Understanding Motor Disorders: A Task-Dynamic Approach

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The Action Lab
From Theoretical Analysis
to Clinical Assessment
to Intervention
How do Humans Control their Movements?

Adaptive Control

Optimal Control

Biomechanics

Bayesian Approach

Feedforward, Feedback Control

Reinforcement Learning
Current Paradigms in Movement Neuroscience

Sternad and colleagues
Adaptation

Skill Acquisition

Coaching and Intervention
Our Approach: From Outside In

A Task-Dynamic Approach
A Task-Dynamic Approach to Actions and Interactions

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The Action Lab
From Actions to Interactions
Life is full of skills ...

... involving a huge variety of actions and interactions with complex dynamics
Three Motor Skills - Three Basic Questions

Redundancy, choice

Times hand opening for ball release

Control of complex objects

Continuous forceful interaction

Stability, Robustness to Perturbations

Rhythmic movements, interception
--- What is Skill? ---

Knapp (1963): “Skill is the learned ability to bring about pre-determined results with maximum certainty, often with minimum outlay of time or energy or both.”

Speed-accuracy trade-off?

Energy minimization?

Decreasing uncertainty or noise?
Solutions that make intrinsic neuromotor noise matter less.

--- *Skill* ---

Sternad, Huber, Kuznetsov, 2014

--- *Skill in Physical Interactions* ---

Solutions that negotiate constraints, switch between continuous and discrete control, exploit forces and resonances, predict object dynamics, ....
Our Task-Dynamic Approach

- Choose task with interesting features
- Mathematical model of task
- Derive space of solutions
- Virtual rendering of the modeled task
- Model-based manipulations
- Analysis of human performance
- Design of interventions
Variability - Skittles

Lord and Lady Grantham, Downton Abbey
From the real game to the virtual experiment ...
The Model

\[ m \ddot{x} = -kx \]
\[ m \ddot{y} = -ky \]

Ball Trajectory:
\[
\begin{pmatrix} x(t) \\ y(t) \end{pmatrix} = \begin{pmatrix} x_p \\ y_p \end{pmatrix} \cos \omega t + \begin{pmatrix} \cos \phi_r & -\sin \phi_r \\ -\sin \phi_r & \cos \phi_r \end{pmatrix} \begin{pmatrix} l \cos \omega t \\ v_r/\omega t \end{pmatrix}
\]

Solution Manifold:
\[
\frac{v_r}{\omega} = \frac{|(-l \sin \phi_r - y_p)x_t + (l \cos \phi_r + x_p)y_t|}{\sqrt{(l + \cos \phi_r x_p + \sin \phi_r y_p)^2 - (\cos \phi_r x_t + \sin \phi_r y_t)^2}}
\]
The Virtual Set-Up
Redundancy and Solution Manifold

Müller & Sternad, *JEPHP*, 2004
What Solutions Do Humans Choose and Why?

Three conceptually different ways to improve performance:

Translate >> Tolerance
Rotate >> Covariation
Scale   >> Noise
Cost = Result(real) – Result(ideal)
Cost = Result(real) – Result(ideal)
\[ \text{Cost} = R(E_{\text{real}}) - R(E_{\text{optimal}}) \]
Experiment: Optimization of Tolerance and Covariation to Make Noise Matter Less

Participants: 12 novices plus 3 experts

Practice: 6 days, 3 blocks of 60 throws/trials, total: 1080 trials

3 expert participants practiced for 16 days, total: 2880 trials
Performance Improvement: Change in Error and Variability
Performance Improvement: Changes in TNC-Costs

- Initially high T-Cost reflects exploration of best strategy
- Expert group decreases T-Cost to almost zero
- C-Cost shows change approximately parallel to N-Cost
N-Cost is highest cost
N-Cost continues to decrease in expert participants
N-Cost is the component least optimized with the slowest time scale
**UCM-Approach (Scholz & Schöner, 1999)**

- Mean value of execution variables $E_M$
- If $R = f(E)$ is known, linearize at $E_M$
- Jacobian of $f$ at $E_M$ gives null space
- Variability parallel to this space $V_{par}$ does not change result
- Variability orthogonal $V_{ort}$ produces deviation in result
- Ratio of $V_{par}$ to $V_{ort}$ quantifies control

**Remarks:**
- Analysis around $E_M$ assumes that it represents perfect solution, bias goes unnoticed
- No differentiation between Noise and Covariation
- No differentiation between Noise and Tolerance
- Exquisitely sensitive to coordinates!!
Coordinate Dependency of Variability Analysis

