Data Driven Dynamic Stability Modeling for Human Gait Analysis & Control of Assistive Devices

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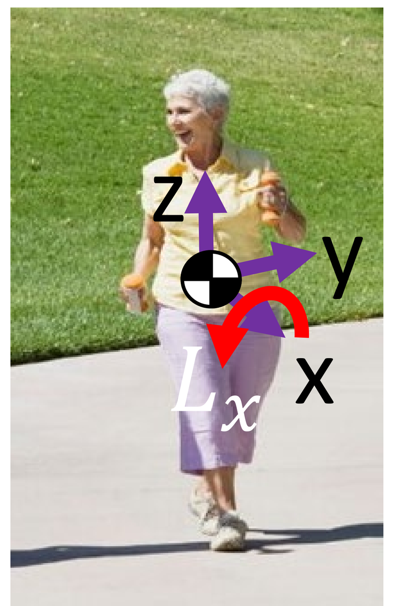
Background



https://brightwatergroup.com/news-articles/5-reasons-to-keep-walking-as-you-get-older/

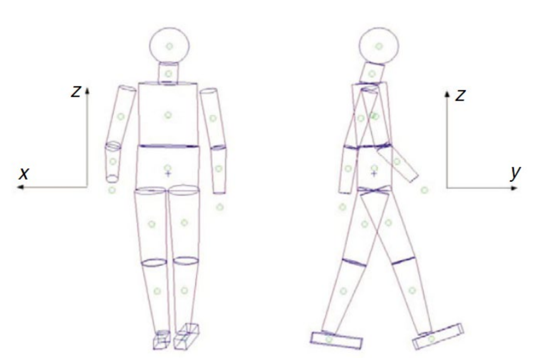
- Elderly people struggle to control their balance, leading to falls
- Whole body angular momentum (WBAM) -> dynamic stability
- Prior momentum based controllers for humanoid robots are hybrid & nonlinear

$$x_{t+1} = \begin{cases} f_1(x_t), if \ \|x_t\| \geq c \\ f_2(x_t), if \ \|x_t\| < c \end{cases}$$

=> More complex for control

Whole Body Angular Momentum

Human Subject Trials at Northwestern of walking on treadmill with perturbations [2]



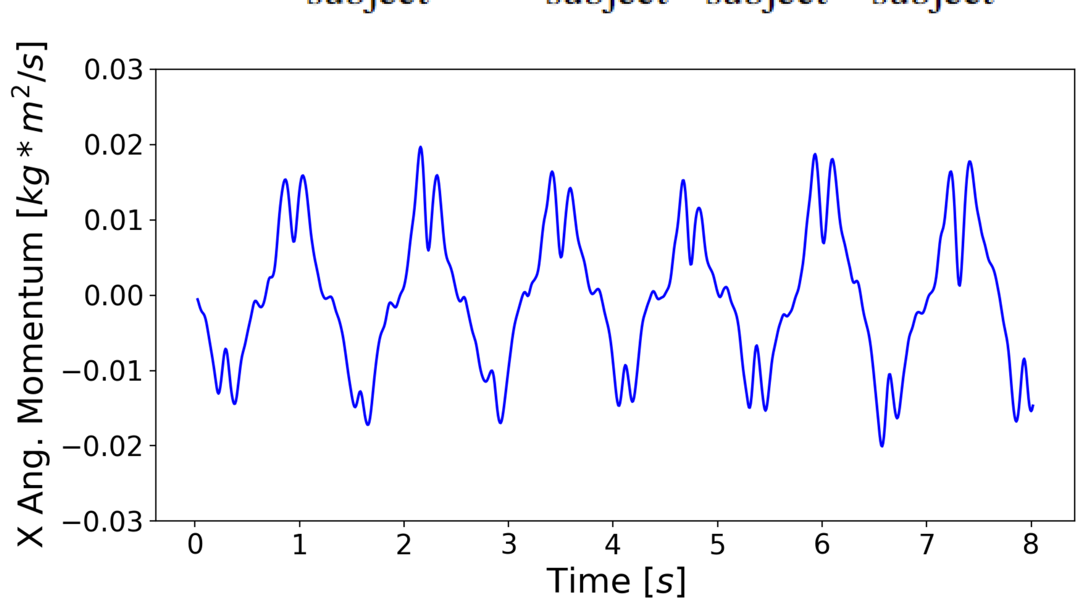
Herr, H., & Popovic, M. (2008).

