Dynamic movement primitives

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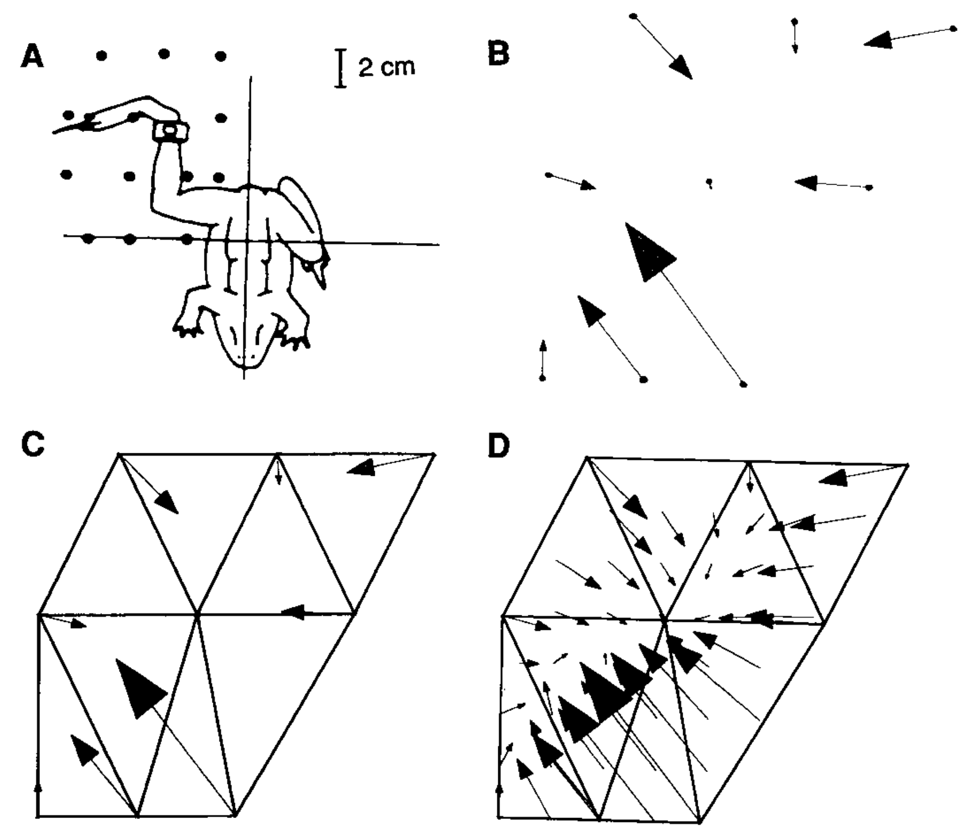
Neural motivation

- Notion that neural networks in the brain and spinal cord generated a limited set of temporal templates
- whose weighted superposition is used to generate any given movement

Evidence for "primitives" in frog spinal cord

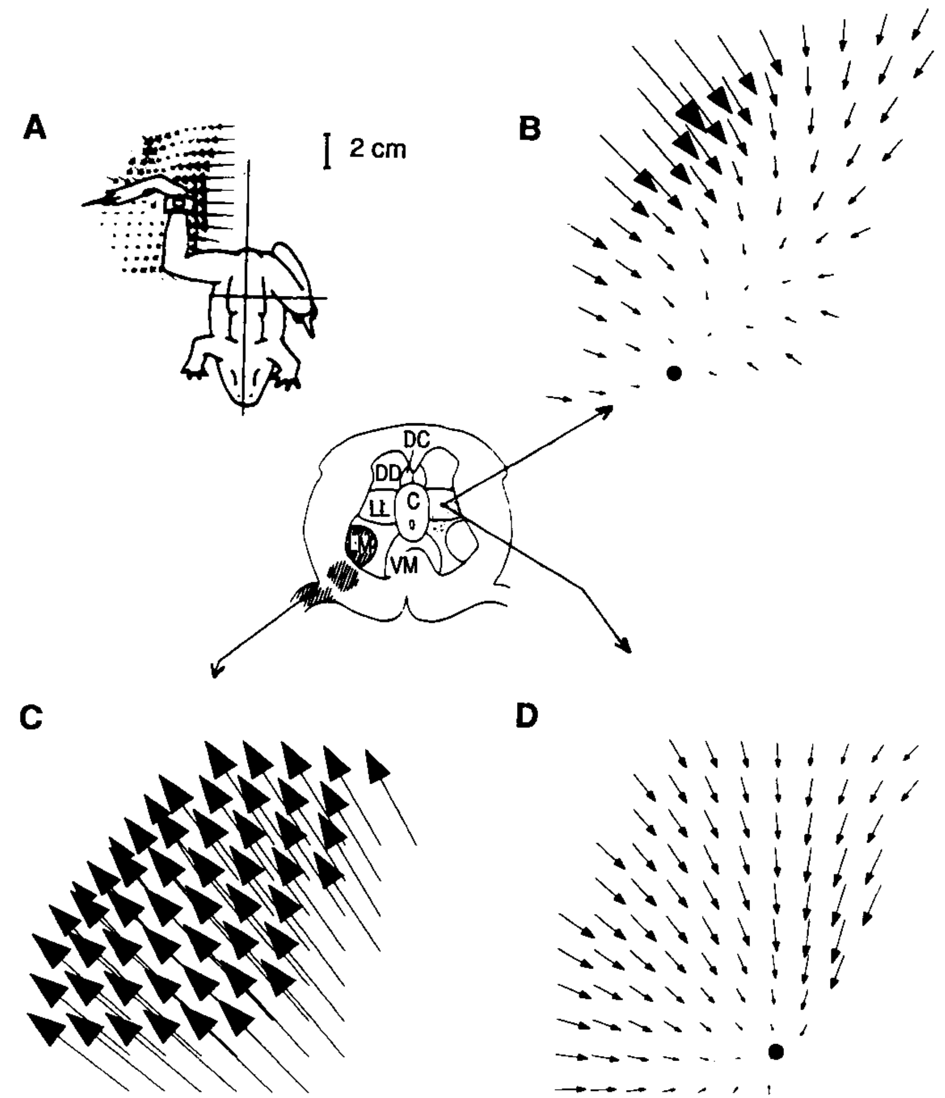
- electrical simulation in premotor spinal cord
- measure forces of resulted muscle activation pattern at different postures of limb
- interpolate force-field



