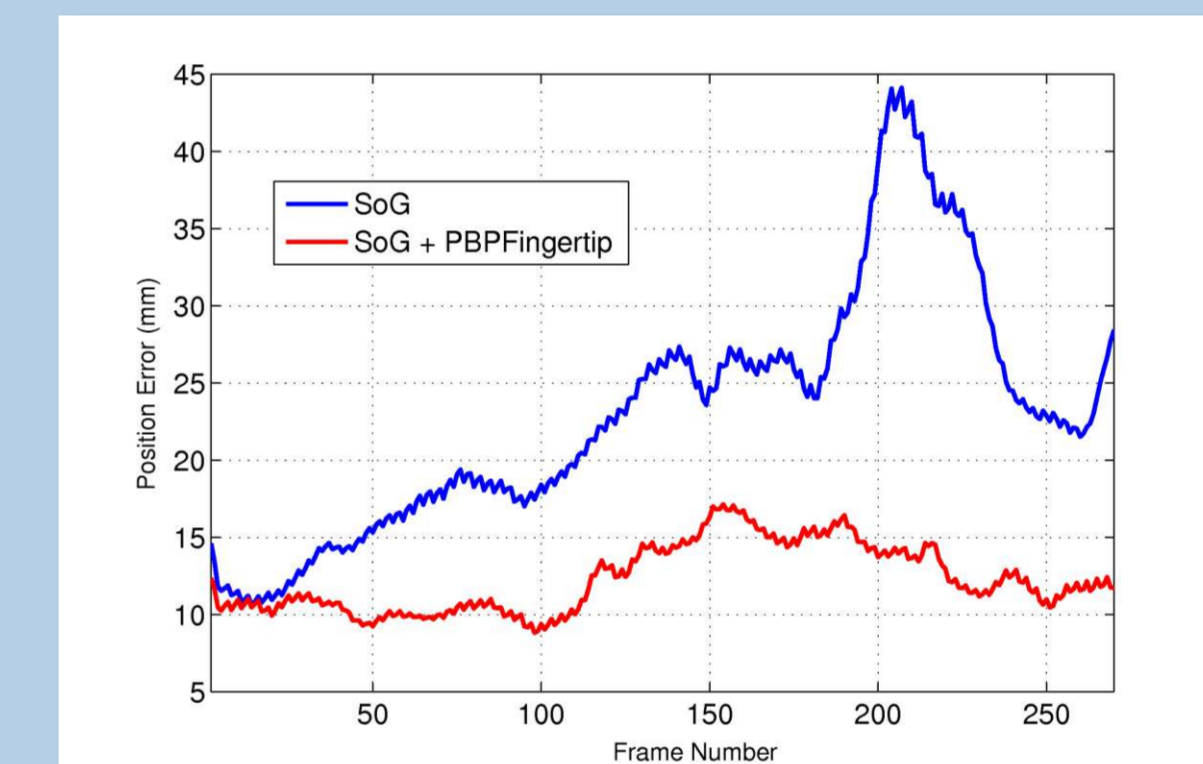
Quantitative Results and Dataset

10 FPS Interactive framerate



The average position error over the entire dataset. Our approach (blue) results in smaller errors.