$$\vec{L} = \sum_{i=1}^{16} [(\vec{r}^{\,i}_{CM} - \vec{r}_{CM}) \times m_i(\vec{v}^{\,i} - \vec{v}_{CM}) + \vec{I}^{\,i}\vec{\omega}^{\,i}] .$$

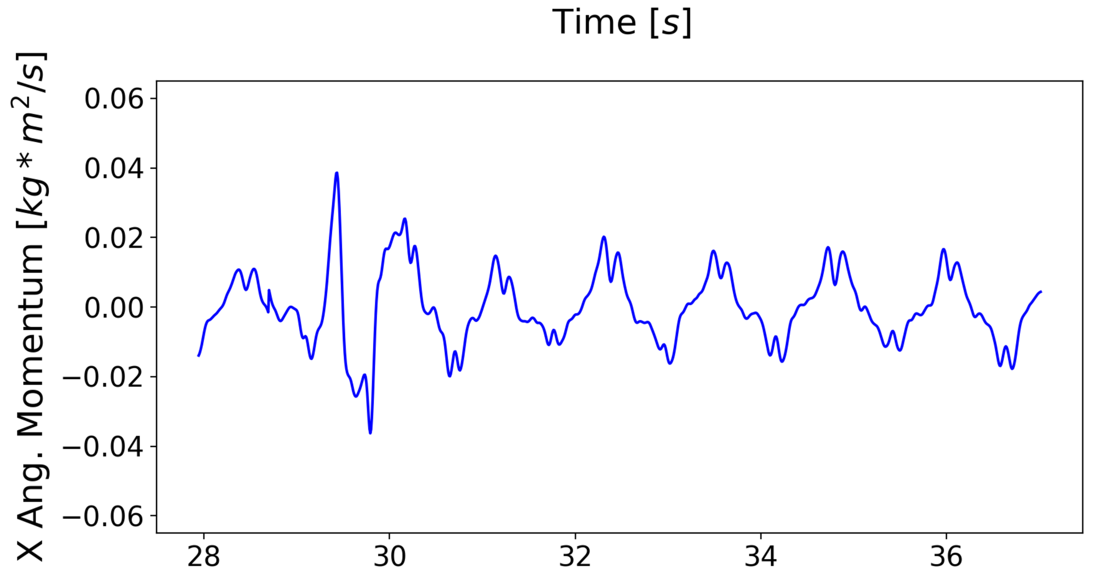
$$\vec{r}_{CM} = \sum_{i=1}^{16} M^i_R \, \vec{r}^{\,i}_{CM} .$$

$$N_{subject} = M_{subject} V_{subject} H_{subject}$$

Stable walking:



Perturbation trial:



Goals

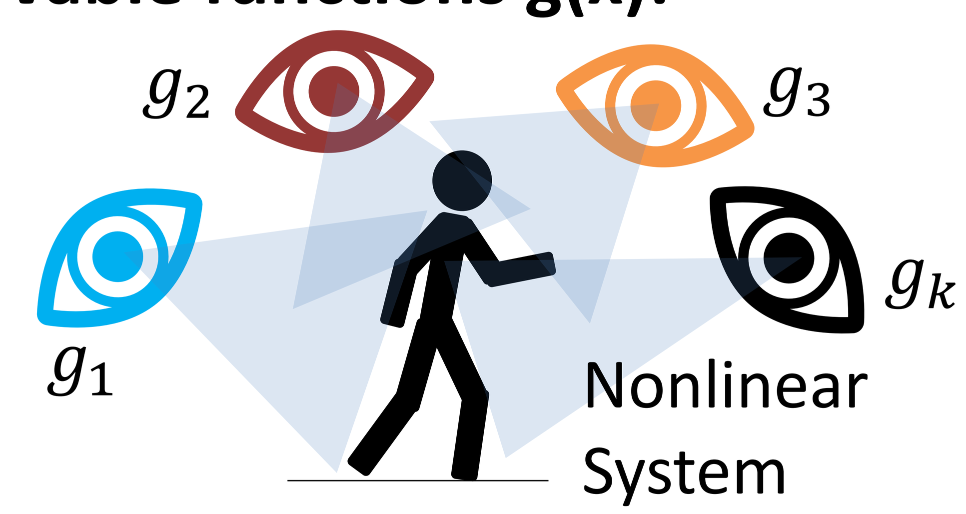
- Find A matrix in $x_{t+1} = Ax_t$ for WBAM
- Analyze resulting linear system & characterizer robustness to perturbation
- Find controller inputs to return state to stable gait limit cycle after perturbation

Modeling

States:

$$x_t = \begin{bmatrix} L_x(t) \\ L_y(t) \\ L_z(t) \end{bmatrix}$$

Observable functions g(x):



- Monomial functions: $g(x) = x^2$
- Radial Basis Functions: $g(x) = e^{(\varepsilon\|x-c\|)^2}$
- Learned via neural network

1. Extended Dynamic Mode Decomposition (EDMD)

$$\chi_t = \begin{bmatrix} x_0 & x_1 & \cdots & x_{N-1} \\ g_1(x_0) & g_1(x_1) & \cdots & g_1(x_{N-1}) \\ g_2(x_0) & g_2(x_1) & \ddots & g_2(x_{N-1}) \\ \vdots & \vdots & & \vdots \\ g_k(x_0) & g_k(x_1) & & g_k(x_{N-1}) \end{bmatrix}$$

$$\chi_{t+1} = \begin{bmatrix} x_1 & x_2 & \cdots & x_N \\ g_1(x_1) & g_1(x_2) & \cdots & g_1(x_N) \\ g_2(x_1) & g_2(x_2) & \ddots & g_2(x_N) \\ \vdots & \vdots & & \vdots \\ g_k(x_1) & g_k(x_2) & & g_k(x_N) \end{bmatrix}$$

$$\chi_{t+1} = A\chi_t$$

Least squares solution:

$$A = \underset{A}{\text{argmin}} \sum_t \|\chi_{t+1} - A\chi_t\|^2$$

$$A = \chi_{t+1}(\chi_t)^{\#}$$

2. Data Direct Encoding

- More uniformly weights data
- Important since perturbation data are sparse

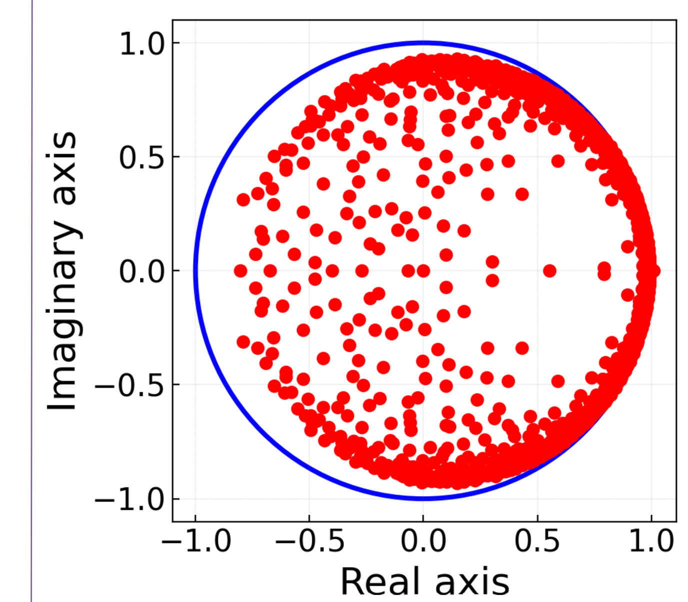
Ng, J., & Asada, H. H. (2023).