[Bizzi, Mussa-Ivaldi, Gizter, 1991]

Evidence for "primitives" in frog spinal cord

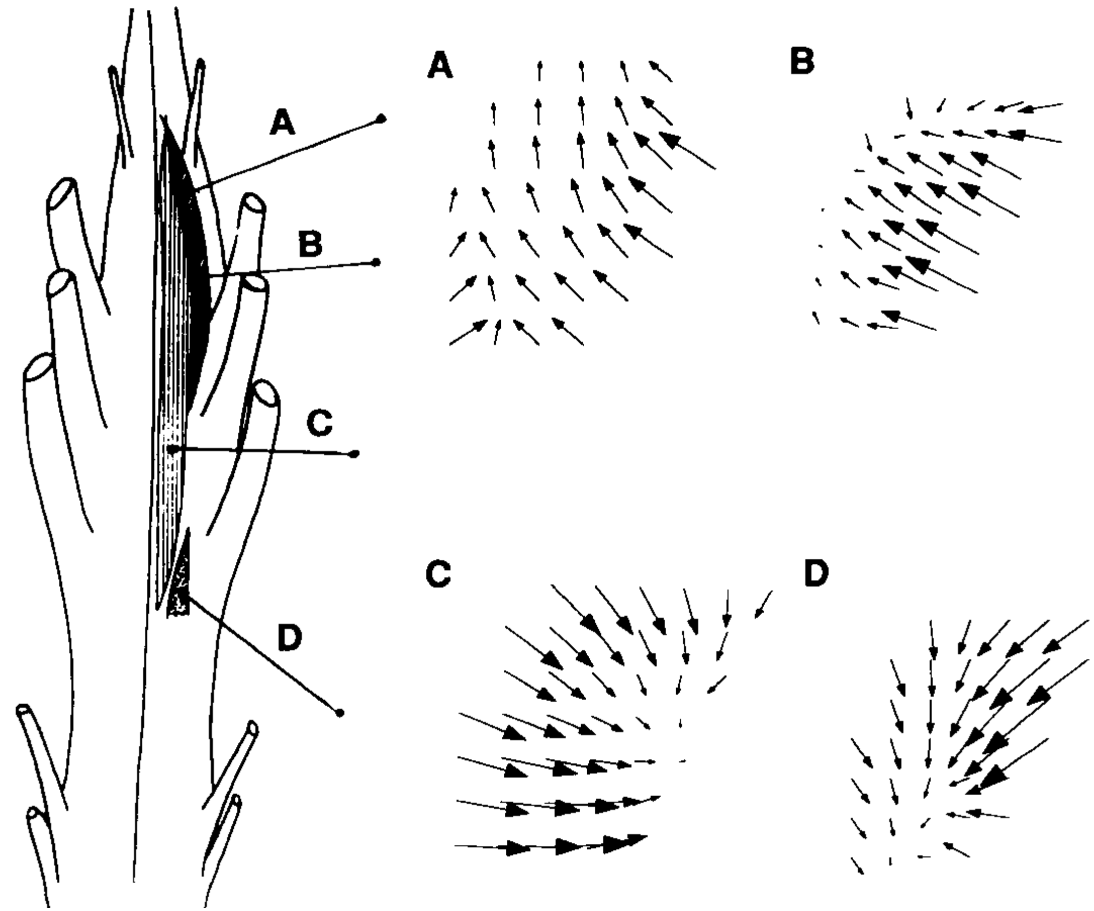
- parallel force-fields in premotor ares vs. convergent force fields from interneurons…



[Bizzi, Mussa-Ivaldi, Gizter, 1991]

Evidence for "primitives" in frog spinal cord

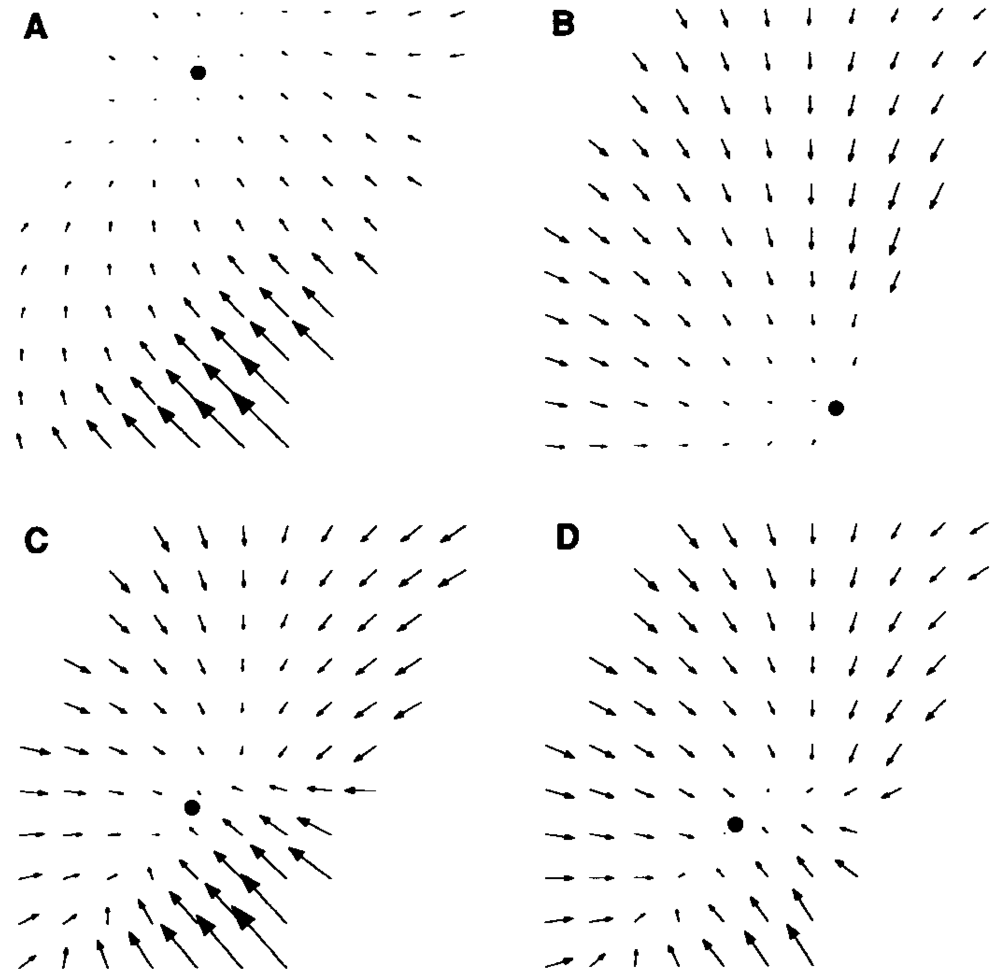
- convergent force-fields occur more often than expected by chance



