

NII International Internship program

Segmented Fusion

Tracking

20171106

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Last Meeting

- ♣ Previously
 - ♣ Tracking
- ♣ To-do
 - ♣ New Skeleton [1]
 - ♣ Add 3D junction
 - ♣ New energy function
 - ♣ Co-Fusion [2]

[1] Cao, Zhe, et al. "Realtime multi-person 2d pose estimation using part affinity fields." *arXiv preprint arXiv:1611.08050* (2016).

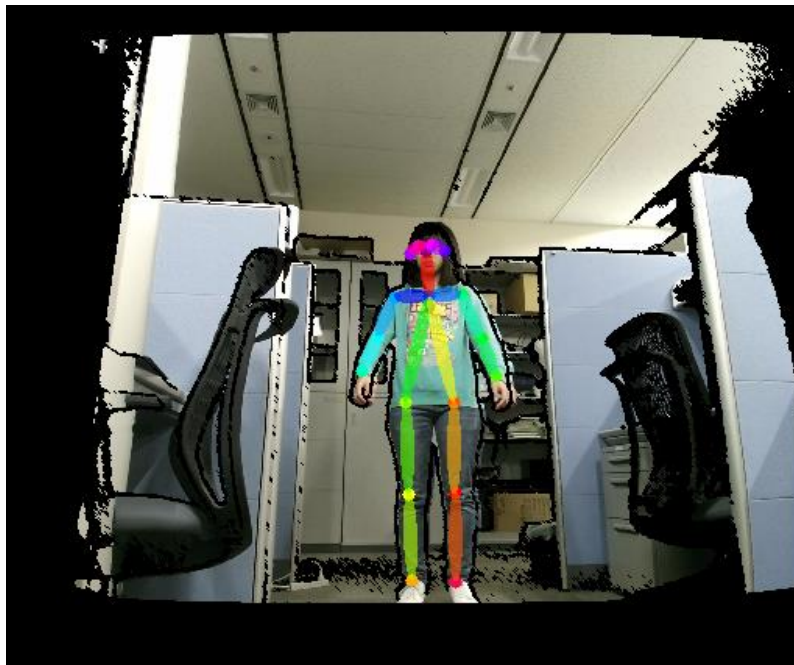
[2] Rünz, Martin, and Lourdes Agapito. "Co-fusion: Real-time segmentation, tracking and fusion of multiple objects." *Robotics and Automation (ICRA), 2017 IEEE International Conference on*. IEEE, 2017.

Presenter: Sylvia

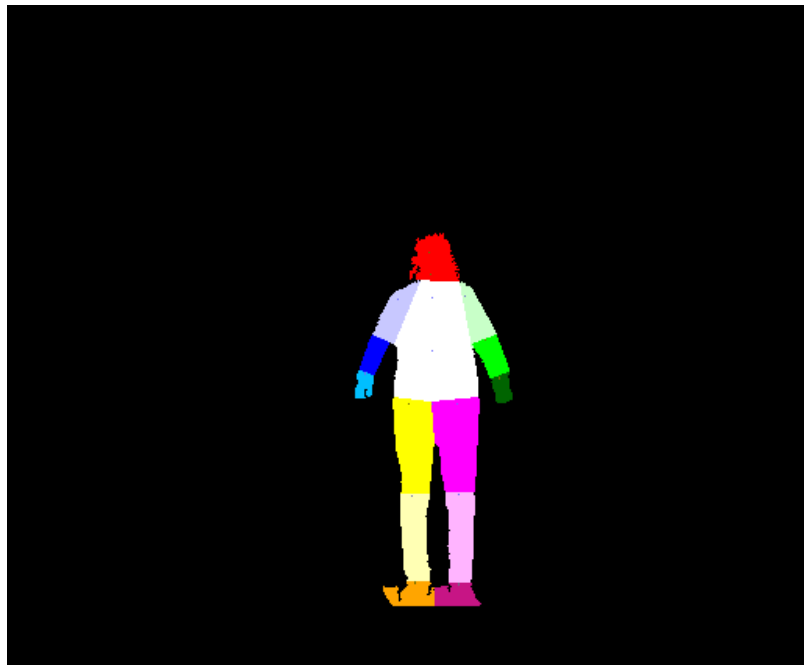
Advisors: Prof. A.Sugimoto, Ass.Prof. D.Thomas

New Skeleton

- ♣ Created new dataset with depth and color images in the same size and estimated new skeleton by [1]



New skeleton



Segment result

[1] Cao, Zhe, et al. "Realtime multi-person 2d pose estimation using part affinity fields." *arXiv preprint arXiv:1611.08050* (2016).

