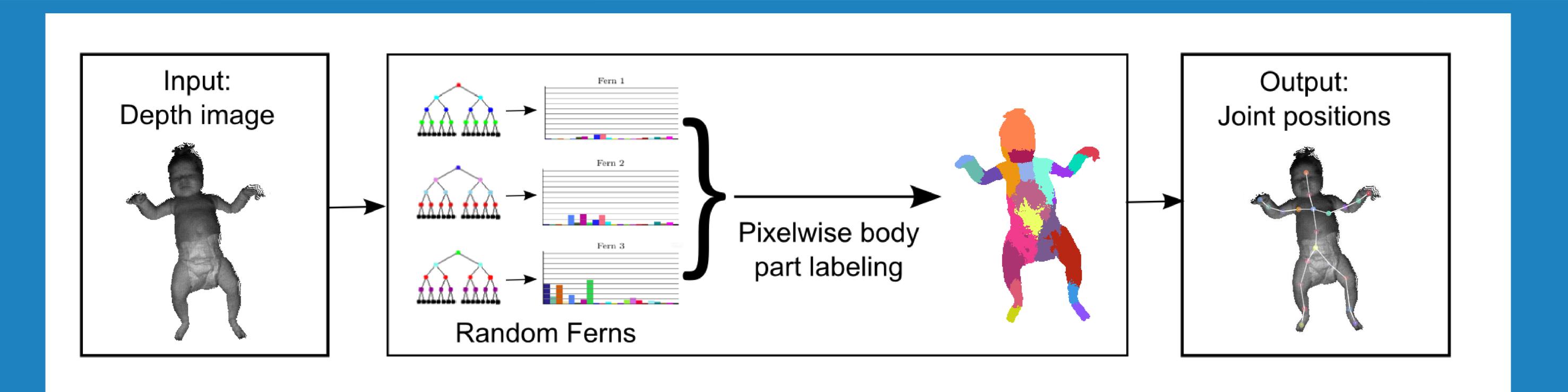


FRAUNHOFER-INSTITUTE OF OPTRONICS, SYSTEM TECHNOLOGIES AND IMAGE EXPLOITATION IOSB



Infant Body Pose Estimation for Motion Analysis

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Motivation

- How to capture 3D movements of infants?
 - Kinect SDK? Minimum size: 1 meter!
 - Attach markers / sensors?

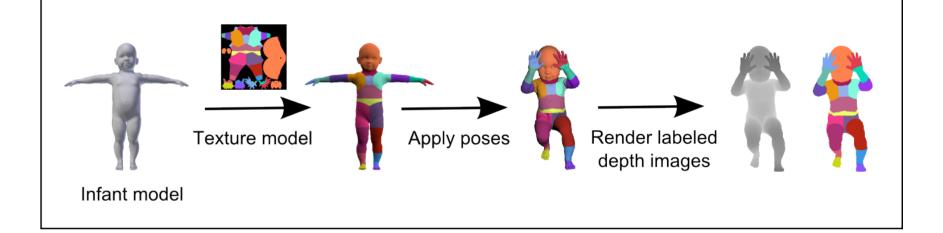


Method: Body pose estimation in depth images using Random Ferns [1]

- Fern: special kind of decision tree
- Input: one pixel of depth image
- Split nodes: binary depth comparison features
- Output: prob. distribution over all body parts
- Highest probability class assigned to pixel
- Joint positions deduced from body part regions

Synthetic training data generation

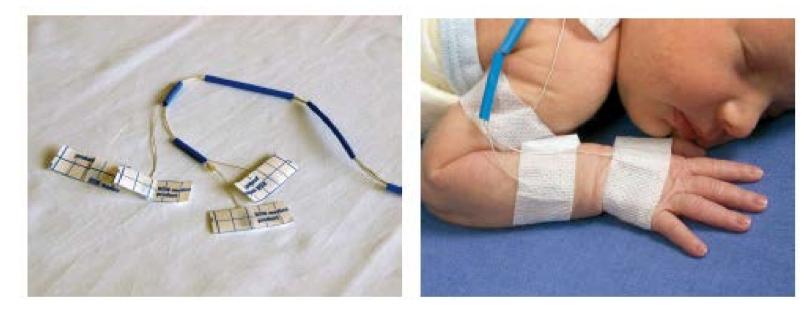
Used for generating probability distributions