[Bizzi, Mussa-Ivaldi, Gizter, 1991]

Evidence for "primitives" in frog spinal cord

- superposition of force-fields from joint stimulation



superposition of A and B

stimulating both A and B locations

[Bizzi, Mussa-Ivaldi, Gizter, 1991]

Mathematical abstraction

- with very loose grounding in neurophysiology!!

[Ijspeert et al., Neural Computation 25:328-373 (2013)]

Base oscillator

- damped harmonic oscillator

$$\tau \ddot{y} = \alpha_z(\beta_z(g - y) - \dot{y}) + f,$$

y: position

- written as two first order equations

$$\tau \dot{z} = \alpha_z(\beta_z(g - y) - z) + f,$$

$$\tau \dot{y} = z,$$

z: velocity

- has fixed point attractor

$$(z, y) = (0, g)$$

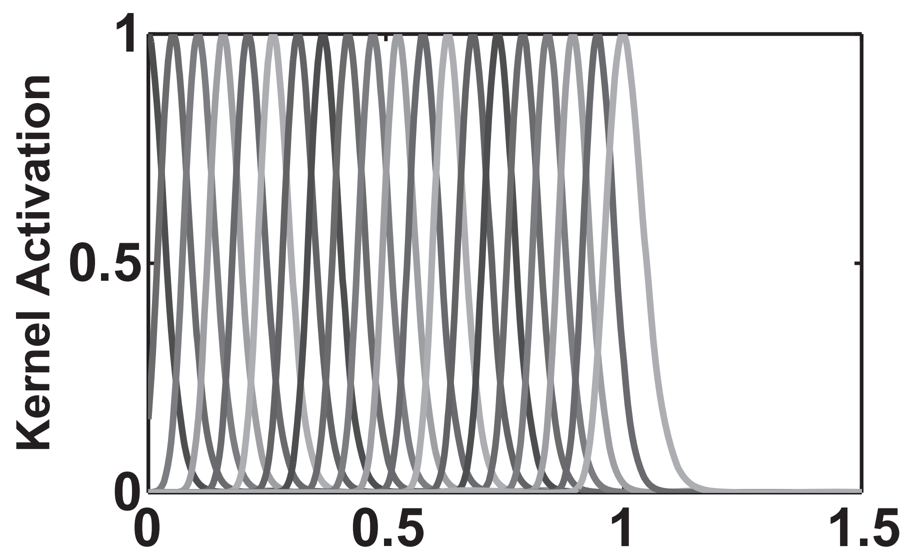
g: goal point

Forcing function

- base functions
- weighted superposition makes forcing function

$$\Psi_i(x) = \exp\left(-\frac{1}{2\sigma_i^2}(x - c_i)^2\right),$$

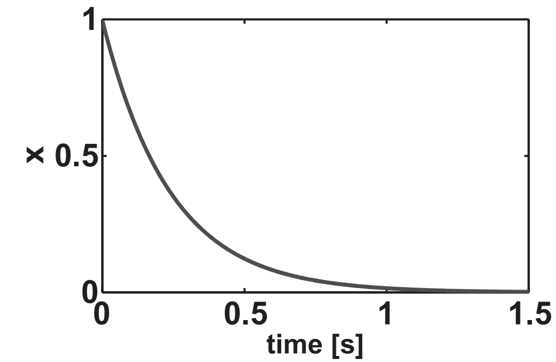
$$f(t) = \frac{\sum_{i=1}^{N} \Psi_i(t) w_i}{\sum_{i=1}^{N} \Psi_i(t)}$$



Time parameter

- timing variable, x

$$\tau \dot{x} = -\alpha_x x,$$



- forcing function scaled with timing variable

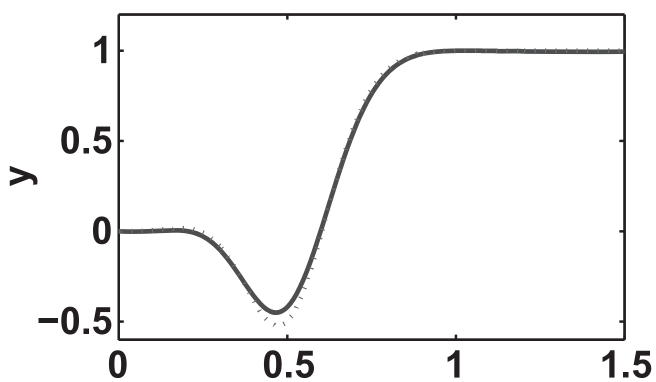
$$f(x) = \frac{\sum_{i=1}^{N} \Psi_i(x) w_i}{\sum_{i=1}^{N} \Psi_i(x)} x(g - y_0)$$

