Probabilistic Pose Estimation using Mixtures of Projected Gaussians


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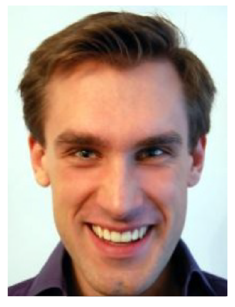
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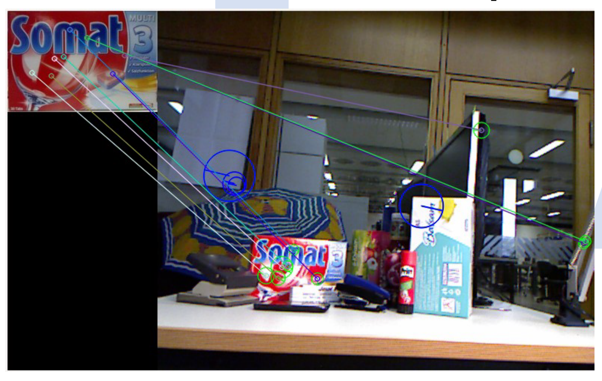
Matched Pair

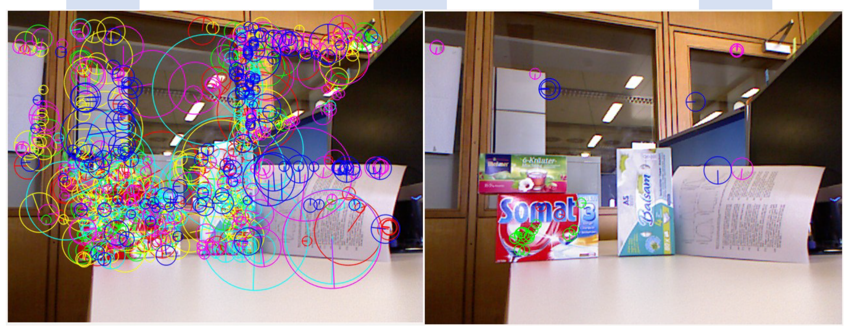
Database Feature
- key point & descriptor in 2D
- 3D position
- 3D orientation

Camera Feature
- rotation in image plane
- RGB-D camera: 3D position



Strength Evaluation

- radius match: similarity of matched features $\lambda \in (0,1)$
- matching strength commited to pose estimation



Stability Evaluation

Goal
- feature stabilization
- outsorting of outliers

Kalman Filter
- pose and variance estimation: impact in pose estimation
- variance respective apprearance rate

Input:
strong and stable matched feature pairs

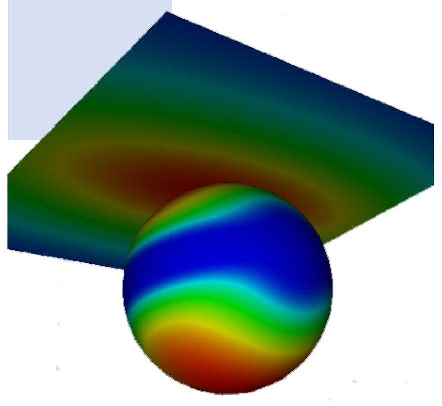
Sensor Model

ideal world
6D feature pose determined & matching 6D feature in database
$\Rightarrow$ object pose

real world
camera data only provides uncertain feature pose information
$\Rightarrow$ information fusion of several matched pairs necessary

Probability Density over 6D Poses in $S_3 \times \mathbb{R}^3$

desired
mixtures of Gaussians, but only for translation possible
problem
rotation on unit sphere S_3, Gaussians on tangent space



rotation
projection of Gaussians to unit sphere
renormalization
term for Gaussians and volume correction term for projection

Parameterization of 6D Pose

3D rotation
unit quaternion $\mathbf{q}_r = a + ib + jc + kd$, with $a + b + c + d = 1$

3D translation
imaginary quat. $\mathbf{q}_t = 0 + ib + jc + kd$,
with $[b, c, d]^\top$ translation vector

6D rigid motion
dual quaternion $\mathbf{dq} = q_r + \epsilon \cdot \frac{1}{2} q_t * q_r$
with $\epsilon^2 = 0$

Mixture of Projected Gaussians

definition
$$\mathcal{M} = (1 - \lambda)\mathcal{U} + \sum_{i=1}^{n} \frac{\lambda}{n} \mathcal{PG}_i$$
unit distribution $\mathcal{U}$ for background noise

fusion
similar to fusion of Mixtures of Gaussians
composition
used to change coordinate systems
element reduction
merge similar elements, drop elements with negligible weights

Output:
probability distribution describing object pose

Mixture of Projected Gaussians

- provides estimator in 6D for object
- provides remaining uncertainty of object pose
- probability for successful grasp (given optimal prasp position reachable)

coordinate systems sampled from object probability distribution

Benefits for Perception

- representation of weak pose information
- efficient calculation
- open to various feature types: surface / object shape features
- allows for forward inference

Selected publications:
- M. Lang, W. Feiten, "MPG - Fast Forward Reasoning on 6 DOF Pose Uncertainty", Inproceedings ROBOTIK 2012
- W. Feiten et al., "6D Pose Uncertainty in Robotic Perception", Advances in Robotics Research, Springer Berlin Heidelberg, 2009

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