- Hypothetical intercept task
  - Planar arm motion—2D
  - Target line—1D

- Different angle definitions lead to different results

Sternad, Park, Müller, Hogan, 2010, PLoS Comp Bio
TNC-Results

UCM (Par/Ort) = 0.92
T-cost: 0.14 cm
N-cost: 20.8 cm
C-cost: 0.66 cm

UCM (Par/Ort) = 2.18
T-cost: 0.14 cm
N-cost: 20.8 cm
C-cost: 12.08 cm
The Arm Trajectory and the Solution Manifold

Cohen & Sternad, J Neurophysiology, 2012
Chu, Park, Sanger, Sternad, TNRSE 2015
Huber, Guo & Sternad, in preparation
Arm Trajectories Align with the Solution Manifold

**Day 1**

**Day 6**

**Day 15**

Release Velocity (deg/s)

Release Angle (deg)

Subject 1

Timing Error = Δt

Error (cm)

Time in Hit Zone = Δt1 + Δt2

Error (cm)

Time (ms)

Ball Trajectory

Ball

Target

Δt

Δt1

Δt2

Hit Zone
Humans are:
- sensitive to error-tolerant solutions,
- they shape their trajectory,
- to create timing-insensitive solutions.

Maximal timing accuracy is 9 ms, similar to reports on rhythmic timing - not 1 ms

Improvement in timing saturates around Day 6, while other measures continue to change

Arm Trajectories Align with the Solution Manifold
Outreach at the Museum of Science in Boston

Living Laboratory
Outreach at the Museum of Science in Boston

Living Laboratory
Results

365 participants, age 5 - 75 years old
4 blocks of 25 trials, 10 min
together with a second experiment
Different Topologies of Solution Space
Interim Notes

• Humans are sensitive to error-tolerant solutions.
• They create timing-insensitive solutions by shaping their arm trajectories and follow-through.

--- Skill ---

Solutions that make intrinsic neuromotor noise matters less.

But:

Is intrinsic noise “untouchable”?
Experiment: Is Intrinsic Noise Malleable?
Results: Error and Variability Decreases

- Mean error and variability continues to decline in all amplification conditions.
Improvement without Speed Accuracy Trade-Off

- Velocity is **not** decreased with practice
- No speed-accuracy trade-off!
- No decrease of velocity - or signal-dependent noise
Stochastic Learning Model and System Identification

\[ \theta_{EX,i} = \theta_{PL,i} + \eta_{EX,i} \]
\[ \theta_{PL,i+1} = \theta_{PL,i} - B e_i + \eta_{PL,i} \]
\[ e_i = \theta_{EX,i} - \theta_{Target} \]

Identify \( B, \sigma_{EX}^2, \sigma_{PL}^2 \) using EM algorithm
Changes in Parameters with Amplification

- Both noise variances decrease with amplification. No change in the control condition.
Interim Conclusions

- Noise is malleable!
- How is this physiologically plausible?
Experiment: Role of Reward

HYPOTHESIS 1
Reward improves performance faster and to lower errors.

CONSTANT group should have lower variability and error.
Role of Reward

HYPOTHESIS 1

Reward improves performance faster and to lower errors.

- 11 daily sessions (1-3 days between)
- Control and Constant group converge to the SAME level of error and variability.

Huber, Kuznetsov & Sternad, in revision
Role of Reward

HYPOTHESIS 2
Reducing error threshold leads to lower error and variability.

Day 1-3
CHANGING
Day 4-6
Day 7-11

Increase or decrease error?

Should reduce error
Role of Reward

HYPOTHESIS 2
Reducing error threshold leads to lower error and variability.
Role of Reward

HYPOTHESIS 3
Reducing error threshold leads to higher error and higher variability.

- Changing group retains performance: error and variability stays low - independent of reward

Huber, Kuznetsov & Sternad, in revision
Role of Reward

**QUESTION**

How is this performance improvement achieved?

- 80% of blocks have Gaussian noise - not due to error corrections
- Rather: reduction of variance of noise!

2640 trials, divided into blocks

Detrended fluctuation analysis and lag-1 autocorrelation analysis of time series of release angle

Huber, Kuznetsov & Sternad, in revision
A SIMPLE LEARNING MODEL

\[ x_{n+1} = x_n - B_1 e_n + a_n \xi \]

\[ e_n = x_n - x_0 \]

\[ \text{if } |e_n| > \text{threshold}, \text{ then } r_n = 0 \]

\[ \text{if } |e_n| < \text{threshold}, \text{ then } r_n = 1 \]

\[ a_{n+1} = a_n - (1 - r_n)B_2 a_n \]

\[ B_1 = .90 \]

\[ B_2 = .0015 \]
Bouncing a Ball - Dynamic Stability

- Choose task with interesting features
- Mathematical model the task
- Analyze solutions of the task
- Virtual rendering of the modeled task
- Model-based manipulations
- Analysis of human performance
- Design of interventions
Our Task-Dynamic Approach