- and with amplitude of movement

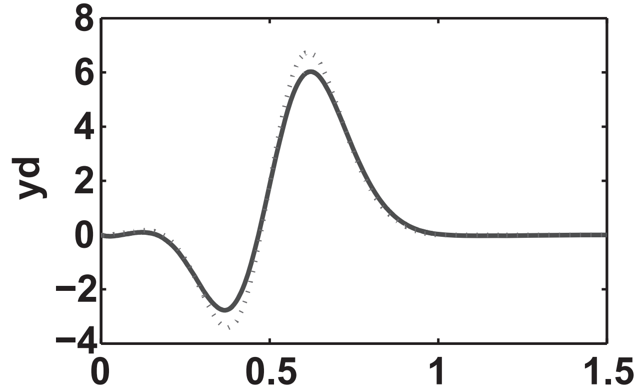
y_0 initial position

$g - y_0$ amplitude

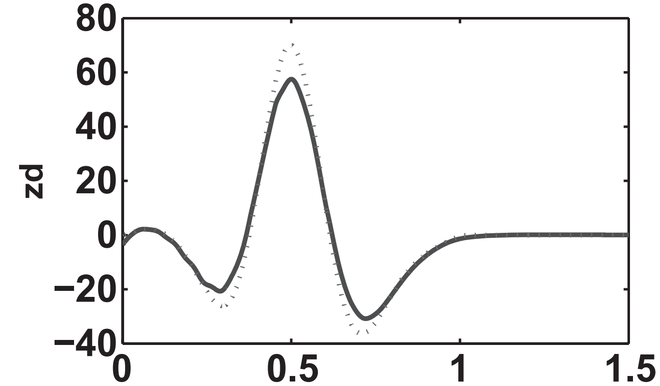
Example



position



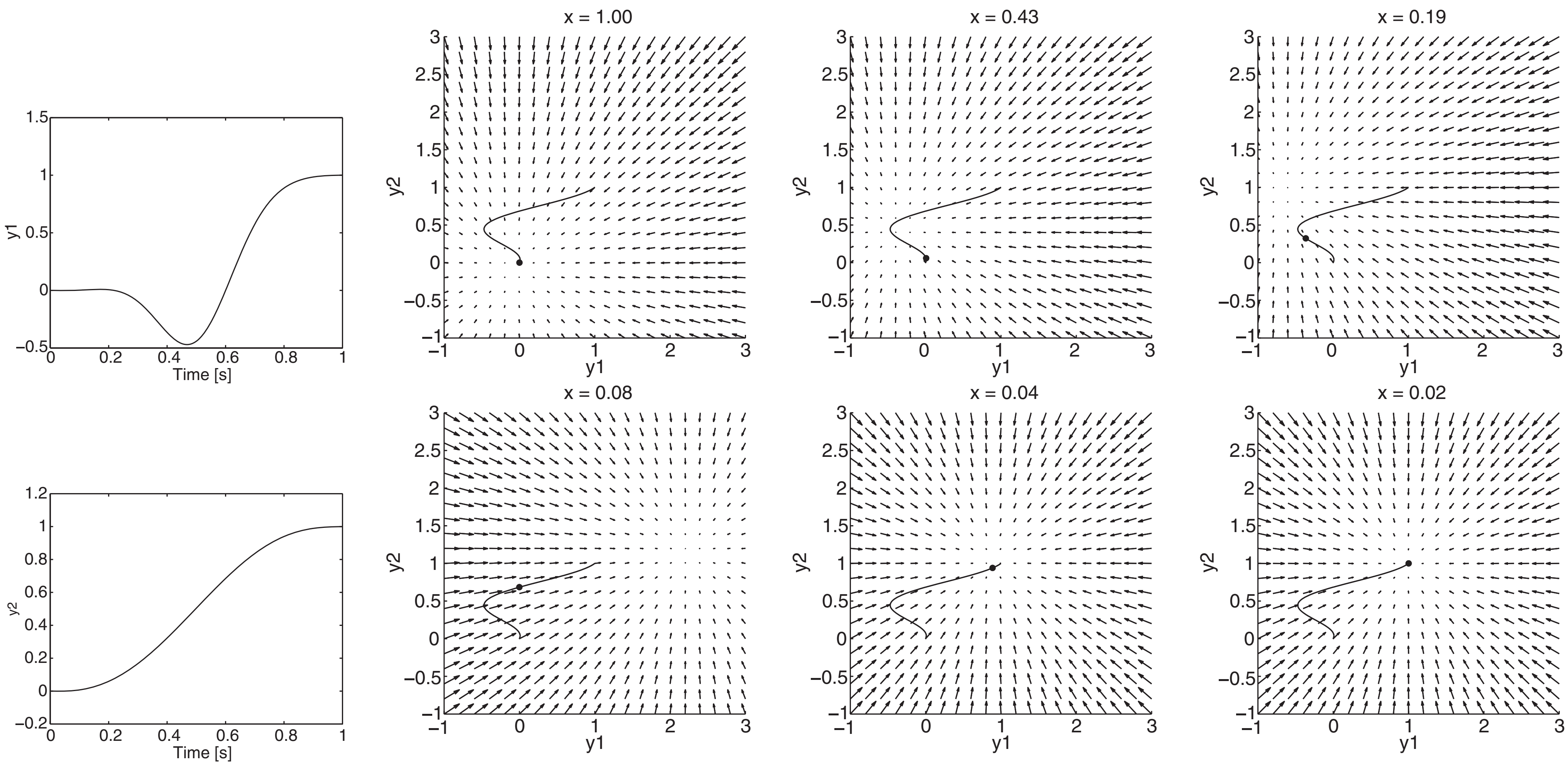
velocity



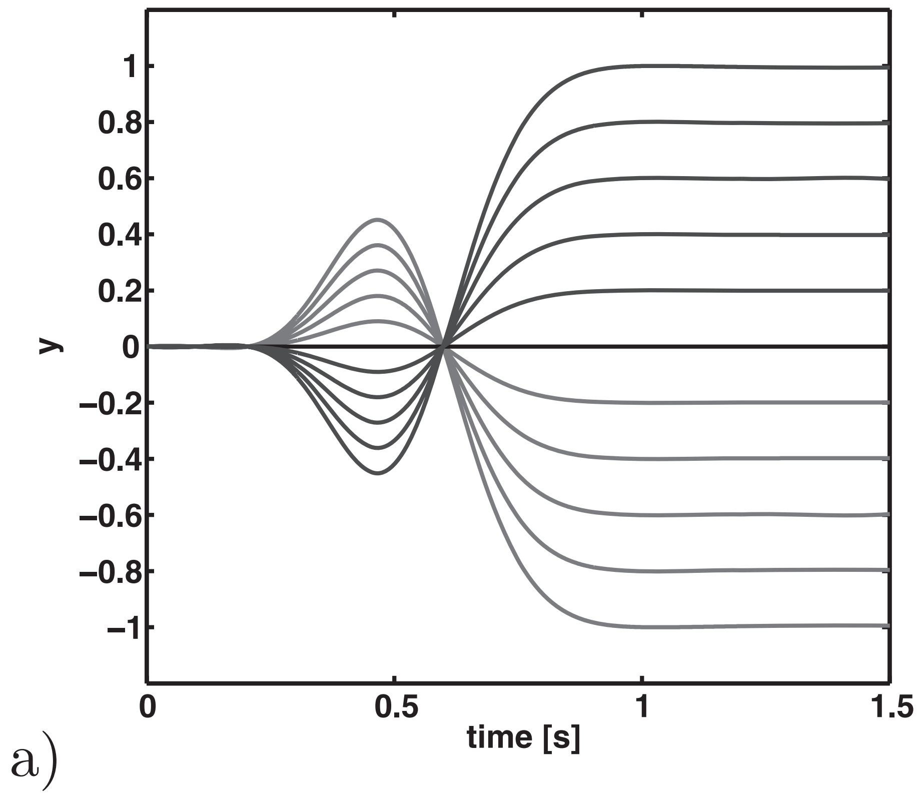
acceleration

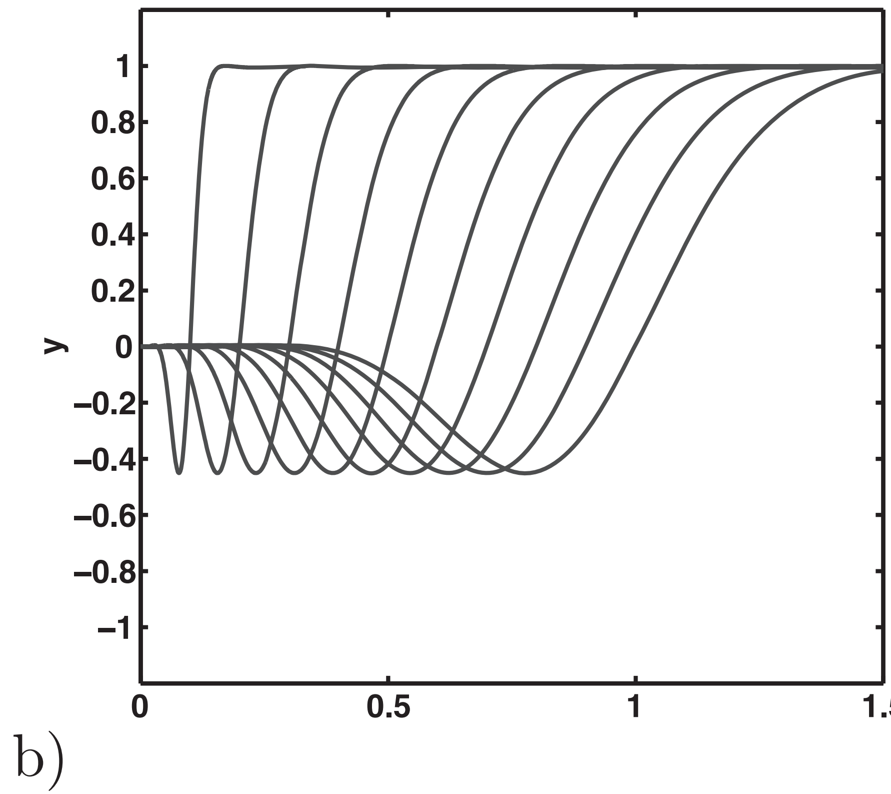
dotted: target
solid: approximation

Example in 2D



Scaling primitives





scale goal from -1 to 1

scale time from 0.15 to 1.7

Learning the weights

- with locally weighted regression
- base oscillator

$$\tau\dot{z} - \alpha_z(\beta_z(g - y) - z) = f.$$

- forcing function from sample trajectory

$$f_{target} = \tau^2\ddot{y}_{demo} - \alpha_z(\beta_z(g - y_{demo}) - \tau\dot{y}_{demo}).$$

- minimize error

$$J_i = \sum_{t=1}^{P} \Psi_i(t)(f_{target}(t) - w_i\xi(t))^2,$$

$$\xi(t) = x(t)(g - y_0)$$

Obstacle avoidance

- inspired by Schöner/ Dose (in Fajen Warren form)
- obstacle avoidance force-let