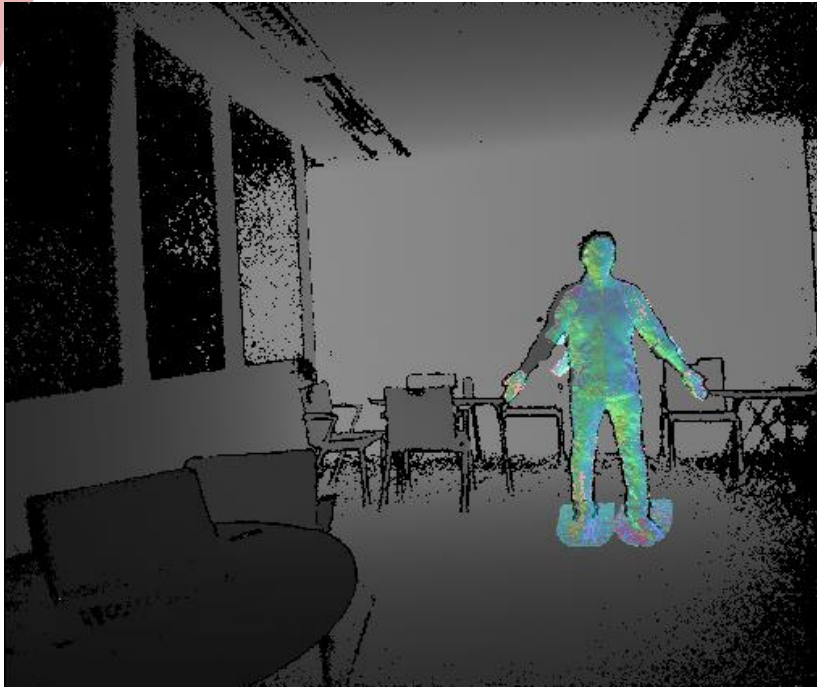
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New energy function

- ♣ $E_{data} = \sum_i \sum_j \|v_j - c_j\|_2$
- ♣ I added a constraint that if 2D point projected from c_j is out of the body, set the fixed cost.
- ♣ Since it costs time to optimize all transformations at once, I optimize transformations separately. First, I optimize data term independently and get the transformations as initialization. Then, the three term function is minimized.