• Choose task with interesting features
• Mathematical model of task
• Derive space of solutions
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• Design of interventions
Assumptions:
Periodic movements of the racket
Inelastic impact captured in the coefficient of restitution \( \alpha \)
Ballistic flight of the ball, gravity constant \( g \)
Mass of racket >> mass of ball

\[
v_{k+1} = (1 + \alpha)A\omega \cos \theta_{k+1} - \alpha v_k + \frac{g\alpha}{\omega}(\theta_{k+1} - \theta_k)
\]

\[
0 = A\omega^2 (\sin \theta_k - \sin \theta_{k+1}) + v_k \omega (\theta_{k+1} - \theta_k) - g/2(\theta_{k+1} - \theta_k)^2
\]

State Variables: \( v_k \), ball velocity after impact
\( \theta_k \), phase of impact

Parameters: \( \alpha \), coefficient of restitution
\( g \), acceleration due to gravity
\( A \), racket amplitude
\( \omega \), frequency of sinusoidal racket trajectory
Stability Analysis

Passive Dynamic Walker

\[ AC \in [-10.90, 0 \text{ m/s}^2] \]

Racket should be slowing down at impact - negative acceleration!
Virtual Set-Up

[Diagram showing the setup with a screen, projector, and virtual ball and racket.]
From the Model to Human Data: Exemplary Trial

Means and SD per trial of 60 bounces
Do Humans Seek Dynamic Stability?

- How robust is this stability if the actor has to change behavior and explore new solutions?

Part I: 48 normal trials

Part II: 10 normal trials, 48 adaptation trials

Sternad (2016)
Boonstra, Wei, & Sternad (in preparation).
Part I: Learning and Dynamic Stability

• Humans find non-intuitive “smart” solutions.
• This solution is insensitive to noise and avoids error corrections.
• Humans exploit dynamic stability.
Part II: Adaptation and Dynamic Stability

- Upon perturbation, error increases; error decreases with practice
- AC shows drop, followed by gradual return to preferred range
Mean and SD of 3 execution variables were determined for each subject in first 10 trials on Day 2.

Distortion ellipsoid centered at mean performance.
Part II: Adaptation and Variability

- Adaptation re-establishes new solution with non overlapping variance.
- Participant takes their variability into account.
- In a redundant task actors can establish more than one solution with dynamical stability.
Experiment: Do Humans Rely on Stability When Facing Perturbations?

★ Do humans fully rely on error-corrective properties of the stable regime?
★ Discrete dynamic system has multistability. How large is the basin of attraction?
★ Are humans sensitive to the boundaries of stability?

Wei, Dijkstra, & Sternad (2007). *J of Neurophysiology*
Prediction 1:
Actors are sensitive to the boundary of basin of attraction and use different strategies for perturbations inside and outside of basin of attraction.

Prediction 2:
2a: With increasing magnitudes of perturbations, relaxation time increases for all $\alpha$.
2b: Relaxation time is shorter for positive perturbations across all $\alpha$.
2c: Higher $\alpha$ exhibit longer relaxation time, but only for positive perturbations.
**Experimental Design**

**Conditions:**

- 4 conditions: 0.5, 0.6, 0.7, and 0.8
  - 20 trials per condition
- 14 perturbation magnitudes for each condition. Every perturbation magnitude presented 8 times randomly in each condition.

*14 perturbation magnitudes* (on ball release velocity):

[±1, ±0.86, ±0.71, ±0.57, ±0.43, ±0.29, ±0.14 m/s]

Labeled as: P-7, P-6, ……P-1, P+1, ……P+6, P+7.

Actual deviations in ball amplitude [-30, +40 cm]
Data Analysis

Example trial with negative perturbation

Dependent Measures
Impact Acceleration of Racket (AC)
Ball Height Error (HE)
Racket Amplitude (AR)
Racket Period (T)
Results:
Height Error: Return to Steady State

Return completed after relatively few cycles even for large perturbations - faster than predicted by model

Different relaxation times for different perturbation magnitudes
Relaxation Time $\tau$ for Perturbations and Coefficient of Restitution

Qualitatively consistent with Predictions 2 derived from basin of attraction:

2a: Large perturbations have longer relaxation time.
2b: Relaxation time is shorter for positive perturbations.
2c: Relaxation times are longer for larger $\alpha$, but only for positive perturbations.
Exit times are longest for small perturbations.
No discontinuous change for perturbations outside the basin of attraction.
Conclusions

- Dynamical stability is a relevant anchor point for rhythmic movements. It allows open-loop control.

- Actors are not sensitive to stability boundaries; yet, the layout of the basin of attraction is reflected in the performance.