$$\tau\dot{z} = \alpha_z(\beta_z(g-y)-z)+f+C_t,$$

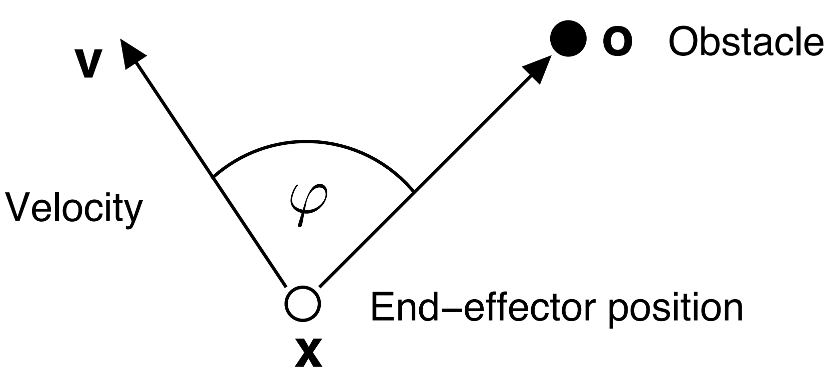
$$\tau\dot{y} = z.$$

$$\mathbf{C}_t = \gamma\mathbf{R}\dot{\mathbf{y}}\,\theta\exp(-\beta\theta),$$

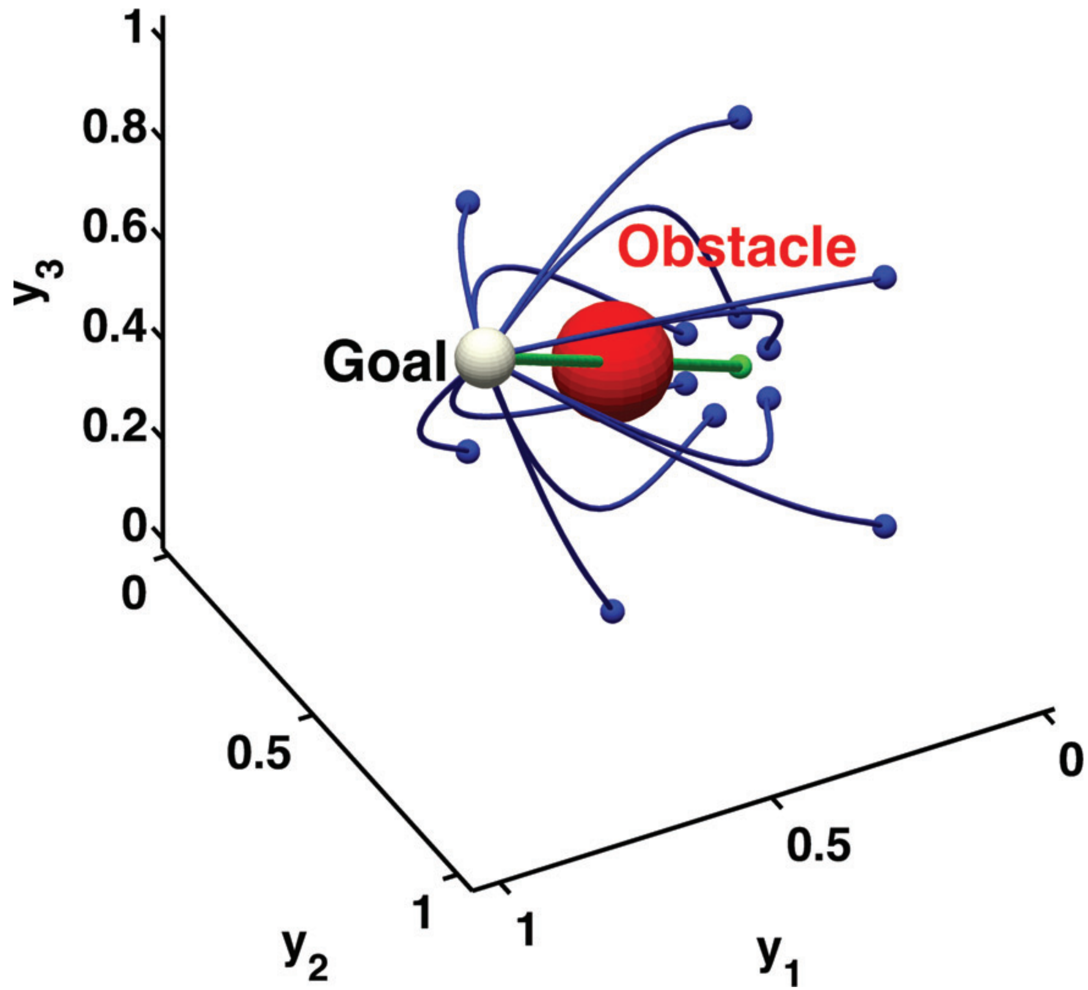
where

$$\theta = \arccos\left(\frac{(\mathbf{o}-\mathbf{y})^T\dot{\mathbf{y}}}{|\mathbf{o}-\mathbf{y}||\dot{\mathbf{y}}|}\right),$$

