A Hierarchical Gaussian Process Control Algorithm for Bimanual Coordination with Hand Rehabilitation Devices

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Background

Bimanual Control in Hand Rehab.

Patients with unilateral impairment rely on their healthy limb.

Results in an overuse of the healthy arm and can lead to injury (Jones et al., 1999; Gambrell et al.; 2008)

When bimanual coordination is necessary, patients typically minimize use of their rehabilitation device, e.g., they employ it only for passive support

Execution time of bimanual tasks compared to unimanual in prosthesis control is much greater and have significantly lower success rates. (Strazzulla et al., 2016)

Basics of Hierarchical Gaussian Processes (HGPs) for Motion

Statistical models for human motion are difficult due to factors like high-dimensionality and motor redundancy. To define the generative model, we decouple the modeling of pose and motion.

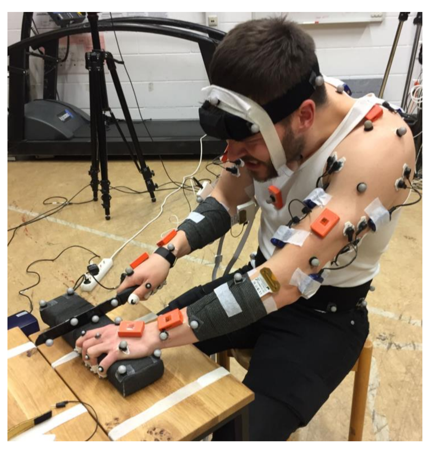
Poses—generated by an observational process from a lower-dimensional latent space (GPLVM)

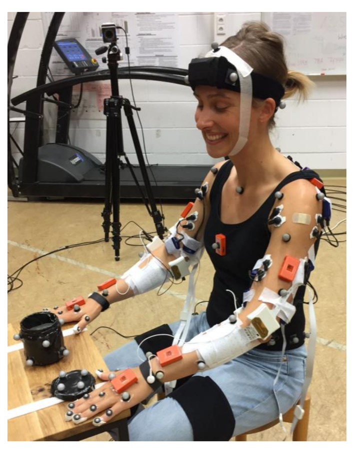
Motion—dynamical process that accounts for transitions between poses in the latent space (GPDM)

Lawrence et al. 2007; Wang et al. 2008

Methods

Experiment





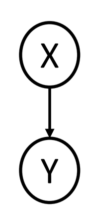
MoCap and EMG in Activities of Daily Living

Electromyography (EMG)
- Bipolar elecrtodes
- HD-EMG (6 8x8 electrode arrays)

Motion Capture (MoCap)
- Vicon Shogun IR Capture
- Xsens Inertial Capture

GPLVMs, GPDMs, Back-constraints (BCs) and Concatenated Latent Spaces

GPLVM

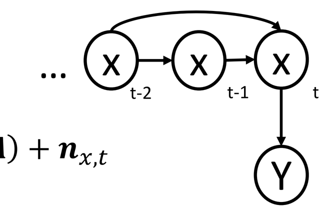


$$\boldsymbol{y}_t = g(\boldsymbol{x}_t; \boldsymbol{B}) + \boldsymbol{n}_{y,t}$$

$$p(Y,X) = p(Y|X)p(X)$$

Lawrence et al., 2004

GPDM

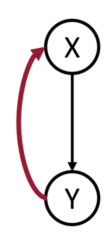


$$\boldsymbol{x}_t = f(\boldsymbol{x}_{t-1}, \boldsymbol{x}_{t-2}; \boldsymbol{A}) + \boldsymbol{n}_{x,t}$$

$$p(X) = p(x_1, x_2) \prod_{n=3}^{N} p(x|x_{t-1}, x_{t-2})$$

Wang et al., 2008

Back-constraint



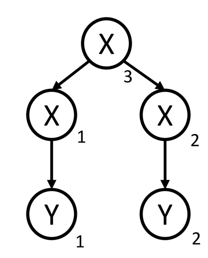
$$x_{nj} = g_j(\boldsymbol{y}_n; \boldsymbol{w})$$