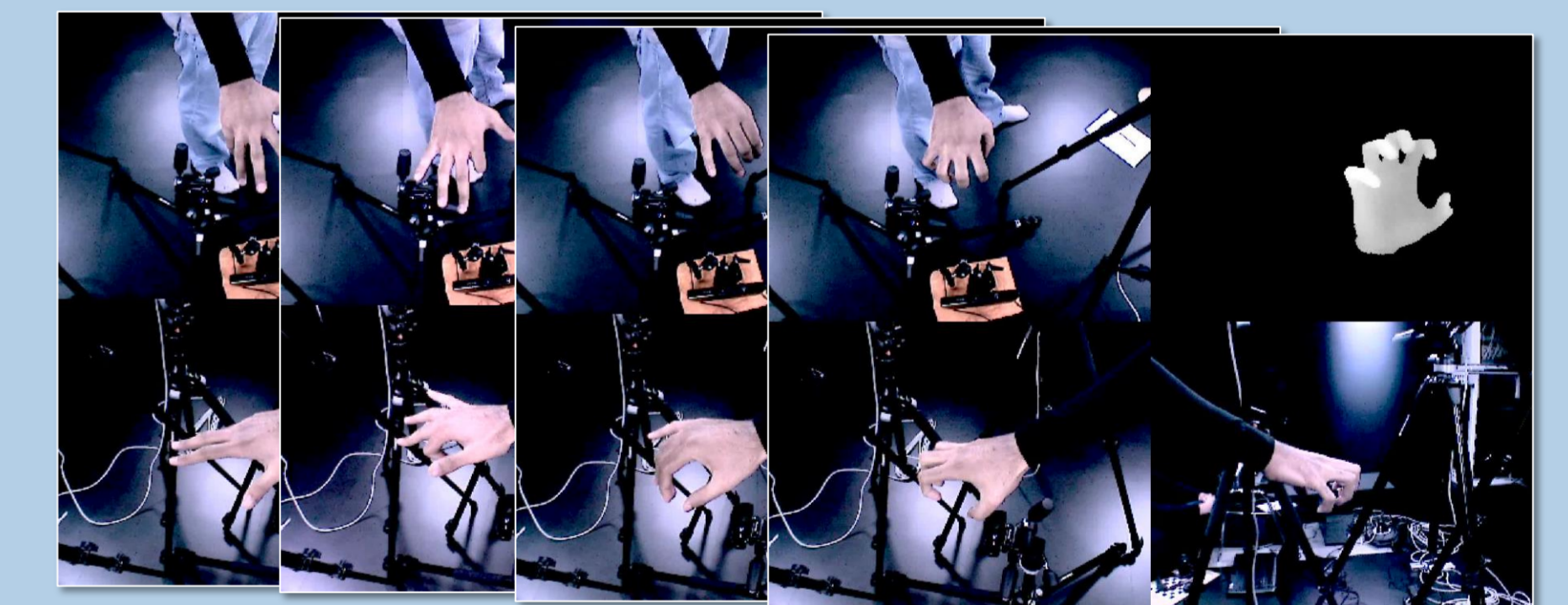
13 mm
average error
over all
datasets



The average position error over the fingerwave dataset. Our hybrid approach (red) does not drift.

Hybrid
approach
avoids error
accumulation

adbadd | fingerwave | pinch | tigergrasp | fingercount | flexel | random



Dexter I

7 RGB+depth sequences | **Slow/fast** finger motion with self-occlusions | **Fingertip annotations** for all frames
Available for download!



handtracker.mpi-inf.mpg.de

Supported by the Max Planck Center for Visual Computing and Communication (MPC-VCC) and the ERC Starting Grant CapReal. Thanks to Han Du, James Tompkin and Thomas Helten.

1 Generative Hand Pose Estimation

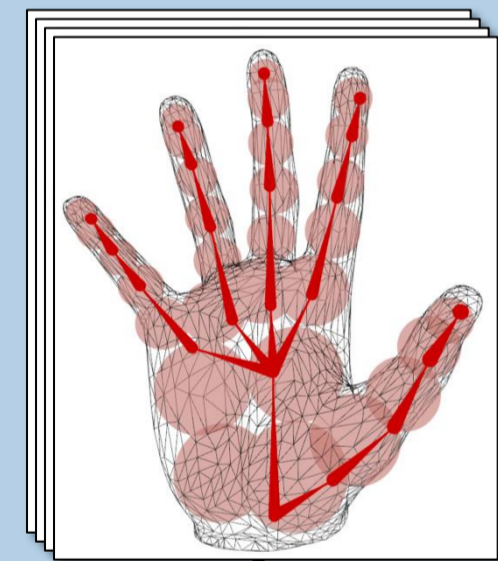
Sum of Gaussians (SoG) Representation [1]

- + Results in mathematically smooth similarity, E
- + Yields analytical formulation of energy function and its derivative

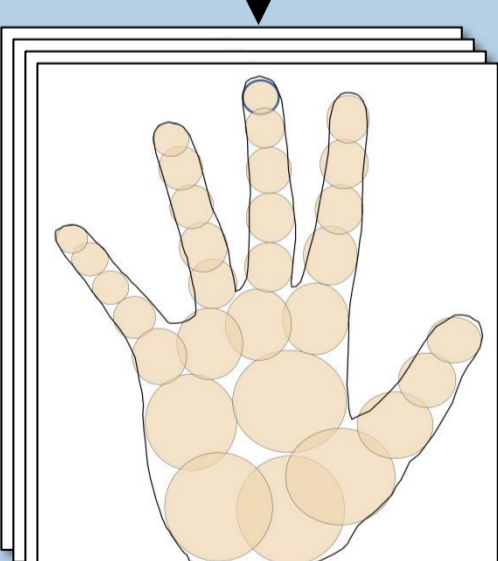
$$B(\mathbf{x}; \mu, \sigma) = \exp\left(-\frac{\|\mathbf{x} - \mu\|^2}{2\sigma^2}\right) \quad E_{ij} = d(c_i, c_j) \int_{\Omega} B_i(\mathbf{x}) B_j(\mathbf{x}) dx$$