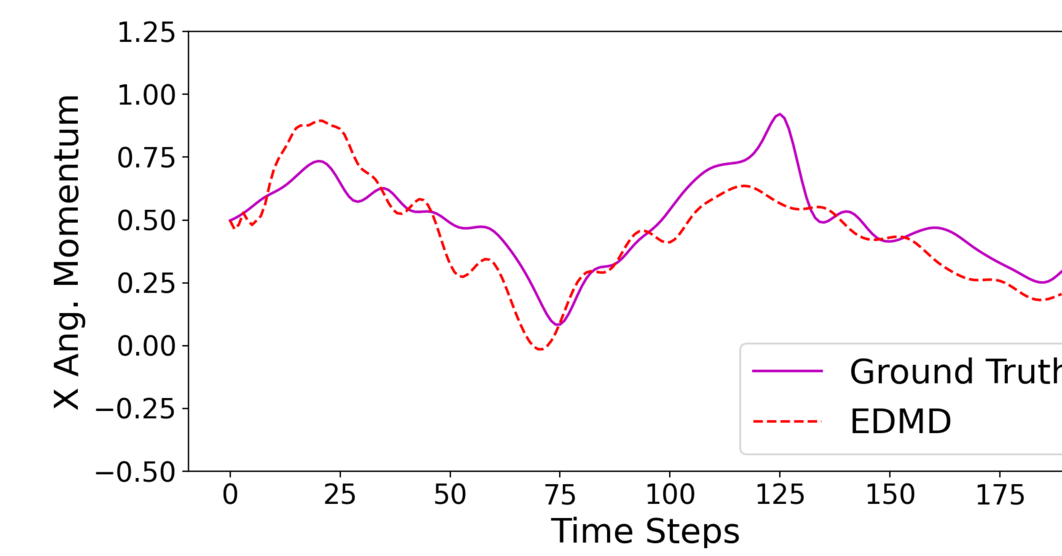
$$A_f = QR^{-1}$$

Preliminary Results

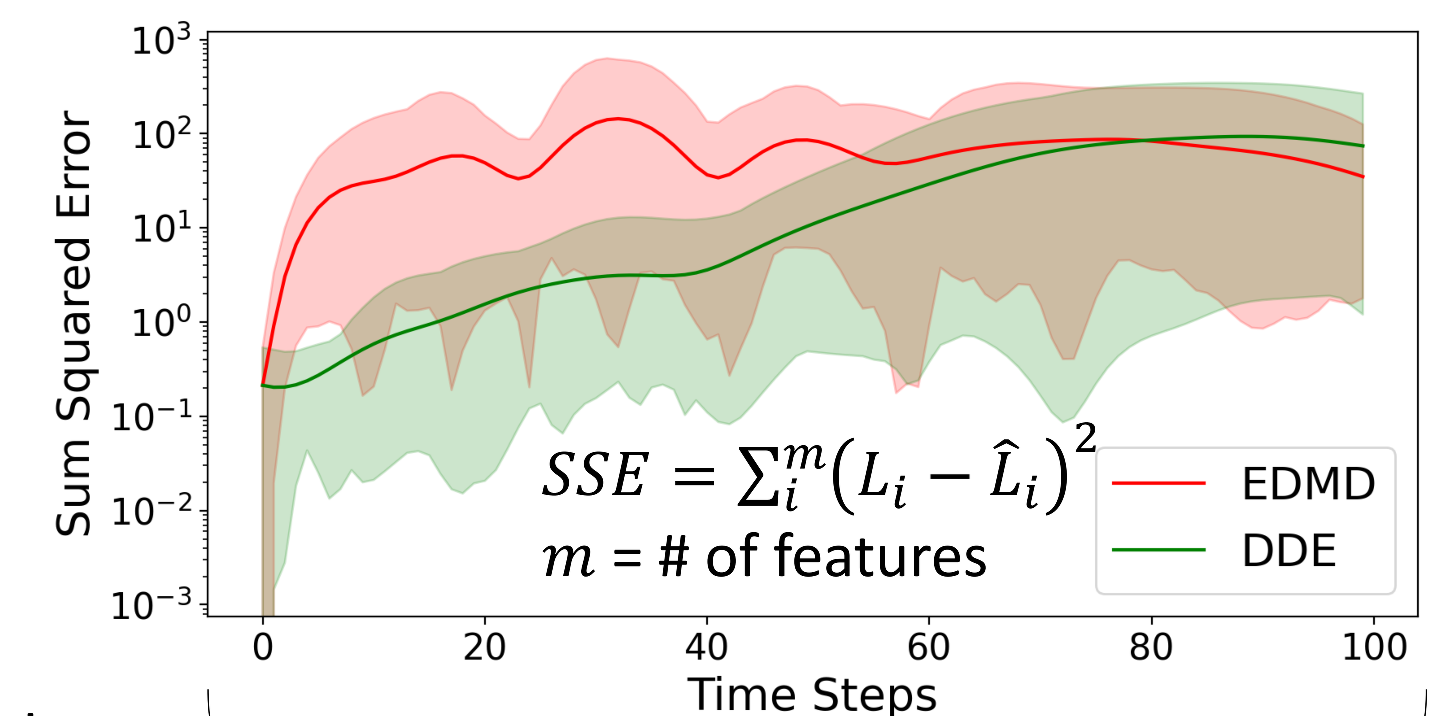
Perturbation Sample Trajectory:

80 RBF functions, 1046 observables





Perturbation Aggregate Error Results:



40 RBF observables

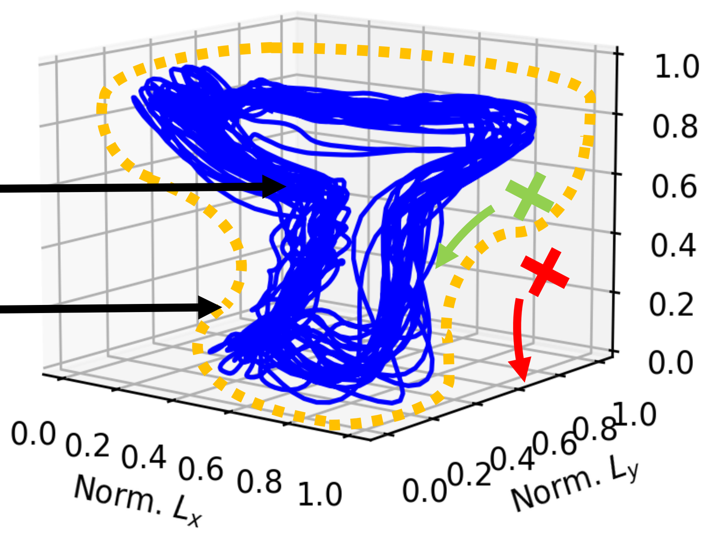
~ 1 gait cycle

Next Steps

- Find inputs that can restore state to stable gait limit cycle
- Identify/create assistive device to deliver these inputs

Stable gait trajectories

Region of attraction



References

[1] Herr, H., & Popovic, M. (2008). Angular momentum in human walking. *Journal of Experimental Biology*, *211*(4), 467–481. https://doi.org/10.1242/jeb.008573
[2] Lee, S. H., & Goswami, A. (2012). A momentum-based balance controller for humanoid robots on non-level and non-stationary ground. *Autonomous Robots*, *33*(4), 399–414. https://doi.org/10.1007/s10514-012-9294-z
[3] Major, M. & Donahue, S. Northwestern. Angular momentum dataset (2022).
[4] Asada, H. H. (2023). Global, Unified Representation of Heterogenous Robot Dynamics Using Composition Operators. *IEEE/ASME Trans. Mechatronics*
[5] Ng, J., & Asada, H. H. (2023). Data-Driven Encoding: A New Numerical Method for Computation of the Koopman Operator. *RA-L*.