$$\boldsymbol{A} = \{\{\alpha_{jn}\}_{n=1}^{N}\}_{j=1}^{q}$$

$$g_j(\boldsymbol{y}_n) = \alpha_{jm} k(\boldsymbol{y}_n; \boldsymbol{y}_m)$$

Lawrence et al., 2006

Latent space concatenation

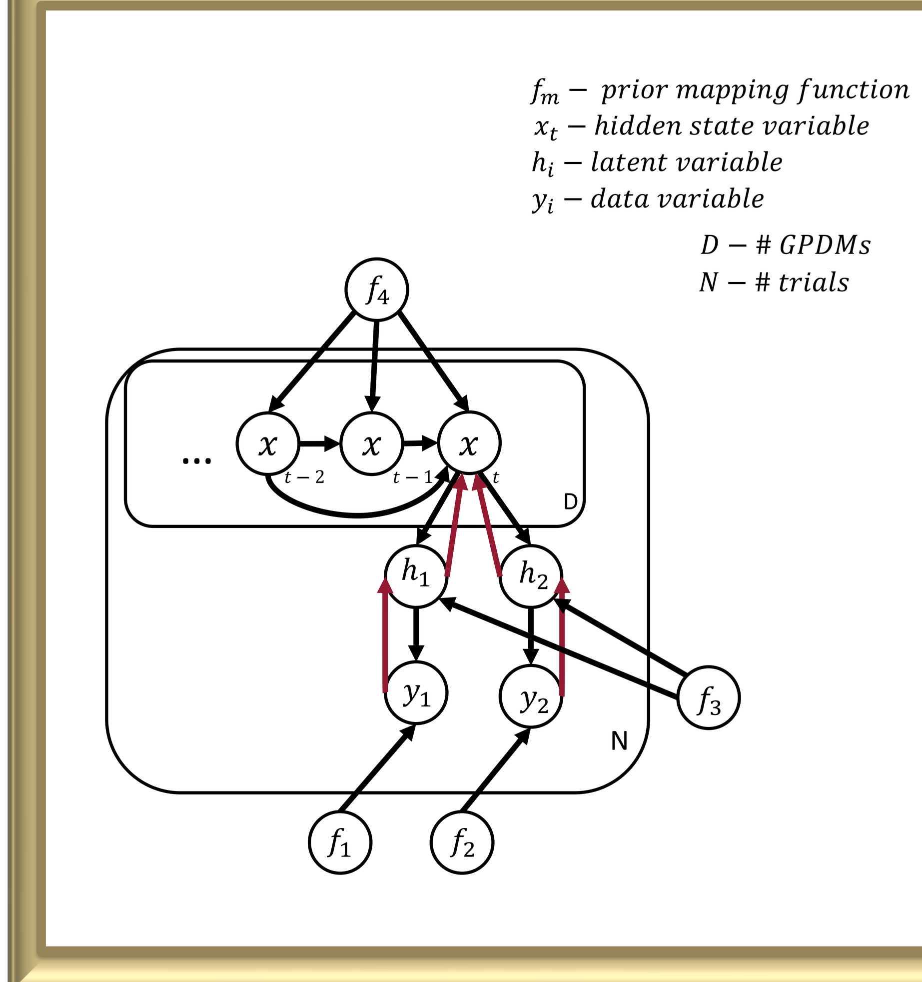


$$p(X_2|X_3)\, p(X_1|X_3) = p([X_1, X_2]|X_3)$$

$$p(Y_1, Y_2, X_1, X_2, X_3) = p(Y_1|X_1)p(Y_2|X_2)p(X_2|X_3)\, p(X_1|X_3)p(X_3)$$

