Discovering and Tracking Human Interaction Patterns from Top View Kinect Depth Sensor

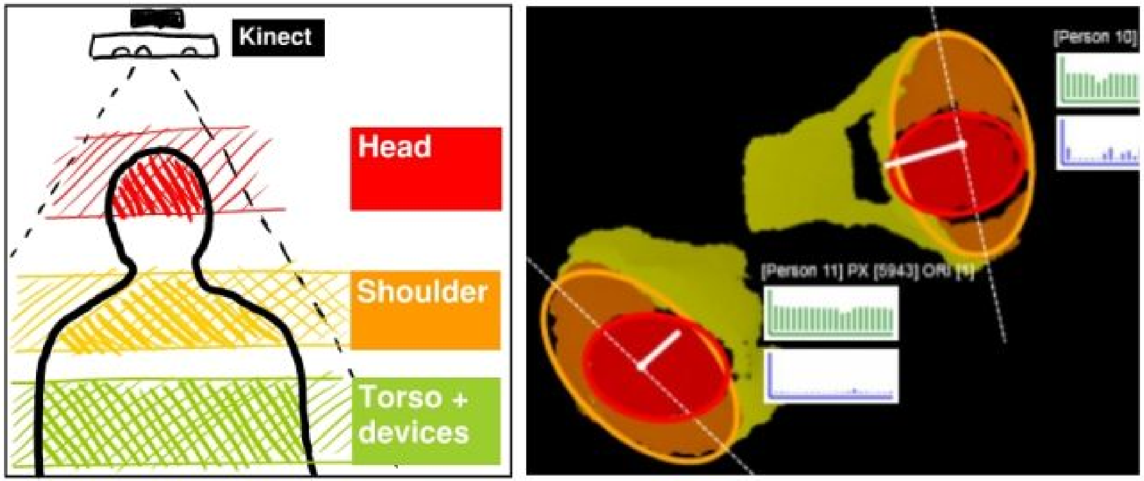
Chi-Jui Wu (Charles)
March 7th, 2016

Motivation

1. A larger playground (field of view)
2. Less occlusion
3. Develop natural interfaces - Understand what people want to do
4. Improve existing interfaces - Help people achieve what they want to do
5. See how people interact with other people and technologies around them

Related Work

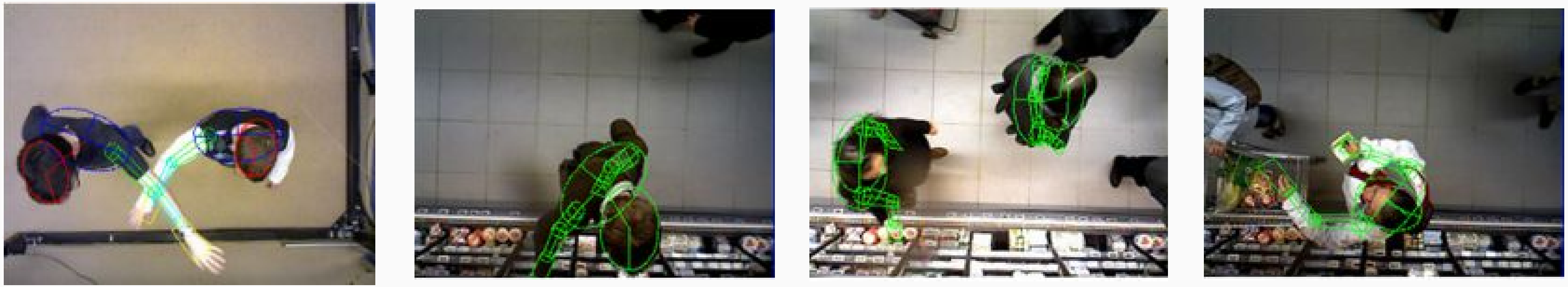
- Marquardt et al. [1] Cross-device interaction and F-formations



[1]