- A blend of active error-corrective control and passive strategy achieve faster return to steady state.
Optimal Control of Racket Trajectories in the Hybrid Task

Experiment

7 gravity conditions: 9.81 m/s² – 0.61 m/s²

Periods: .700 s – 2.8 s

Ronsse, Wei, & Sternad (2010) *J Neurophysiology*
Systematic change in racket trajectories with period:

- From sinusoidal to discrete
- Increase in variability
Two-Layered Control Model

Layer 1: Determines states of next impact: racket position, velocity, and time
Layer 2: Generates continuous trajectory to this target impact
Desired impact:

\[
\dot{r}_{\text{des},k} = \frac{ab_k^- + \sqrt{2g(b_{\text{apex}}^* - b_k)}}{1 + \alpha}
\]

Cost function for generating continuous trajectory:

\[
Q = \left\| r_{k+1} - r_{\text{des},k+1} \right\|^2 + \left\| \dot{r}_{k+1} - \dot{r}_{\text{des},k+1} \right\|^2
\]

\[
+ w_{\text{rest}} \int_{t_k}^{t_{k+1}} \left\| r(t) - r_0 \right\|^2 dt + w_{\text{energy}} \int_{t_k}^{t_{k+1}} \left\| u(t) \right\|^2 dt
\]

Deviation from rest position

Racket variables:

\[
x(t) = \left[ r(t), \dot{r}(t), f(t), r_{\text{des},k+1}, \dot{r}_{\text{des},k+1} \right]
\]

Two sources of noise
Simulation Results

DATA

MODEL

position [mm]

rescaled velocity [mm/s]

normalized time

$g_1$

$g_2$

$g_3$

$g_4$

$g_5$

$g_6$

$g_7$
Systematic changes across gravity conditions:
- Variability
- Feedback gain
- Autocorrelation

Results: Simulation and Data
Summary and Outlook

★ Attempt to model movements in a hybrid task with discrete events, similar to locomotion: specification of the target foot placement and generation of the foot trajectory

★ Discrete and rhythmic components under separate control

★ To be done:

★ Connection with previous dynamic model

★ Take redundancy of impacts into account

★ Test by applying perturbation to racket trajectory
--- Conclusions and Reflections ---

Solutions that make intrinsic neuromotor noise matter less.

--- Skill in Physical Interactions ---

Solutions that switch between continuous and discrete control, exploit forces and resonances, dynamic stability
Predictability:
Carrying a Cup of Coffee:
Interaction with Nonlinear Dynamics

Hasson, Sternad, *Frontiers in Neurology*, 2014,
Our Task-Dynamic Approach

- Choose task with interesting features
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The Model Behind the Task

Cart and Pendulum

Virtual Interface

Equations of Motion

\[
\ddot{x}(m+M) = \left(ml\dot{\theta}\cos{\theta} - ml\dot{\theta}^2\sin{\theta}\right) + F_A
\]

\[
\dot{\theta} = \cos{\theta} \left(\frac{\ddot{x}}{L}\right) - \sin{\theta} \left(\frac{g}{L}\right)
\]
The Virtual Interaction

Instruction:
- Move rhythmically (at 1 Hz)
- Choose preferred movement amplitude
Inverse dynamics calculations:

Initial conditions

\[ x = A \sin \omega t \]
\[ \dot{x} = A \omega \cos \omega t \]
\[ \dot{\theta} = 0 \]
\[ \theta_0 \]
Inverse dynamics calculations:

Initial conditions

\[ x = A \sin \omega t \]
\[ \dot{x} = A \omega \cos \omega t \]
\[ \dot{\theta} = 0 \]
\[ \theta_0 \]
Predictability - and Alternative Hypotheses

**Mutual Information**

\[ MI(x; F) = \int \int p(x, F) \log_e \left( \frac{p(x, F)}{p(x)p(F)} \right) dx dF \]

**Mean Squared Force**

\[ MSF = \frac{1}{nT} \int_0^{nT} F(t)^2 dt \]

**Smoothness**

\[ \text{Jerk} = \frac{1}{T(\theta_{\text{max}} - \theta_{\text{min}})} \int_0^T |\dot{\theta}| dt \]
Results: Predictability and Mutual Information

- Subjects did not minimize effort or force
- Subjects did not minimize smoothness
- Subjects sought predictable solutions
--- Conclusions ---

--- Skill in Physical Interactions ---

Solutions exploit forces and resonances, predict object dynamics, and make it more predictable.
Our Approach: From Outside In
--- Skilled Actions and Interactions ---

Variability - Skittles

Stability - Bouncing a Ball

Predictability - Carrying a Cup of Coffee
Thank you very much!

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