The 6th COE Doctoral and Post-Doctoral Researchers
Technical Presentation

Unscented Kalman Filter in Hand Pose Estimation

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I. The Current System
II. Objective
III. Proposed Methodology
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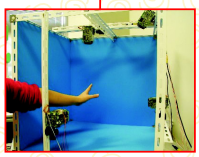
Current System

- model-based multiple camera -

Multiple viewpoint camera
Obtain silhouette images
(Silhouette images)
Convert 2D to 3D Volumetric Data
(Voxel model)
Hand model fitting
Estimated Hand pose



[Ueda *et al* 2003]

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[Ueda *et al* 2003]

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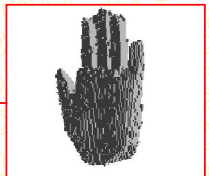

Reconstruction of voxel model

[Ueda *et al* 2003]

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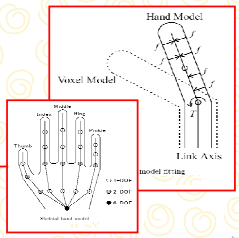

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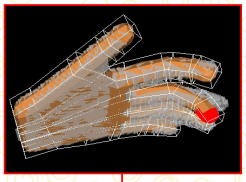
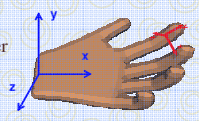


[Ueda *et al 2003*]

Proposed System

- Disadvantages of current system
  - Estimation of global & local pose: not simultaneous
  - High computational time
  - Thumb not estimated properly
- Proposed System
  - Use predictive filter



Hand Pose = Global Pose + Local Pose

Proposed Methodology

Multiple viewpoint camera

Obtain silhouette images

(Silhouette images)

Convert 2D to 3D Volumetric Data

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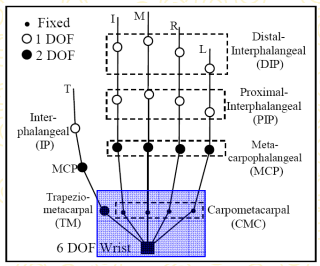
Unscented Kalman Filtering

Estimated Hand pose

Skeletal Hand Model



Unscented Kalman Filter

- Applied to Hand Pose Estimation -

Initialization

Prediction

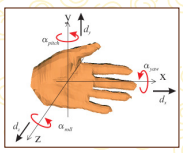
2n+1 particles and weights

Propagate states

Propagate observations

Weighting

Correction



$$\mathbf{X} = [\alpha_x, \alpha_y, \alpha_z, p_x, p_y, p_z, \theta_1, \cdots, \theta_{21}, \dot{\alpha}_x, \cdots, \dot{\theta}_{21}]^T$$

(state vector)

$$\mathbf{X}_{init} = [0,0,0,0,0,0,0,\cdots,0,0,\cdots,0]^T$$

Unscented Kalman Filter

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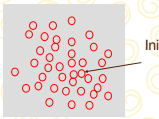

Initial value

Particle Propagation | weights

$$\begin{cases} x_{k-1}^0 = \bar{x}_{k-1} & \Rightarrow w_0 \\ x_{k-1}^i = \bar{x}_{k-1} + \left(\sqrt{(n+\lambda)\Sigma_{k-1}}\right)_i & \Rightarrow w_i \\ x_{k-1}^i = \bar{x}_{k-1} - \left(\sqrt{(n+\lambda)\Sigma_{k-1}}\right)_i & \Rightarrow w_i \end{cases}$$

Unscented Kalman Filter
- Applied to Hand Pose Estimation -

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STATE DYNAMICS

$$\mathbf{X_k} = \begin{bmatrix} \mathbf{I} & \Delta t\mathbf{I} \\ \mathbf{0} & \mathbf{I} \end{bmatrix} \mathbf{X_{k-1}} + \mathbf{Q_k}$$

(noise)

Mean and Covariance

$\hat{\bar{x}}_k \quad \hat{\Sigma}_k$

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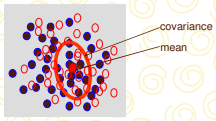

Non-linear propagation of Observation

$$\hat{y}_k^i = h(\hat{x}_k^i, \upsilon_k)$$

(noise)
(non-linear function)
(propagated state)

Mean and Covariance

$\hat{\bar{y}}_k \quad \hat{\Sigma}_{yyk}$

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cross-covariance

$$\Sigma_{xy_k} = \sum_{i=0}^{2n} {}^c\omega_{k-1}^i \left[\hat{x}_k^i - \hat{\bar{x}}_k\right]\left[\hat{y}_k^i - \hat{\bar{y}}_k\right]^{\mathrm{T}}$$

Kalman gain

$$K_k = \Sigma_{xy_k}\Sigma_{yy_k}$$

Unscented Kalman Filter
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mean

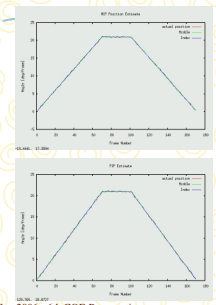
$$\bar{x}_k = \hat{\bar{x}}_k + K_k\left(y_k - \hat{\bar{y}}_k\right)$$

covariance

$$\Sigma_k = \hat{\Sigma}_k + K_k\Sigma_{yy_k}K_k^{\mathrm{T}}$$

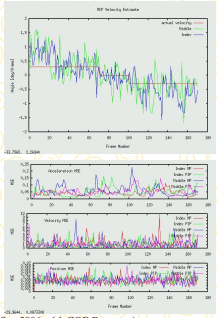
$\bar{\mathbf{X}}_k = [6.2 \quad 12.9 \quad 12.8 \quad 0 \quad 0 \quad 0 \quad \cdots \quad 0 \quad 0 \quad \cdots \quad 1.1]^{\mathrm{T}}$

Simulation Results: 2 Fingers



- State
  - MCP and PIP joints
- Observation
  - Joint angle
  - Size of state is less than observation matrix

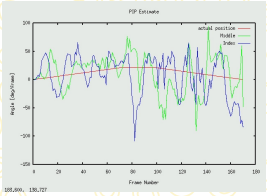
Simulation Results: 2 Fingers



- Mean Square Error
  - Position estimate has low error
  - Velocity and Acceleration estimate has bigger errors

Simulation Results: 2 Fingers

- State
  - MCP and PIP joints
- Observation
  - Joint angle
  - Size of state and observation matrix are equal



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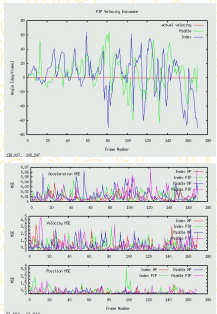

- Mean Square Error
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Conclusion

- Presented UKF in Hand Pose Estimation
- Simulation results
- Future Tasks
  - Test other observation function: 2D or 3D
  - Real-camera system implementation

END

Thank You!!