Related Work

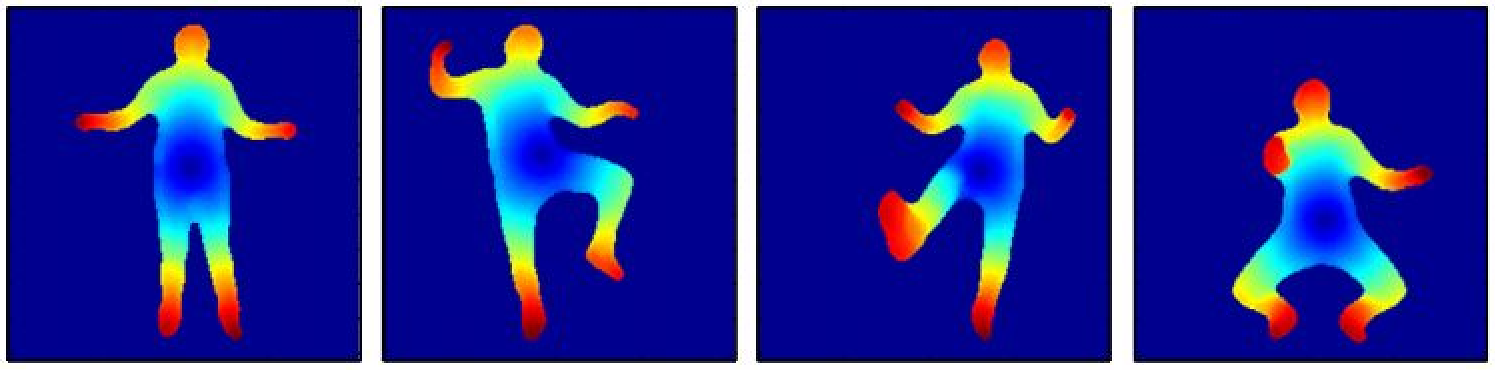
- Migniot and Ababsa [2] Real-time top view human skeleton tracking using particle filter



[2]

Related Work

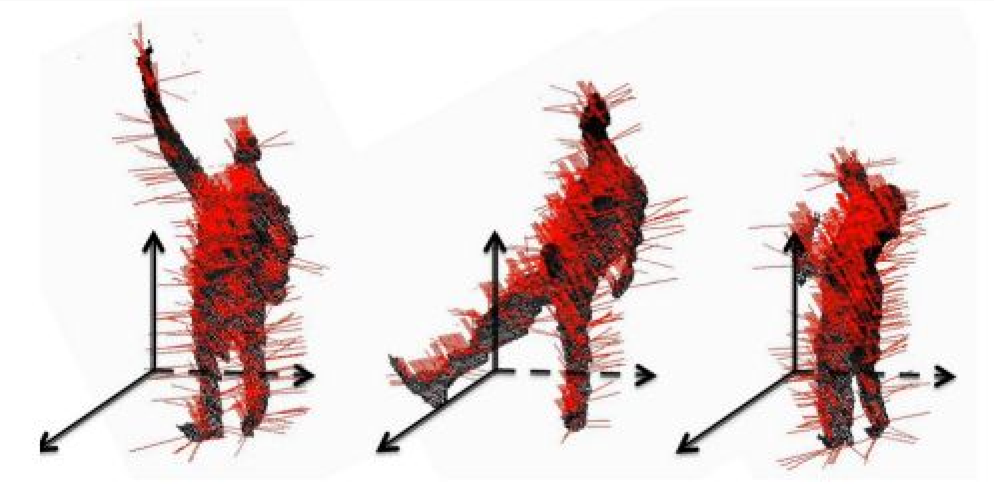
- Schwarz et al. [3] Real-time skeleton tracking using geodesic distances and optical flow



[3]

Related Work

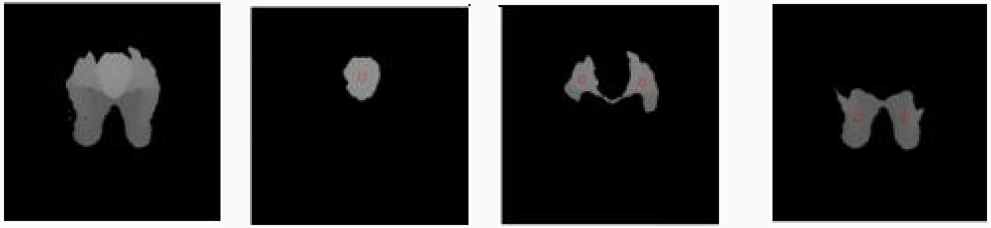
- Oreifej and Liu [4] Activity recognition from depth images using HON4D (89% accuracy on the MSR datasets)



[4]

Related Work

- Lin et a. [5] Daily activity recognition using depth thresholding and dynamic time warping



[5]

Contributions/Goals

1. Improve the state-of-the-art top view activity detection and tracking techniques
2. A real-time activity tracking system with a top view Kinect (and other sensors)
3. A set of tools which provides insights into how people interact or collaborate with other people and technologies around them
4. Open source code (and documentation)