$d(c_i, c_j)$ is the Wendland function

3D SoG Hand Model
 $\mathcal{K}(\mathbf{x}) = \sum_{i=1}^n B_i(\mathbf{x})$



Projection $\Psi(\cdot)$

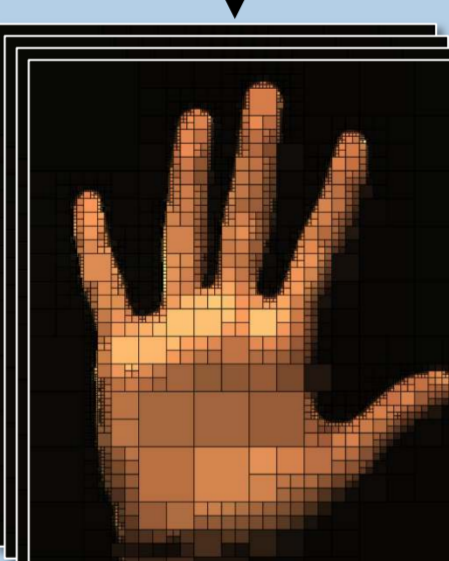


Projected Hand Model

Multiview RGB Input

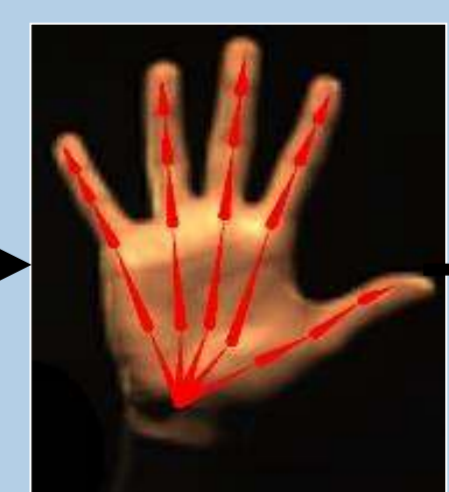


Quadtree clustering



2D SoG Image

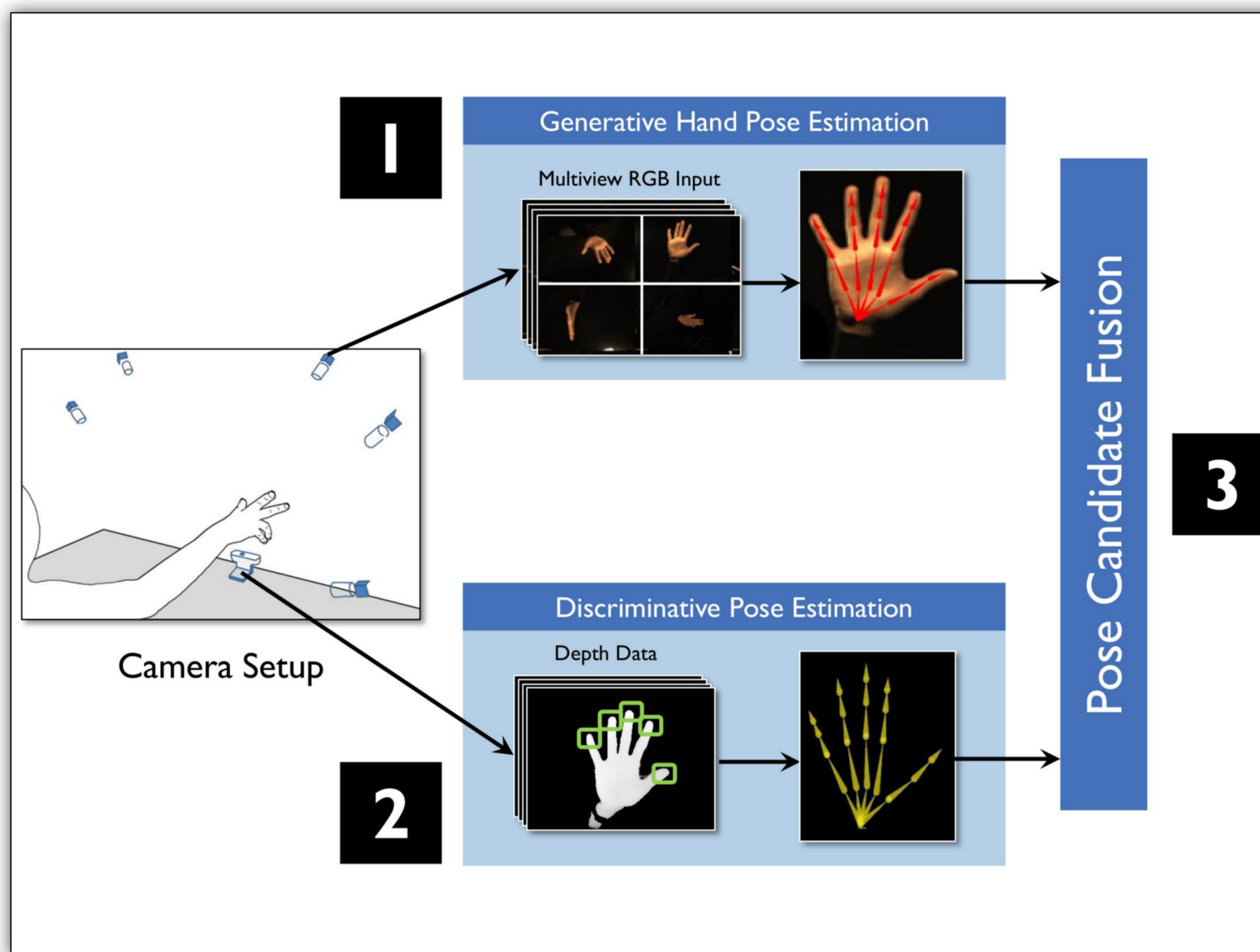
Pose optimization using similarity measure, E and joint limits
 $\mathcal{E}(\theta) = E(\theta) - w_l E_{lim}(\mathcal{M}\theta)$