Taubert et al., 2011

Bimanual Coordination Generative Model



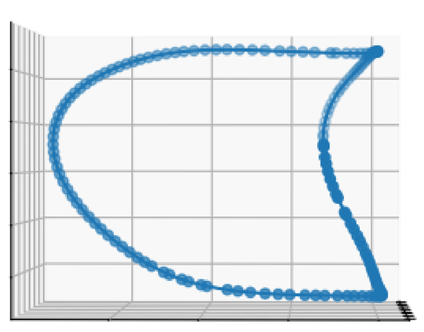
Geometric BCs

Angle between data points – $\theta_i = \arctan(\frac{L_{i,1}}{L_{i,0}})$

Circular BC

$x_i = \cos(\theta_i)$ $\quad C_{ij,0} = k(x_i, x_j)$

$y_i = \sin(\theta_i)$ $\quad C_{ij,1} = k(y_i, y_j)$



Lawrence et al. 2006

Toroidal BC

$x_i = (\mathrm{R} + \mathrm{r} * \cos(\theta_i))\cos(n * \theta_i)$

$y_i = (\mathrm{R} + \mathrm{r} * \cos(\theta_i))\sin(n * \theta_i)$

$z_i = \mathrm{r} * \sin(n * \theta_i)$

$C_{ij,0} = k(x_i, x_j)$

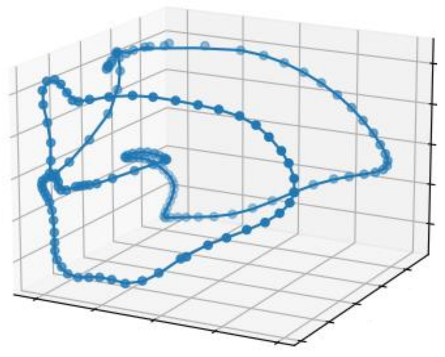
$C_{ij,1} = k(y_i, y_j)$

$C_{ij,3} = k(z_i, z_j)$

R – outer torus radius

r – inner torus radius

n – number of winds around torus

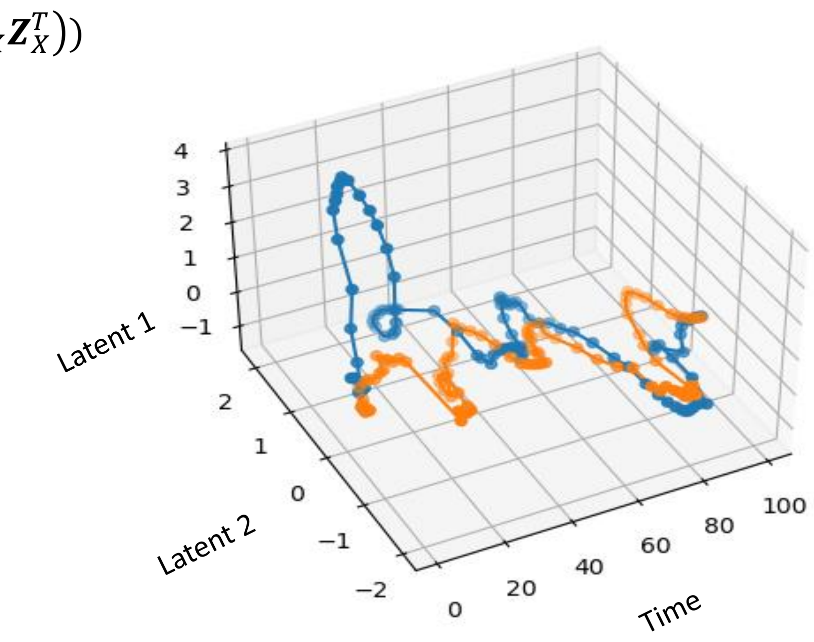


GP Dynamical Mixture Model (GPDMM)

$$p(\boldsymbol{X}^*|\boldsymbol{X}, \boldsymbol{Y}, z_k) = \frac{p(\boldsymbol{x}_1^*)}{\sqrt{(2\pi^{(M-1)d}|\boldsymbol{K}_{\boldsymbol{X}^*}|^d}} \exp(-\frac{1}{2} tr(\boldsymbol{K}_{\boldsymbol{X}^*}^{-1} \boldsymbol{Z}_X \boldsymbol{Z}_X^T))$$