Human Body Tracking

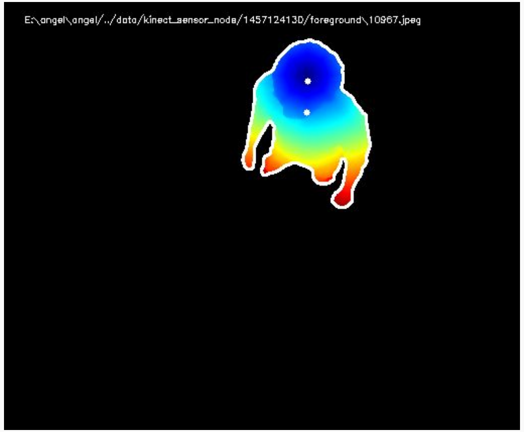
Technique: compute geodesic distances from the head center

Assumption: highest depth band of each contour is the head area

Limitations: unstable orientations, self-occlusion

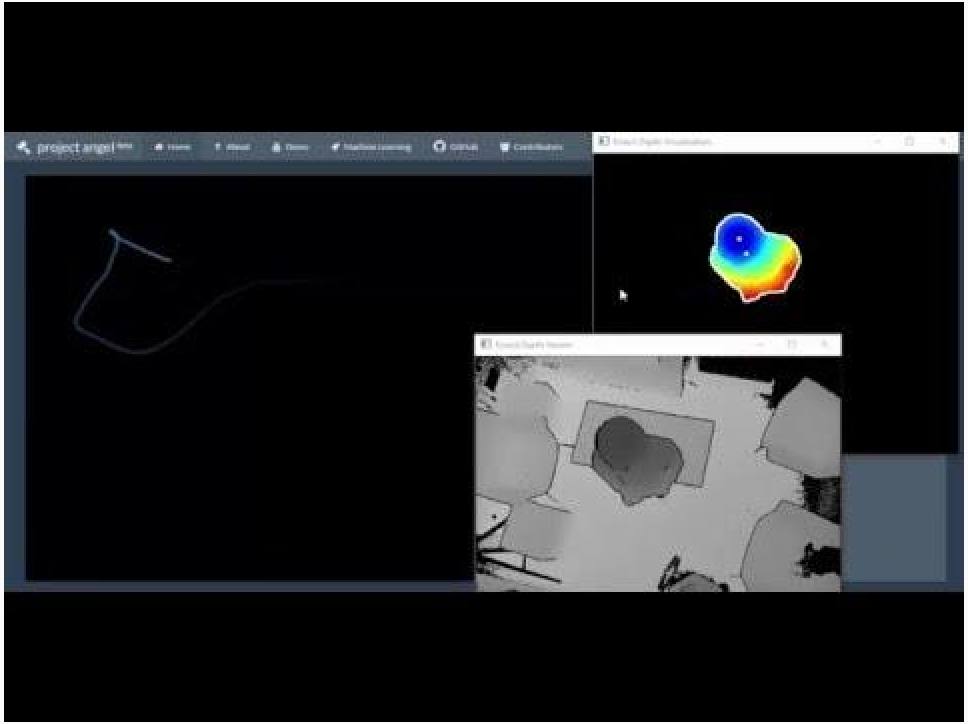
Kinect

My C++ program

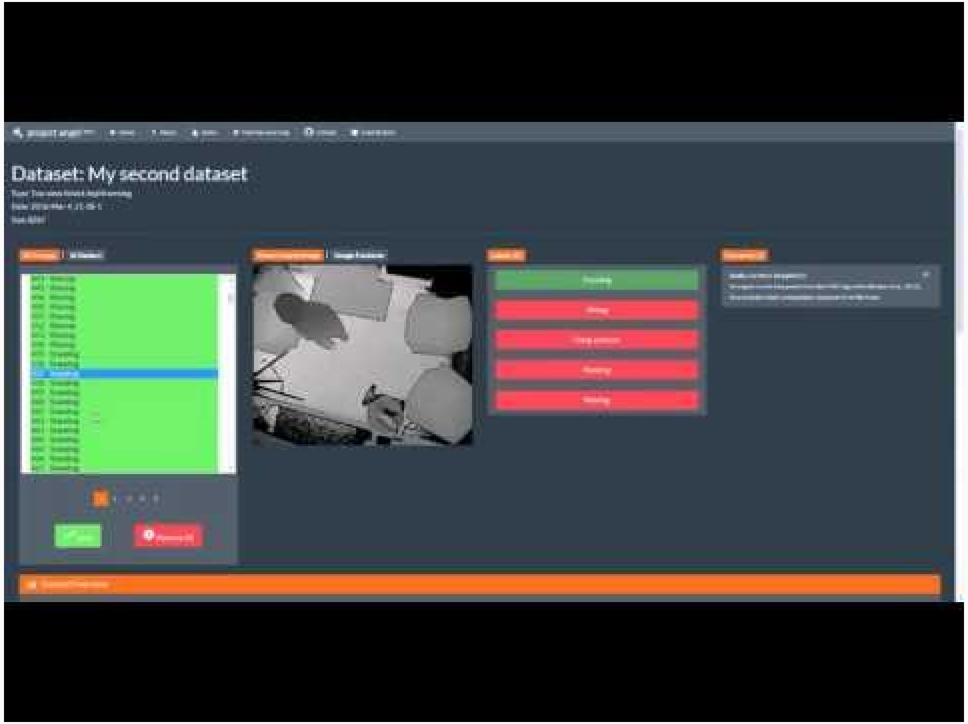


Demo: Human Body Tracking

Demo: Human Body Tracking RESTful API



Demo: Project Angel Web Application

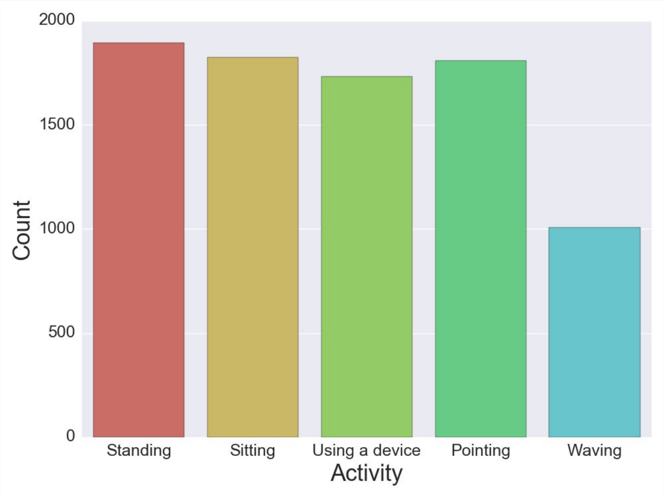


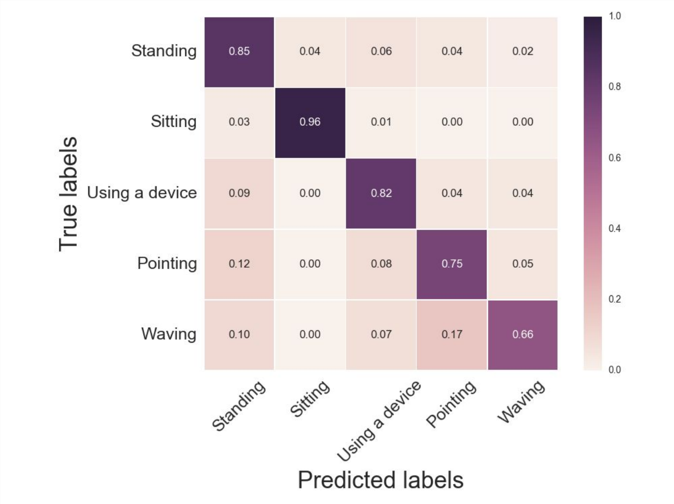
Machine Learning

Features: geodesic distances and depths of body corner key points were used as a baseline measure

Algorithm: Random Forest

Data size: 8267





Evaluation

1. More challenging datasets, multi-label classification, different data sources
2. Larger testing sets
3. System evaluation study for the real-time tracking system
4. Tracking accuracy and precision

Next Steps

1. Incorporate machine learning models into the real-time tracking system
2. Increase the size and difficulty of the datasets (e.g. group activities)
3. Improve and validate models
4. Explore other features (as described in related work)
5. System evaluation
6. From detection to tracking
7. Integrate other sensors (e.g. heart rate monitor, accelerometer) and devices (e.g. mobile devices, IoTs)
8. Explore applications (e.g. interactive machine learning)

Questions?

[1] Marquardt, Nicolai, Ken Hinckley, and Saul Greenberg. "Cross-device interaction via micro-mobility and f-formations." Proceedings of the 25th annual ACM symposium on User interface software and technology. ACM, 2012.

[2] Migniot, Cyrille, and Fakhreddine Ababsa. "Hybrid 3D–2D human tracking in a top view." Journal of Real-Time Image Processing (2014): 1-16.

[3] Schwarz, Loren Arthur, et al. "Human skeleton tracking from depth data using geodesic distances and optical flow." Image and Vision Computing30.3 (2012): 217-226.

[4] Oreifej, Omar, and Zicheng Liu. "Hon4d: Histogram of oriented 4d normals for activity recognition from depth sequences." Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition. 2013.

[5] Lin, Shu-Chun, et al. "Representative Body Points on Top-View Depth Sequences for Daily Activity Recognition." Systems, Man, and Cybernetics (SMC), 2015 IEEE International Conference on. IEEE, 2015.