Evaluating Human Hand Pose

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Project Progress Presentation

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Human-centered Assistive Robotics

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Overview

- Task introduction
- Project works
- Results and evaluations
- Future works





Motivation



Hand Pose Estimation

> One of the most crucial parts in hand tracking technique





Motivation

Get information from image **Hand Tracking Build hand model** Hand pose estimation Kinematic model **Evaluate** Using Likelihood function $L(\Theta, \mathcal{P})$ Θ denotes motion parameters ${\cal P}$ denotes 3D points cloud





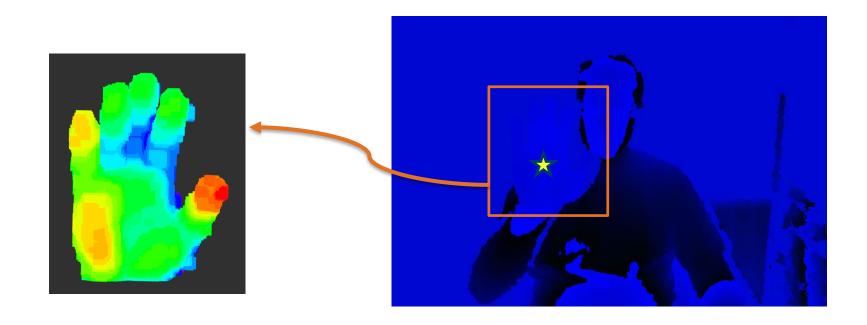
Tasks

- Convert depth image into 3D points cloud
- Build Kinematic hand model
- Define sphere based likelihood function
- Evaluation





Hand segmentation and data set conversion



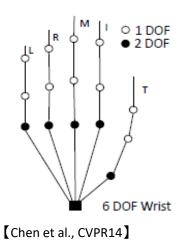
- Crop desired hand region from the depth image.
 (Hand center and hand frame boundary are given)
- Convert depth image segmentation into 3D points cloud.





Build hand model skeleton

Hand model skeleton



- Assume each finger as one chain
- Define chain pose using DH parameter

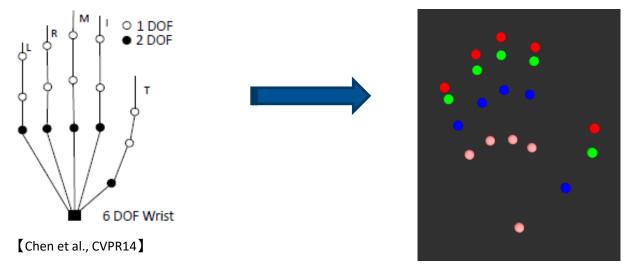




Build hand model skeleton

Hand model skeleton

Hand skeleton visualized in rviz

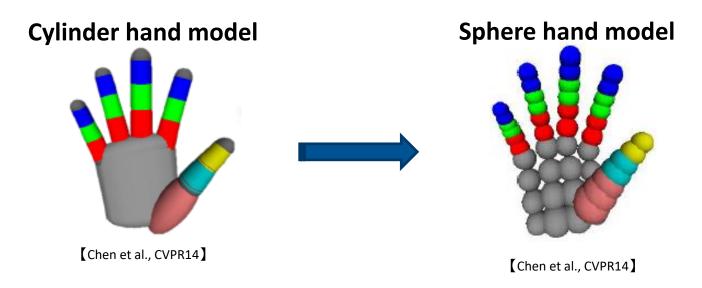


- Define 26 degrees of freedom hand motion model
- Use 26 spheres
- Build forward kinematic hand model skeleton.





Construction of sphere hand model

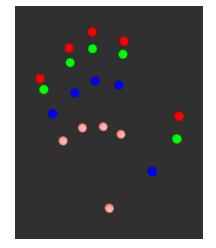


- Inspired by cylinder hand model, The sphere model is denoted as $\mathcal{M}(\Theta) = \{s_i\}_{i=1}^{48}$, each sphere $s = \{c(\Theta), r\}$ has center $c(\Theta)$ and radius r.
- The radius r are different

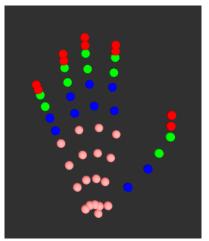


Construction of sphere hand model

Hand skeleton visualized in rviz



Sphere hand model visualized in rviz



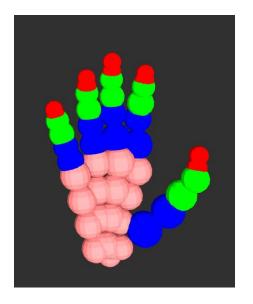
Model the other 22 spheres into the skeleton.



