Human Motion Modeling and Tracking with Gaussian Process Dynamic Model

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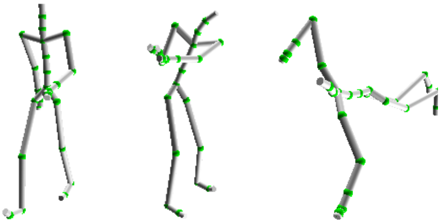


Figure: Walk, Golf Swing and Swim Motions from CMU Motion Data

- **Data Property**: High-Dimensional Observation
- **Goal**: Human Motion Modeling & Tracking

Introduction, Con't

- **What to do**?
  - Modeling: Low-Dimensional Latent Representation
  - Tracking: State Estimation & Prediction
- **How to do**?
  - Modeling: Gaussian Process Dynamic Model (GPDM)
  - Tracking: Bayesian Filtering
- **Why to use them**?
  - Flexible Bayesian Framework
  - Strong Connections
- **How to use them**?
  - Interaction between GPDM and Bayesian Filtering

Modeling:

Gaussian Process Dynamic Model (GPDM)

State Space Model (SSM) for Dynamic Systems

Prediction Model:

$$\mathbf{x}_t = \mathbf{f}_\mathbf{x}(\mathbf{x}_{t-1}) + \mathcal{N}(0, \sigma_x^2 I) \longrightarrow p(\mathbf{x}_t | \mathbf{x}_{t-1}) \tag{1}$$

Observation Model:

$$\mathbf{y}_t = \mathbf{f}_\mathbf{y}(\mathbf{x}_t) + \mathcal{N}(0, \sigma_y^2 I) \longrightarrow p(\mathbf{y}_t | \mathbf{x}_t) \tag{2}$$

- $\mathbf{x}_t \in \mathbb{R}^{D_x}$: state vector
- $\mathbf{y}_t \in \mathbb{R}^{D_y}$: observation vector
- $\mathbf{f}_\mathbf{x}(\cdot)$ and $\mathbf{f}_\mathbf{y}(\cdot)$: nonlinear functions

- **Gaussian Process Prior On Nonlinear Functions**

  [C. E. Rasmussen and C. K. I. Williams, 2006]

  - $f_{\mathbf{x}}(\cdot) \sim \mathcal{GP}(0, k_{\zeta_x}(\mathbf{x}, \mathbf{x}'))$
  - $f_{\mathbf{y}}(\cdot) \sim \mathcal{GP}(0, k_{\zeta_y}(\mathbf{x}, \mathbf{x}'))$
  - $\Theta = (\zeta_x, \zeta_y, \sigma_x^2, \sigma_y^2)$

- **Training Set for SSM**
  - For Prediction Model: $\mathcal{X}_{T_0} = \{(\mathbf{x}_{i-1}, \mathbf{x}_i)\}_{i=2}^{T_0}$
  - For Observation Model: $\mathcal{Y}_{T_0} = \{(\mathbf{x}_i, \mathbf{y}_i)\}_{i=1}^{T_0}$

- **Standard GP Regression for SSM**
  - $p(\mathbf{x}_t | \mathbf{x}_{t-1}, \Theta, \mathcal{X}_{T_0})$
  - $p(\mathbf{y}_t | \mathbf{x}_t, \Theta, \mathcal{Y}_{T_0})$

- **Challenge**:

  Unknown states $\mathbf{x}_{1:T_0}$ in the training set

- **Solution**:
  - Minimizing $-log(p(\mathbf{x}_{1:T_0}, \Theta | \mathbf{y}_{1:T_0}))$ with respect to $\mathbf{x}_{1:T_0}, \Theta$
  - The low dimensional $\mathbf{x}_t$ where $D_x \ll D_y$

Tracking:

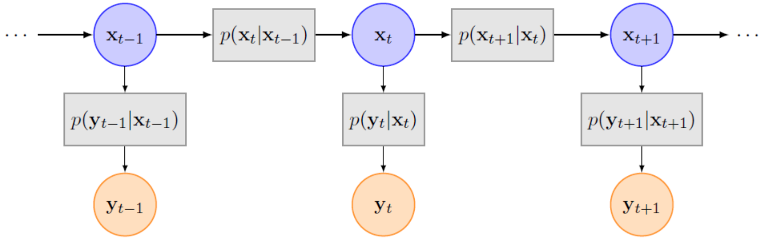
Bayesian Filtering

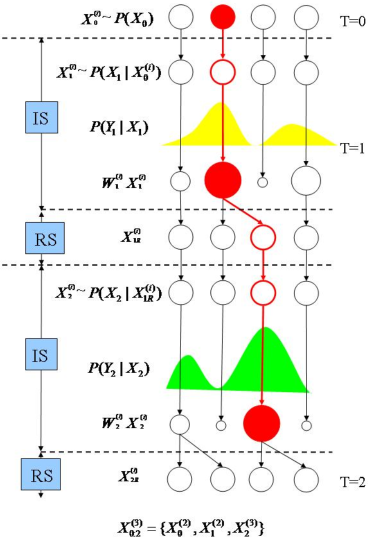
Bayesian Filtering

$$p(\mathbf{x}_{t-1}|\mathbf{y}_{0:t-1}) \xrightarrow{\text{Predict}} p(\mathbf{x}_t|\mathbf{y}_{0:t-1}) = \int p(\mathbf{x}_t|\mathbf{x}_{t-1})p(\mathbf{x}_{t-1}|\mathbf{y}_{0:t-1})d\mathbf{x}_{t-1}$$

Update

$$p(\mathbf{x}_t|\mathbf{y}_{0:t}) = \frac{p(\mathbf{y}_t|\mathbf{x}_t)p(\mathbf{x}_t|\mathbf{y}_{0:t-1})}{p(\mathbf{y}_t|\mathbf{y}_{0:t-1})}$$





$X_0^{(i)} \sim P(X_0)$
T=0
$X_1^{(i)} \sim P(X_1 | X_0^{(i)})$
IS
$P(Y_1 | X_1)$
T=1
$W_1^{(i)} X_1^{(i)}$
RS
$X_{1R}^{(i)}$
$X_2^{(i)} \sim P(X_2 | X_{1R}^{(i)})$
IS
$P(Y_2 | X_2)$
$W_2^{(i)} X_2^{(i)}$
RS
$X_{2R}^{(i)}$
T=2
$X_{0:2}^{(3)} = \{X_0^{(2)}, X_1^{(2)}, X_2^{(3)}\}$

Particle Filtering Based On GPDM [J. Ko and D. Fox, RSS2005]

- **Modeling SSM by GPDM** ($t = 1$ to T_0)
  - $p(\mathbf{x}_t|\mathbf{x}_{t-1}, \Theta, \mathcal{X}_{T_0})$
  - $p(\mathbf{y}_t|\mathbf{x}_t, \Theta, \mathcal{Y}_{T_0})$
- **Tracking by Particle Filter** ($t > T_0$)
  - $p(\mathbf{x}_t|\mathbf{y}_{T_0+1:t})$ using $p(\mathbf{x}_t|\mathbf{x}_{t-1}, \Theta, \mathcal{X}_{T_0})$ and $p(\mathbf{y}_t|\mathbf{x}_t, \Theta, \mathcal{Y}_{T_0})$
- **Drawback**
  - GPDM will be fixed during tracking!

Thank you for your attention