$$\mathbf{r} = (\mathbf{o}-\mathbf{y})\times\dot{\mathbf{y}}.$$



Obstacle avoidance

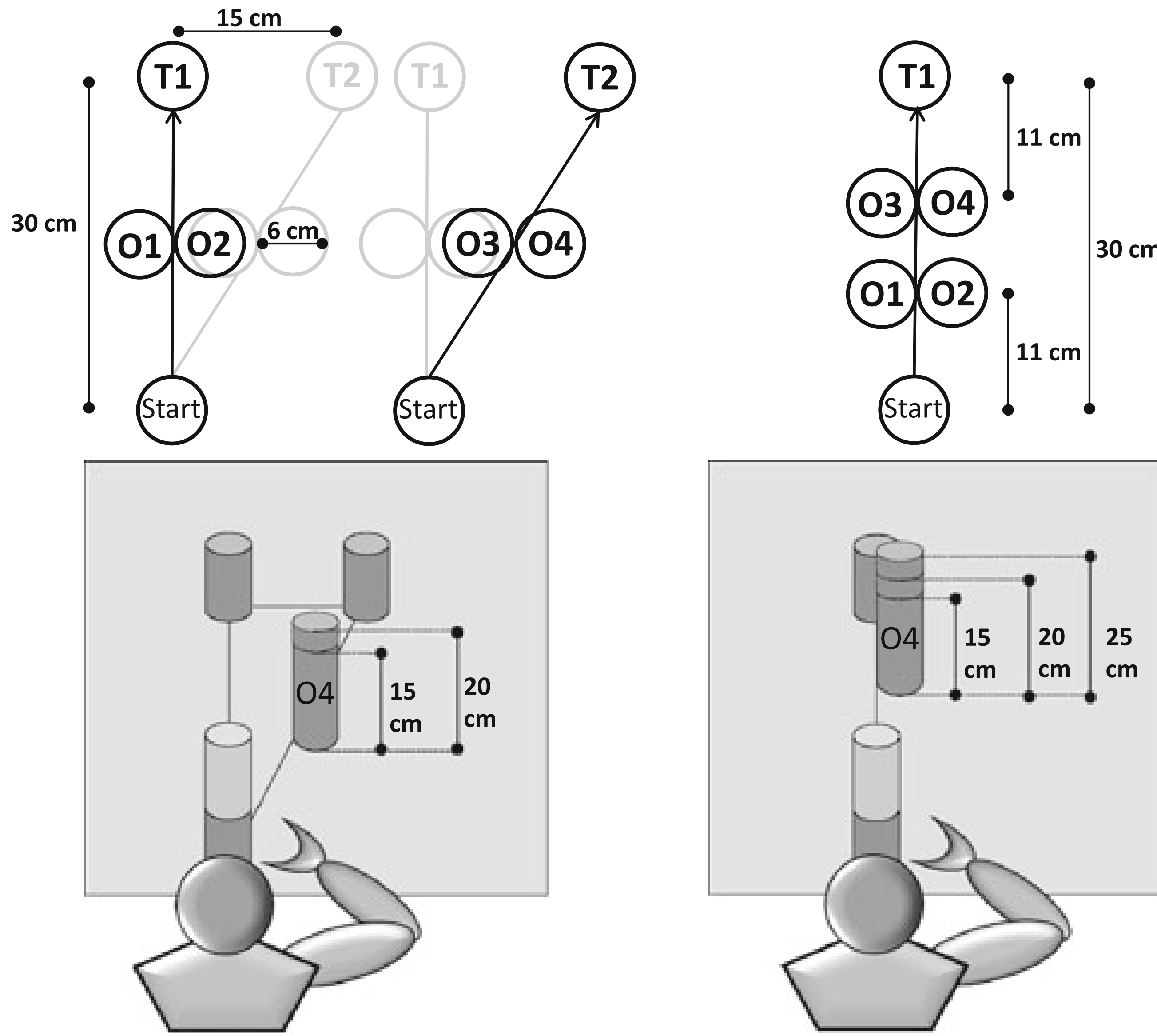


But: human obstacle avoidance is not like that…

- => Grimme, Lipinski, Schöner, 2012

Experiment

- naturalistic movements: hand moving objects to targets while avoiding obstacles
- spatial arrangement of obstacles is varied…
- may that apparent complexity of movements emerge from simple invariant elementary movements?



[Grimme, Lipinski, Schöner, EBR 2012]