Estimated Hand Pose Θ_G

Optimization
using a modified conditioned gradient descent algorithm.

[1] C. Stoll, N. Hasler, J. Gall, H. Seidel, and C. Theobalt, Fast articulated motion tracking using a sums of Gaussians body model, in Proc. of ICCV 2011.

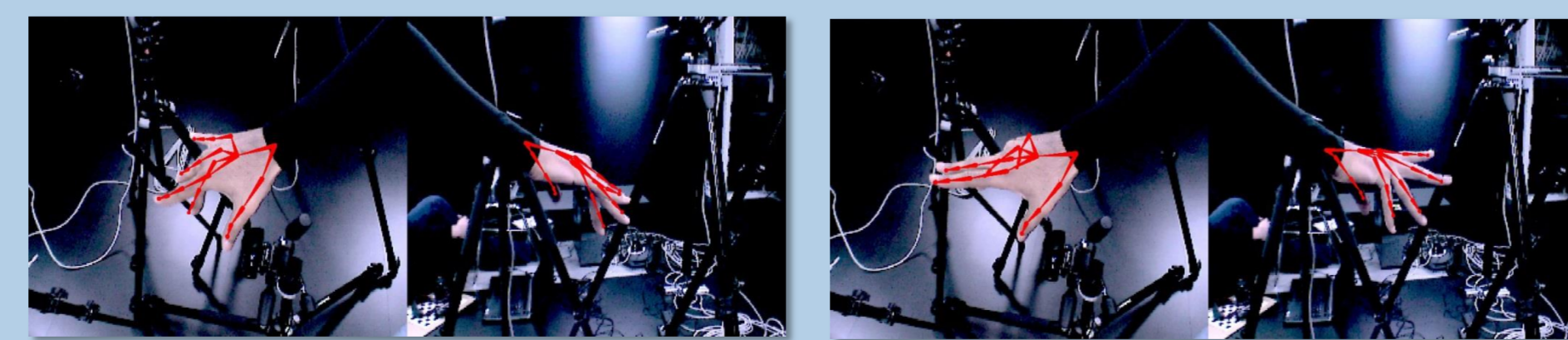


3 Pose Candidate Fusion and Results

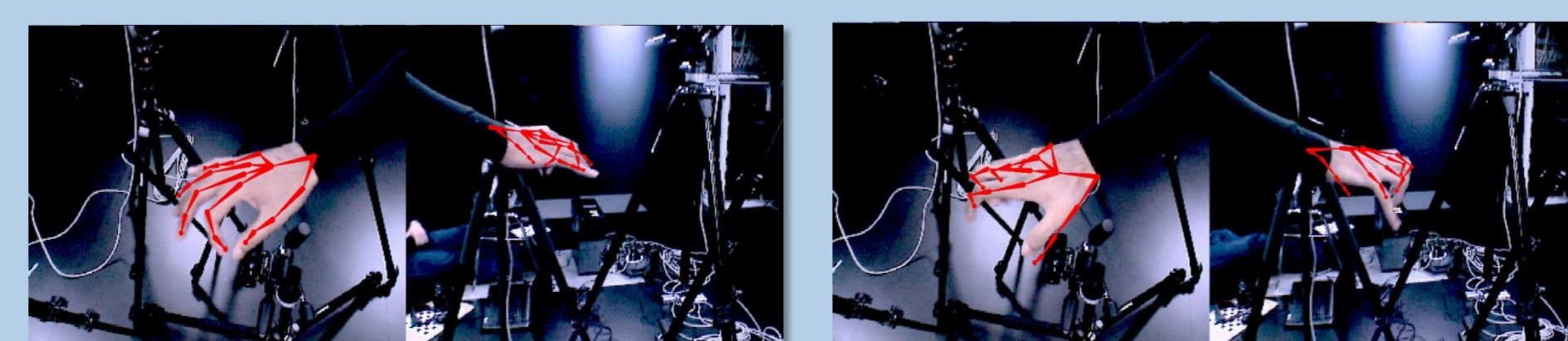
Hybrid Pose Fusion

- + Helps recover from local optima (see 4) that occur in generative pose estimation
- + Enables automatic pose initialization

$$\Theta_F = \arg \max_{\Theta \in \{\Theta_G, \Theta_D\}} \{\mathcal{E}(\Theta_G), \mathcal{E}(\Theta_D)\}$$