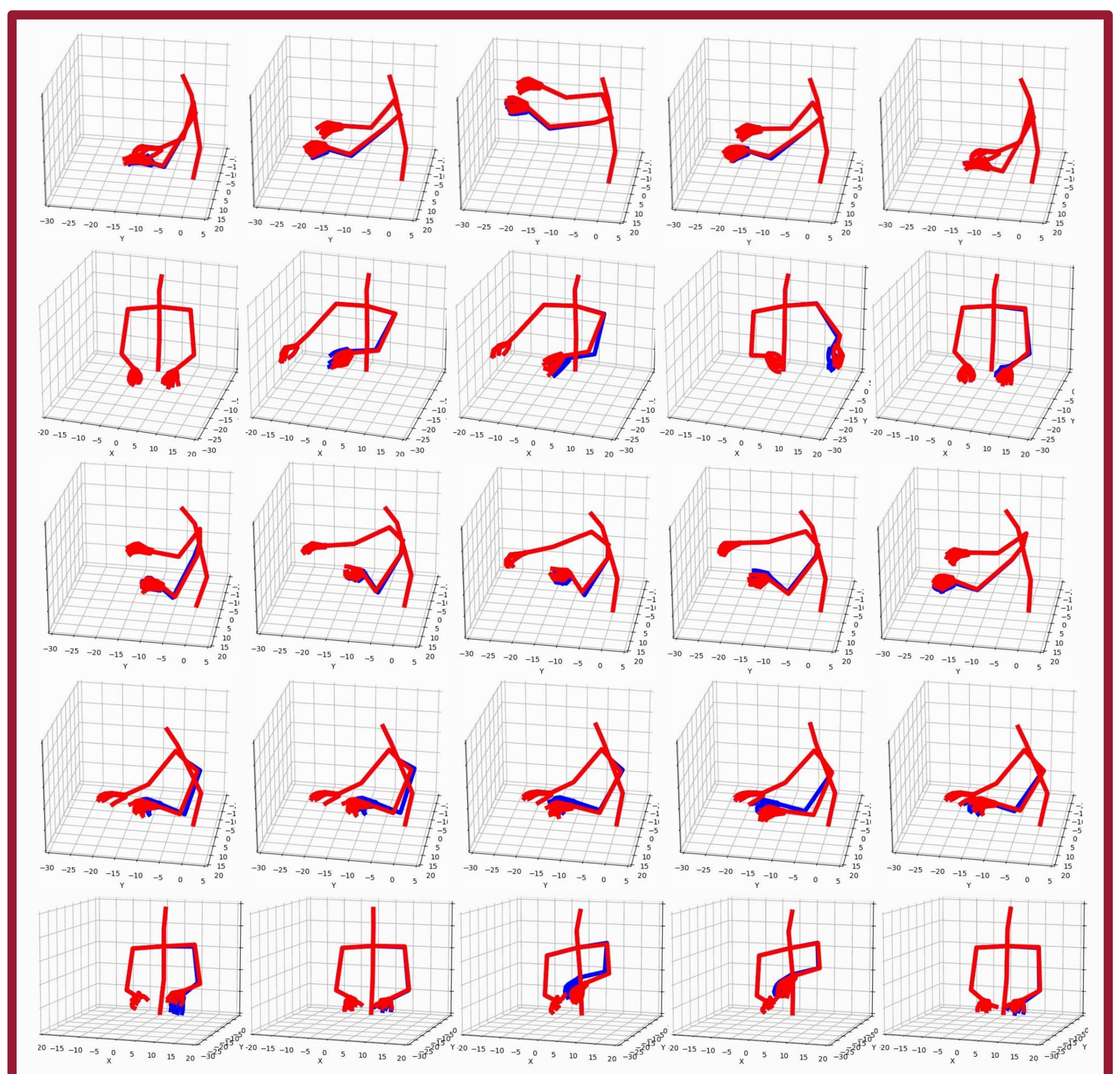
- $\boldsymbol{Z}_X = \boldsymbol{X}_{2:N}^* - \boldsymbol{C}^T \boldsymbol{K}_X^{-1} \boldsymbol{X}_{2:N}$
- $\boldsymbol{K}_{X^*} = \boldsymbol{D} - \boldsymbol{C}^T \boldsymbol{K}_X^{-1} \boldsymbol{C}^T$
- $C_{ij} = k_x(x_i, x_j^*)$
- $D_{ij} = k_x(x_i^*, x_j^*)$

$$p(z_k|\boldsymbol{X}^*) = \frac{p(z_k)p(\boldsymbol{X}^*|z_k)}{\sum_k^K p(z_k)p(\boldsymbol{X}^*|z_k)} \qquad p(z_k) = \frac{n_k}{N}$$



Results

Generation of Left Arm in Bimanual Tasks



Prediction of the left arm (red) overlaying true values of the sequence (blue) using circular back-constraints with a limited training dataset.

Average Squared Distance Over Variance Between the Prediction and True Value

Type of BC \ Number of Actions in GPDMM	1	2	3	4	5
Baseline	24.97	16.84	18.88	28.27	31.18
Circular BC	9.81	10.86	12.88	20.25	19.60
Toroidal BC	8.96	9.24	11.59	21.54	22.95

HPG Python Package Features and Comparison

Package Features	GPy	CompSens Package
GPs/GPLVMs	✓	✓
Varied optimization methods	✓	✓
Kernels	✓	✓
Inference functions	✓	✓
Back-constraints	Inflexible; not geometric	✓
GPDMs (1st and 2nd order)	X	✓
Hierarchical structure	X	✓
Initialization procedures	Linear PCA	✓
Node-based computation	X	✓
Dynamics testing toolkit	X	✓
Automatic movement identification	X	✓
Graphical User Interface (GUI)	X	O
Hyperparameter/Intermodel Optimization	X	O
Sparse GPLVM (for real-time interactions)	X	O

Outlook

- Ambiguate starting conditions so that sequence classification is shown to improve over longer sequences
- Test algorithm over a greater diversity of parameters and trials to determine optimal conditions
- Devise a more critical metric to show model's success (e.g., one that is more robust to small and rather inconsequential time shifts)
- Incorporate EEG and Inertial MoCap
- Include sparse GPLVM for efficient computations
- Compare model with state-of-the-art solutions

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