

# Skeleton Tracking

## using range images

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# Overview

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# Motivation

- ▶ parent - infant experiments
- ▶ adult showing "cup nesting" task to infant
- ▶ detecting relations between parents and infants limb motions
- ▶ necessity to detect skeleton topology for both parent and infant
- ▶ *OpenNI* is currently not capable of detecting infants as blobs of interest, thus skeleton tracking is not possible
- ▶ *NITE* skeleton tracking framework is closed source, modifying source code is not possible



# Motivation

- ▶ currently tracking colored markers for infant skeleton detection
- ▶ using OpenNI for parent skeleton detection
- ▶ markerless tracking algorithm for both parent and infant desirable
- ▶  $\Rightarrow$  implementing skeleton tracking from scratch



# Framework

- ▶ simple module-based framework
- ▶ every module can define different implementations (controlled by factory pattern)
- ▶ implementations have to define the same interface
- ▶ user can define parameters from the outside before initialization
- ▶ module implementations easy exchangeable for testing purposes



# General Pipeline

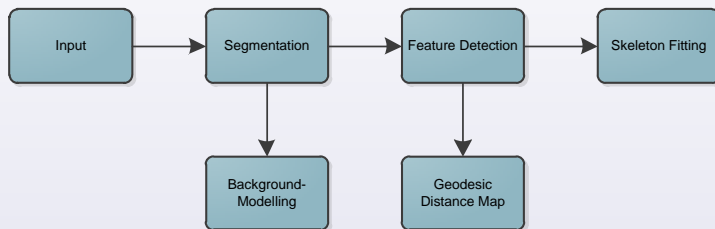


Figure: Pipeline



# Input

- ▶ Retrieving input data
- ▶ Generating depth map and 3D map
- ▶ Reconstructing projection matrix and intrinsic parameters using correspondences from depth and 3D map.  $\Rightarrow$  Mapping 3D points to 2D image plane.
- ▶ Saving image streams to disk



# Segmentation

- ▶ Depth map has to be separated into foreground and background objects
- ▶ Segmentation of foreground image into homogenous regions
- ▶ Finding relevant user blobs to analyze
- ▶ Simplest approach: assuming background to be constant. Taking first image as static background image, subtracting running image and detecting the biggest region as user blob.
- ▶ Later:
  - ▶ spatial clustering
  - ▶ detection and deletion of planar objects
  - ▶ detection and segmentation of moving objects





# Segmentation



Figure: Segmentation



# Feature Detection

- ▶ Detect outstanding feature points on the segmented foreground image
- ▶ important feature points:
  - ▶ Torso (center of gravity of user blob)
  - ▶ Head
  - ▶ Left & Right Hands
  - ▶ Left & Right Feet
- ▶ once every feature point has been found and labeled correctly, it is possible to fit a skeleton inside
- ▶ automatic labeling needs heuristics or training a classifier. Here: No implicit labeling, but trying to let skeleton tracking decide automatically which feature point corresponds to which joint (automatic labeling).



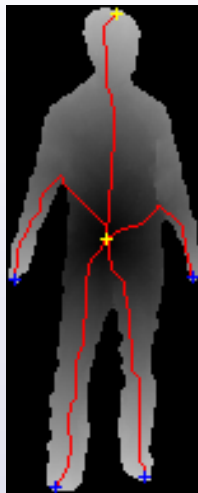
# Geodesic Distance Map

General idea:

- ▶ 3d point cloud as a graph
- ▶ every graph node is connected with each of its 4 (cross) or 8 (full) neighbouring nodes
- ▶ edge weight = metric distance in 3D space
- ▶ compute the shortest distance from every graph node to the center of gravity
- ▶ shortest path algorithm: modified Dijkstra-Algorithm



# Geodesic Distance Map



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# Geodesic Distance Map

## Advantages:

- ▶ features correspond to local maxima in the distance map (points farthest away from the center of gravity)
- ▶ feature distances almost invariant to pose
- ▶ taking user topology into account
- ▶ predecessor map allows for topology skeleton reconstruction, once all feature points have been detected

## Disadvantages:

- ▶ necessity to remove edges from the graph to avoid wrong geodesic paths
- ▶ local maxima detection subject to uncertainties



# Geodesic Distance Map

## Approaches to local maxima detection

- ▶ non-maxima suppression: finding local maxima inside a mask by suppressing non-maxima and emphasizing maxima
- ▶ finding maxima in the derivative by analyzing the function and looking for zero crossings
- ▶ clustering approaches
- ▶ geodesic isolines / isopatches



# Geodesic Distance Map

Current feature detection:

- ▶ *Analogy: Consider the persons outline as a pond filled with water. Throw a small stone in the middle and find the regions that the wavefront reaches at last.*
- ▶ Undersample geodesic distance map
- ▶ represent distances as iso patches, i.e. regions with approximately the same distance to the center of gravity (appropriate values: 10 - 30 cm)
- ▶  $\Rightarrow$  Local maxima detection: find patches that don't have neighbouring patches with a higher average distance



# Geodesic Distance Map

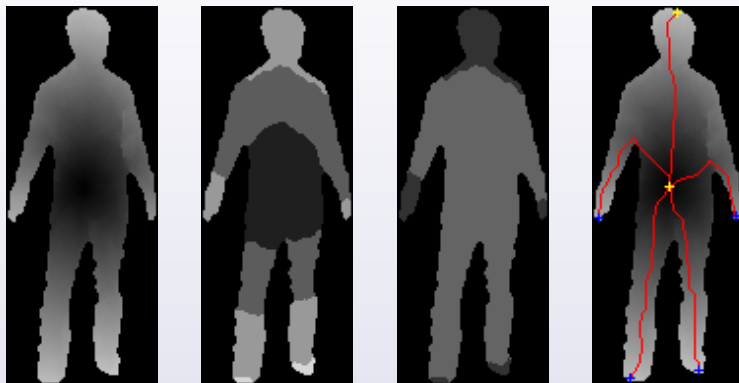


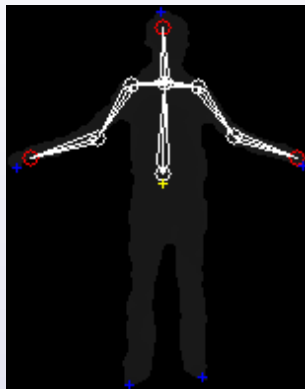
Figure: Feature-Detection





# Skeleton Fitting

- ▶ Goal: Matching a skeleton topology inside the users point cloud and detected features
- ▶ skeleton has to be inside the body



# Energy-Minimization

- ▶ Problem: Given a skeleton topology, find a joint configuration that best fits the users point cloud
- ▶ Upper body skeleton: 9 joints, connected with 8 bones.
- ▶ Every bone has 3 DOF (unconstrained)
- ▶  $\Rightarrow 24 + 3 \text{ DOF (XYZ-Position of root joint)} = 27 \text{ DOF}$
- ▶ Approximation by the use of energy minimization



# Energy-Minimization

- ▶ Every joint  $k$  defines an energy function  $E_k$ .
- ▶ Minimization of  $E(P) = \sum_{k=0}^n E_k(P_k)$  with  
 $P = \{P_1, P_2, \dots, P_k\}$ ,  $P_k$  being the set of parameters that joint  $k$  relates upon.
- ▶ define  $E$  in such a way that it has one strong minimum and optimally no side minima (or only significantly weaker ones)



# Energy-Minimization

- ▶ Finding the minimum by the means of local optimization (Newton method, Levenberg-Marquard algorithm, and more)
- ▶ Approximating the functions derivative at a starting point
- ▶ stepping "downhill" in the direction to the assumed minimum
- ▶ stopping, when the change in energy between two consecutive steps is below a threshold



# Energy Function for End-Affectors

- ▶ distance to nearest feature point inside a search radius
- ▶  $\Rightarrow$  set this joint as *assigned* and assign the feature point with the label of this joint
- ▶ if there is no feature point nearby, use mean distance to  $k$  nearest neighbours from 3D point cloud
- ▶  $\Rightarrow$  set this joint as *unassigned*.



# Energy Function for Non-Affectors

- ▶ if the next joint in skeleton hierarchy is assigned, let this joint attract to the path from the assigned feature point to the center of gravity.  $\Rightarrow$  distance from joint position to nearest point on geodesic path
- ▶ if the next joint is unassigned, use mean distance from  $k$  nearest neighbours from 3D point cloud



# Skeleton Constraints

- ▶ defining minimum and maximum parameter ranges for every joint in every DOF
- ▶ important for the algorithm
- ▶ restricting joint motions to only possible poses
- ▶ need to be defined accurately for every parameter dimension



# Demonstration

## Demonstration

Current stage of development





# Problems

- ▶ Tracking approach  $\Rightarrow$  can loose tracking from time to time
- ▶ possibility to get stuck at local minima
- ▶ algorithm highly dependent on feature detection and labeling
- ▶ minimization algorithm computational complex



# Future Prospects

- ▶ speed up minimization process
- ▶ improve energy functions for each joint
- ▶ improve automatic joint labeling for better assignments
- ▶ geodesic distance map needs to handle special cases more robustly
- ▶ better user segmentation





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