Tracking results for finger articulations



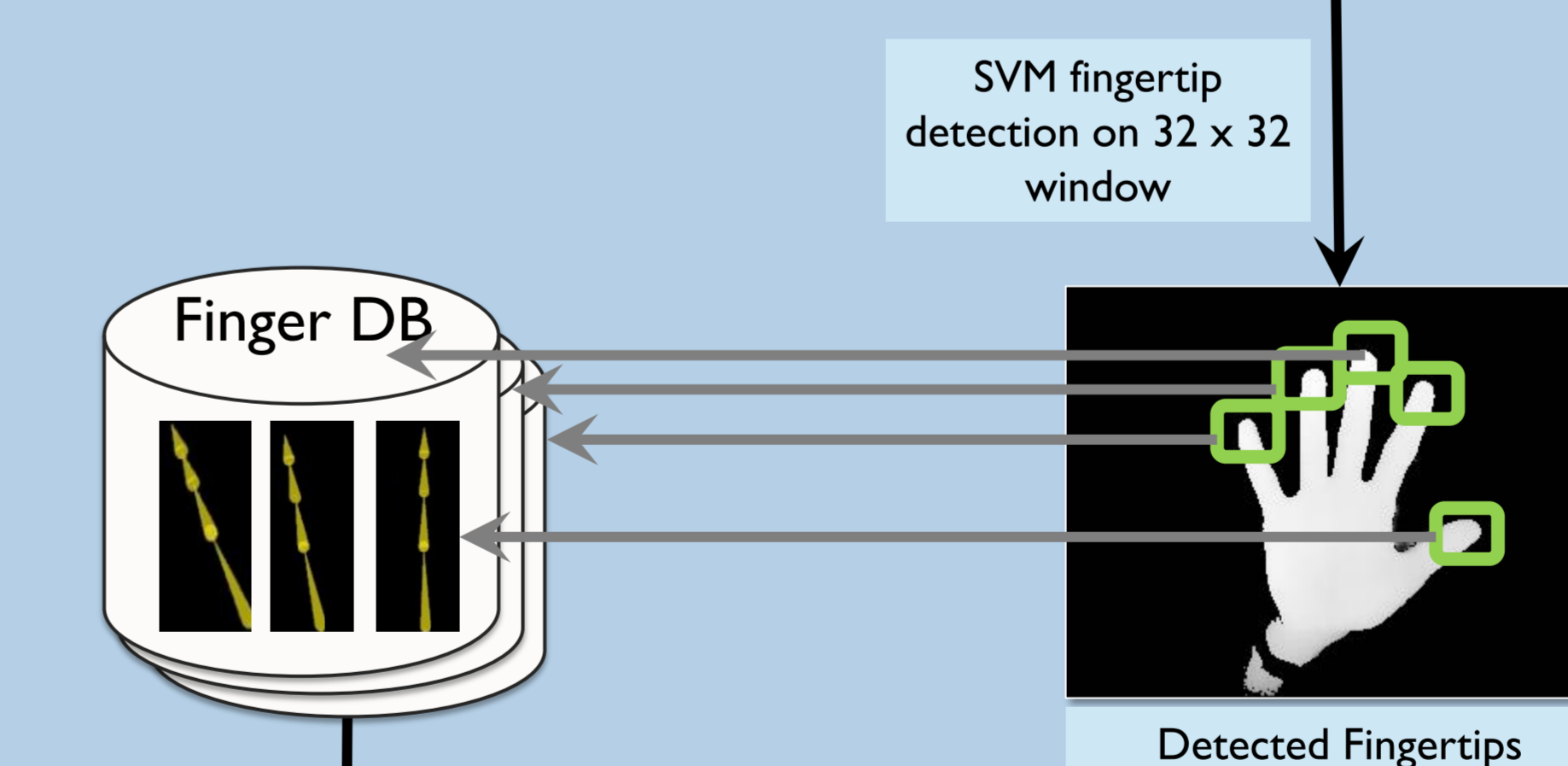
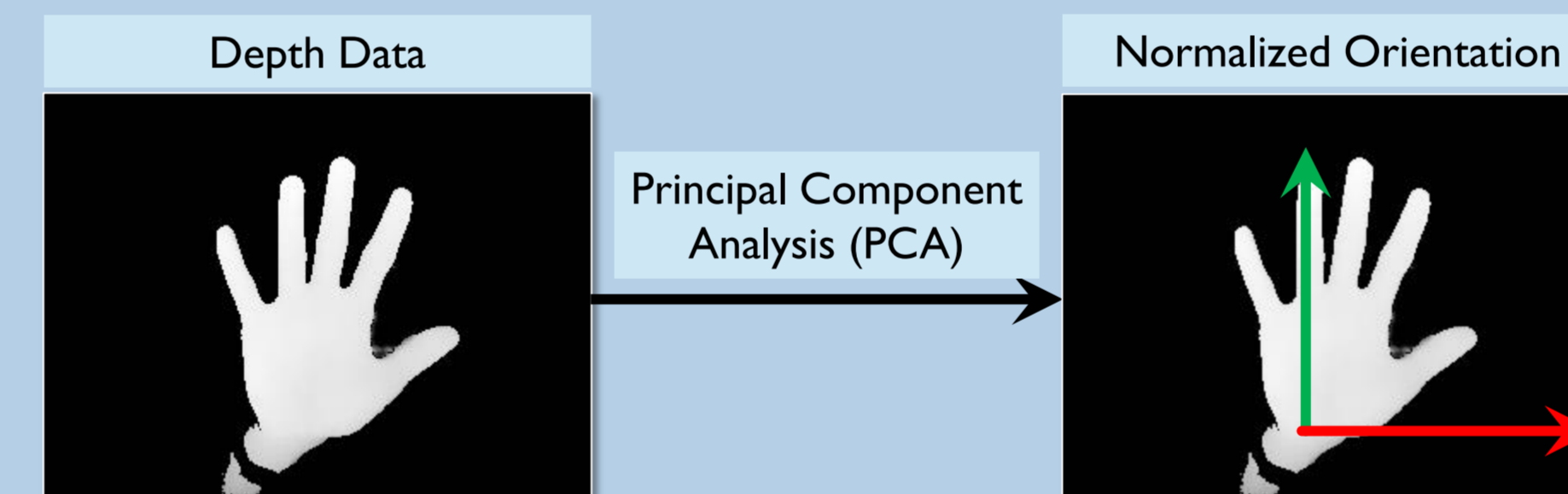
Tracking under challenging motions and image blur

2 Discriminative Pose Estimation

Part-based Pose Retrieval

- + Allows creation of a small pose database for each finger
- + Enables recovery of partial hand pose

Example: Part-based database: 5×81 poses
Global pose database: 10^{10} poses
Assuming 3 discretizations per DoF



Hypothesize and test pose candidates
 $\delta(\sigma_i, \bar{\theta}) = \frac{1}{r} \|\mathbf{x}_i - \mathbf{x}_i^c\|_2$



Lookup

using a nearest neighbor search in the database of finger poses.