New energy function



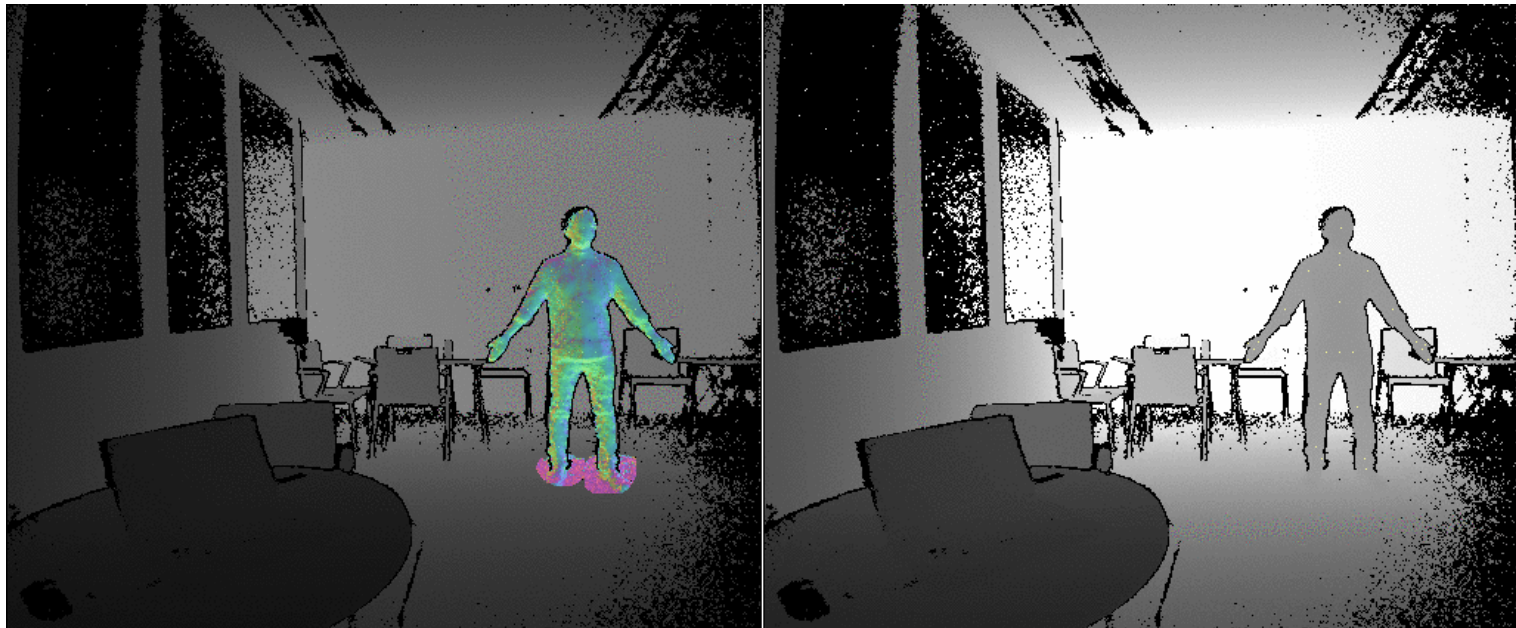
Optimized at once
Time: 331s



Optimized separately
Time: 129s

New energy function

- ♣ When the camera motion is big:



New energy function

- ♣ When the camera motion is big:

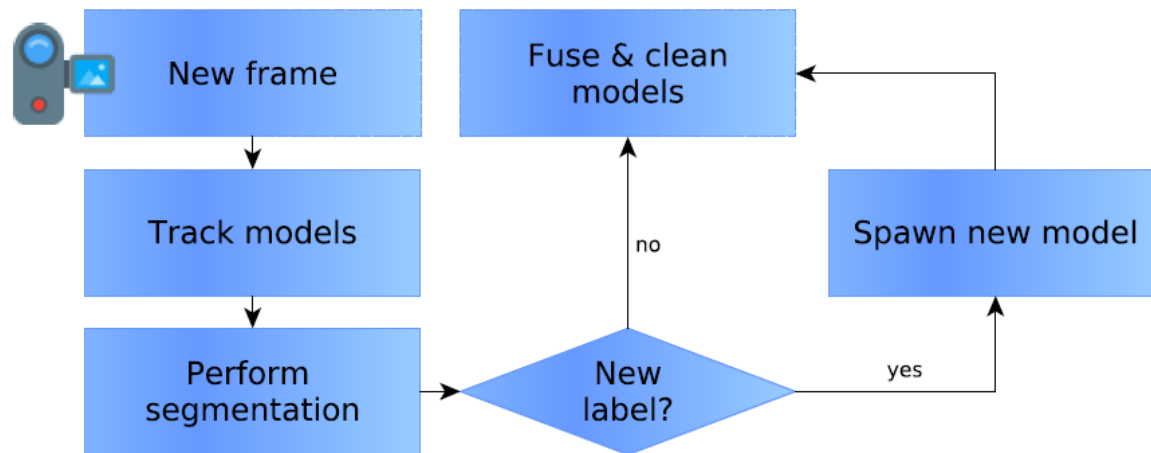


New energy function

- ♣ Result of tracking 20 frames without fusion



- ♣ Co-Fusion is a dense SLAM system that takes a live stream of RGBD images and segments the scene into different objects while simultaneously tracking and reconstruction their 3D shape in real time.



pipeline

Segmentation

- ♣ There are two alternative grouping strategies – motion segmentation and object instance segmentation.

Motion Segmentation

- ♣ After the tracking step, the system have new estimated for the model M_t rigid transformations $\{\mathbf{T}_{\mathbf{tm}}\}$.
- ♣ The motion segmentation problem is a labeling problem, where the labels are the M_t .
- ♣ The cost function has two term: the unary potentials $\varphi_u(x_i)$ and the pairwise potentials $\varphi_p(x_i, x_j)$.

$$E(\underline{\mathbf{x}_t}) = \sum_i \varphi_u(x_i) + \sum_{\underline{i < j}} \varphi_p(x_i, x_j)$$

\mathbf{x}_t is labeling result in the frame t

i, j are indices over the super-pixels ranging from 1 to S

Motion Segmentation

- ♣ The unary potentials $\varphi_u(x_i)$ are the estimated ICP alignment costs that apply the rigid transformation associated with each label as defined in E_{icp}^m . For each super-pixel with the outlier label, the cost is determined by the cost of best fitting label.
- ♣ The pairwise potentials $\varphi_p(x_i, x_j)$ is

$$\varphi_p(x_i, x_j) = \underline{\mu(x_i, x_j)} \sum_{m=1}^K \underline{w_m k_m(f_i, f_j)}$$

$\mu(x_i, x_j)$ is the classic Potts models that penalized nearby pixels taking different labels

$k_m(f_i, f_j) = \exp(-\frac{1}{2}(f_i - f_j)^T \Lambda_m (f_i - f_j))$, where f_i, f_j are the 6D feature vector and Λ_m is the inverse covariance matrix

Motion Segmentation

- ♣ After optimize the labeling, the system perform post-processing steps to merge models which have similar rigid transformations, and to spawn the new label(object) when the region of outliers is too large, or to put a missing label out of active model list.

Next step

- ♣ Add junction term or as initial