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Adjustment of hand spheres

Calibrated sphere hand model visualized in rviz



Calibrate value of each sphere radius





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Definition of sphere based likelihood function

$$D(p,s)=abs(||p-c||_2-r)$$
 [Chen et al., CVPR14]

- $D(\bullet)$ denotes the Euclidean distance from point p to its closest sphere surface
- c is the sphere center and r is the sphere radius.
- Define $D(\bullet)$ as one point cost value





Definition of sphere based likelihood function

$$L(\Theta, \mathcal{P}) = \sum_{p \in sub(\mathcal{P})} D(p, s_{x(p)})^2$$
 [Chen et al., CVPR14]

- Define $L(\cdot)$ as cost value function, Θ denotes motion parameters and $\mathcal P$ denotes 3D points cloud
- Cost value indicates the difference between hand pose estimation and the given hand pose from image.
- The minimal cost value indicates the optimal pose estimation which has largest likelihood





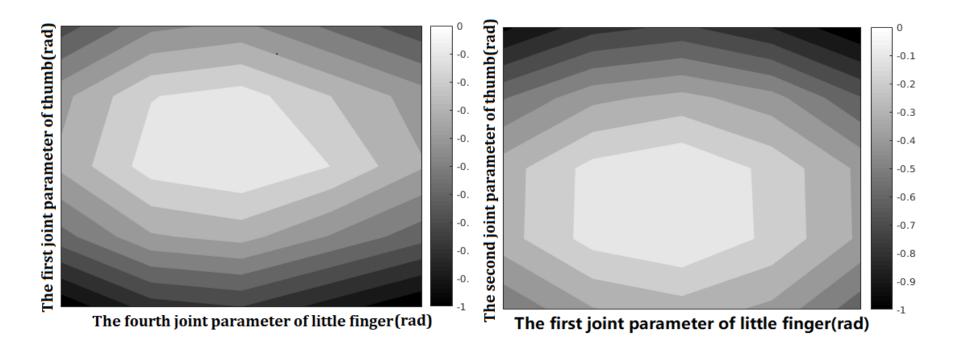
Evaluation of the sphere hand model

- For further evaluation, vary the ground truth of two randomly dimension
- Vary the joint parameters in the range of $[-10^o, 10^o]$
- Vary the coordinate parameters in the range of [-0.4m, 0.4m]





Evaluation of the sphere hand model

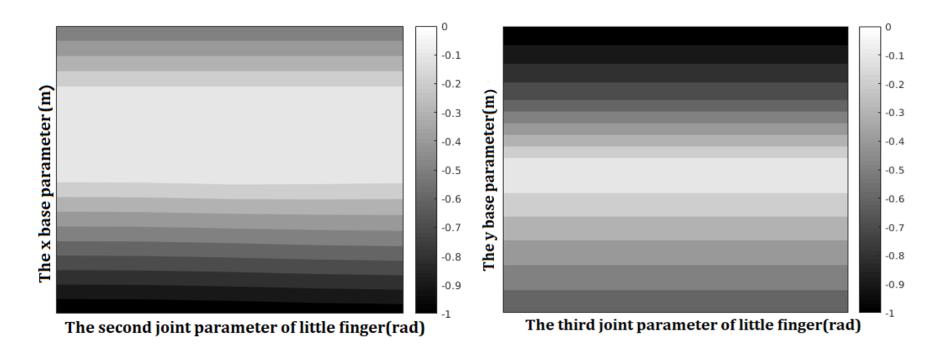


The brightest region indicates the local minima of the cost function





Evaluation of the sphere hand model



In all situations, cost value converge to the local minima at the ground truth





Conclusion

- From the evaluation results, the sphere hand model is successfully implemented
- Sphere based cost function is successfully implemented to evaluate the hand model





Future works

- There will be collisions in penetration of the two finger.
 - Additional penalization norms







Reference

- QIAN, Chen, et al. Realtime and robust hand tracking from depth. In: *Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition*. 2014. S. 1106-1113.
- TOMPSON, Jonathan, et al. Real-time continuous pose recovery of human hands using convolutional networks. *ACM Transactions on Graphics (ToG)*, 2014, 33. Jg., Nr. 5, S. 169.