Comparison to Kinect approach [2]

Training time reduced by 2 orders of magnitude with similar amount of data

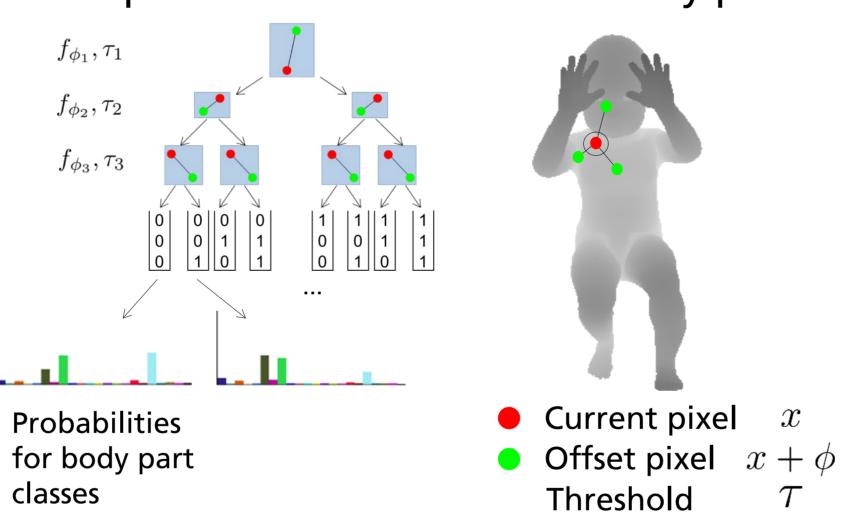
Optical markers [Meinecke2006]



Electromagnetical sensors [Karch2011]

No!

→ Our approach: **Markerless 3D pose** estimation using Random Ferns [1]



Evaluation: PDT13 data set - avg. joint error

Ours: 130 mm

Kinect SDK: 96 mm

Evaluation: infant sequence – average joint error in mm

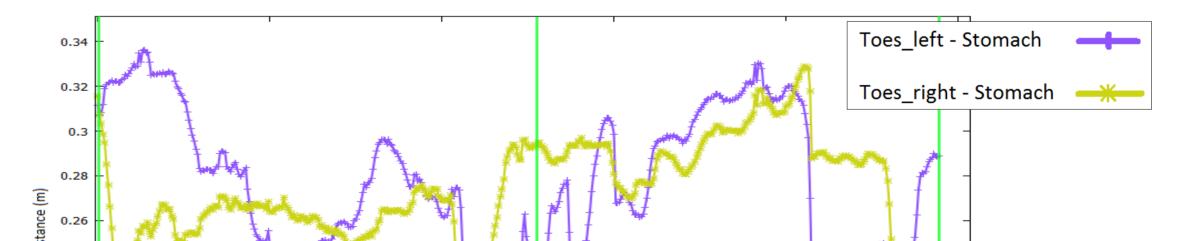
Joint / body part	Head	Neck	ShoulderR	ShoulderL	ElbowR	ElbowL	HandR	HandL
Avg. error	37	20	27	73	24	20	44	149
Joint / body part	Body center	HipR	HipL	KneeR	KneeL	FootR	FootL	Mean
Avg. error	30	33	12	45	49	28	30	41

Improving body part labeling





Motion analysis: distance toes – stomach



400

200

[1]: Training poses from Input depth CMU MoCap data set image adults, 180k images

Baby-like training poses - 2k images

More ferns + kinematic chain reweighting

Frame numbe

100

[1] Hesse et al., "Estimating Body Pose of Infants in Depth Images using Random Ferns", ICCVW 2015 [2] Shotton et al., "Real-time human pose estimation in parts from single depth images", CVPR 2011



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