Hybrid One-Shot 3D Hand Pose Estimation by Exploiting Uncertainties

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http://lrs.icg.tugraz.at/research/hybridhape/
Hand Pose Estimation

- from single depth images
- in 3D

image and annotation from ICVL Hand Posture Dataset
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- from single depth images
- in 3D

image and annotation from ICVL Hand Posture Dataset
### Traditional Approaches

<table>
<thead>
<tr>
<th>Model based/Generative</th>
<th>Data driven/Discriminative</th>
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</thead>
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*images from [Oikonomidis et al., BMVC 2011] and [Tang et al., CVPR 2014]*
Traditional Approaches

Model based/
Generative

Data driven/
Discriminative

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Initialisation, drift, …

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initialization, drift, …

accuracy, training data, anatomy, …
Main Idea

- Hybrid
- Exploit Uncertainties
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• Hybrid
• Exploit Uncertainties

(Graphical) Hand Model
Main Idea

- Hybrid
- Exploit Uncertainties

(Graphical) Hand Model

Optimise
Main Idea

- Hybrid
- Exploit Uncertainties

(Graphical Hand Model)

Hand Pose Estimation by Exploiting Uncertainties
Main Idea

- Hybrid
- Exploit Uncertainties

![Graphical Hand Model]

~100% more frames correct @23mm
Main Idea (Example)
Main Idea (Example)

Input
Main Idea (Example)

Input

Uncertainty of learned regressor
Main Idea (Example)

Input

Uncertainty of learned regressor

Most confident positions
Hand Pose Estimation by Exploiting Uncertainties

Main Idea (Example)

Input

Most confident positions

Uncertainty of learned regressor

Optimization considering Uncertainty
Proposal Generation

Random Forest

- showed good results for pose estimation from depth
e.g., [Shotton et al., PAMI 13], [Tang et al., ICCV 13], …
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Hand Model

- to enforce constraints in hybrid approach
Hand Model

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Optimisation

Objective:

• Find pose parameters, best fitting the proposals considering their certainty
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\[ s_r (\mathcal{P}, \mathbf{h}) \]

proposals \( \mathcal{P} \)

hypothesis \( \mathbf{h} \) (pose parameters; 26 DoF)

Similarity measure
Optimisation

Objective:

- Find pose parameters, best fitting the proposals considering their certainty

$$\max_r \left( w_r \cdot s_r(\mathcal{P}, h) \right)$$

- Proposals $\mathcal{P}$
- Hypothesis $h$ (pose parameters; 26 DoF)
- Confidence for $r^{th}$ proposal
- Similarity measure
Optimisation

Objective:

• Find pose parameters, best fitting the proposals considering their certainty

\[
\mathbf{h}^* \triangleq \arg \max_{\mathbf{h}} \sum_{j=1}^{J} \max_r \left( w_{jr} \cdot s_{jr}(P, h) \right)
\]

Confidence for \( r \)th proposal

Similarity measure

• Selects proposals, which – together – best form an anatomically valid pose
Optimisation

Objective:

- Find pose parameters, best fitting the proposals considering their certainty

\[ h^* \triangleq \arg \max_h \sum_{j=1}^{J} \max_r \left( w_{jr} \cdot s_{jr}(\mathcal{P}, h) \right) \]

- Selects proposals, which – together – best form an anatomically valid pose
- Optimisation by Particle Swarm Optimisation (PSO)
Optimisation: Stepwise

- Mitigate search space growth
Optimisation: Stepwise

- Mitigate search space growth

Given global position and orientation of palm

fingers can move almost independently
Optimisation: Stepwise

- Mitigate search space growth

Given global position and orientation of palm

Fingers can move almost independently

6 DoF
Optimisation: Stepwise

- Mitigate search space growth

Given global position and orientation of palm

fingers can move almost independently
Results: Contribution
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“TrackSeq” (Synthetic Sequence)
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“TrackSeq” (Synthetic Sequence)
Results: State-of-the-art

“TrackSeq” (Synthetic Sequence)

- vs. FORTH [Oikonomidis et al., BMVC 2011]
Results: State-of-the-art

ICVL Dataset

- vs. LRF [Tang et al., CVPR 14]

Inaccurate annotation: e.g., “bone lengths” varying between frames, …
Results: State-of-the-art

NYU Dataset

- vs. (hybrid) NYU ConvNet [Tompson et al., ToG 14]
Conclusions

- Hybrid approach
- Model based optimisation aware of internals from discriminative step
- Stepwise optimisation (wrt. hand anatomy)

- In general, more robust but for some joints slightly less accurate
- Possible solution: additional model based step considering depth data
Many thanks

A collaboration between
TU Graz and FORTH
Qualitative Results
Error Cases (NYU)

Mean error: 12mm
Max. error: 39mm

Mean error: 14mm
Max. error: 58mm
Error Cases (ICVL)

Mean error: 18mm
Max. error: 28mm

Mean error: 16mm
Max. error: 47mm