paths

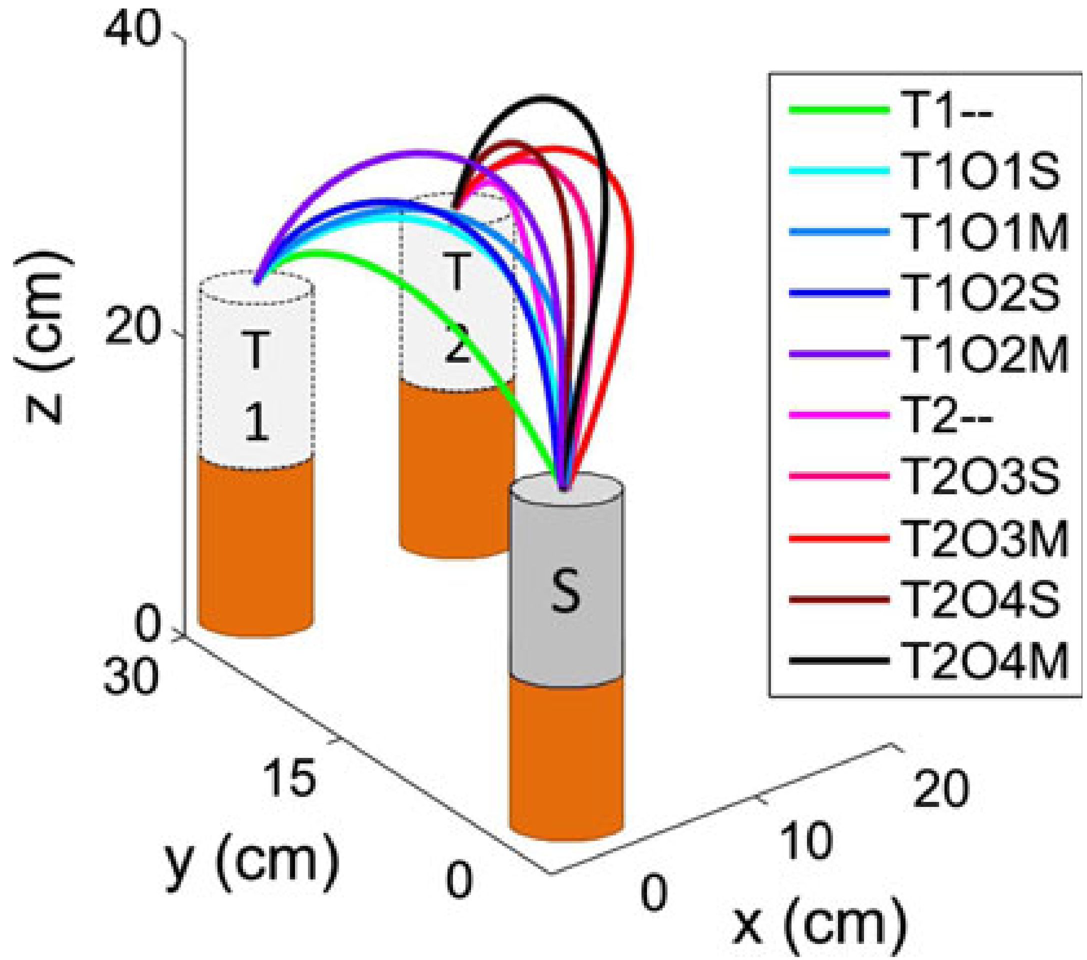
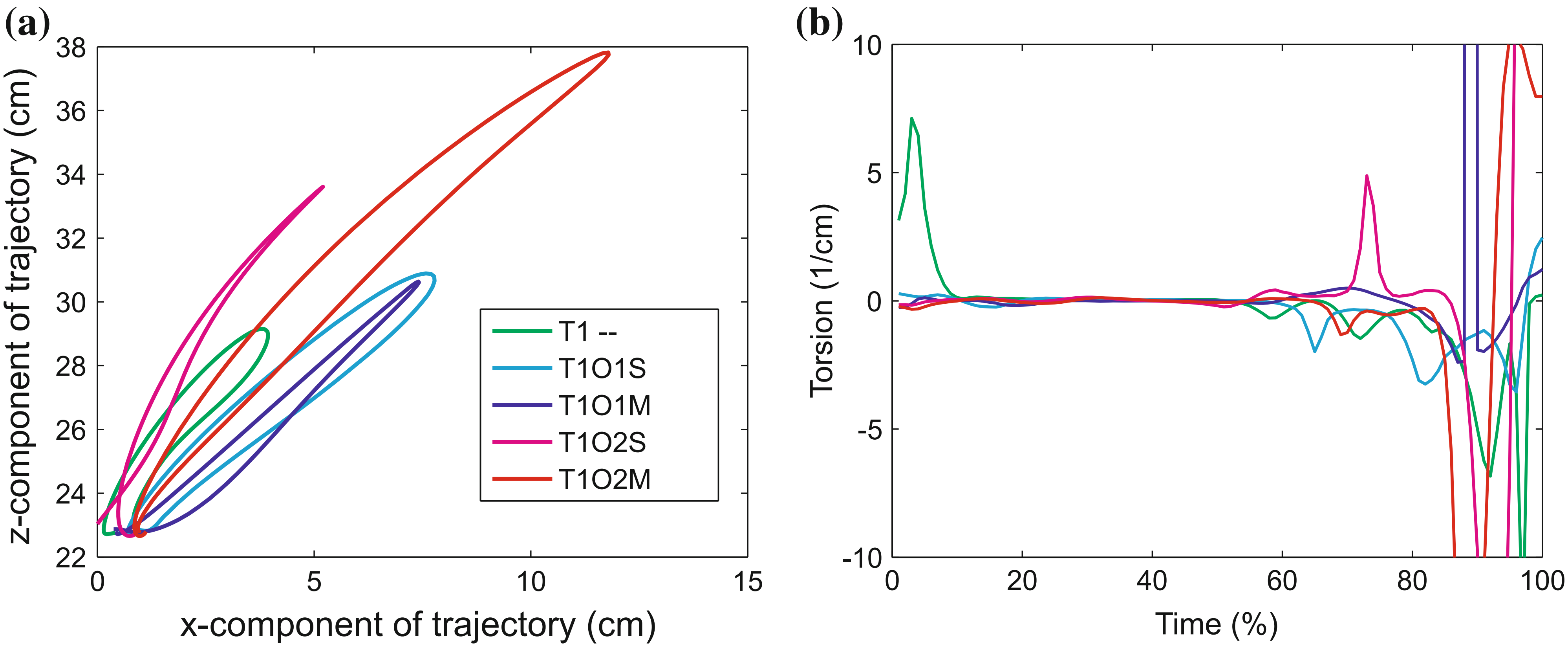
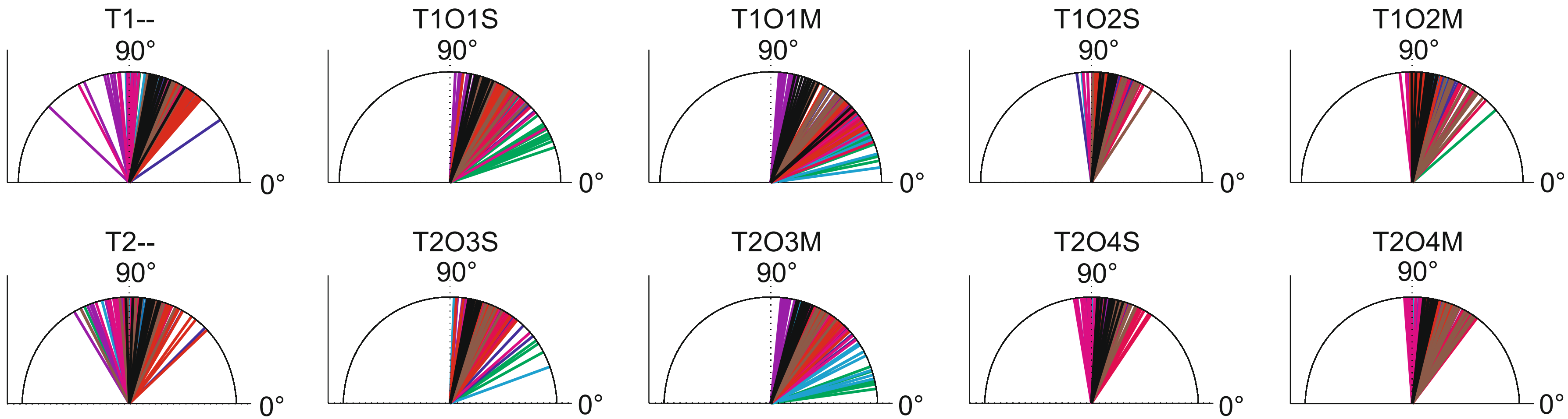


Fig. 3 Mean (over all participants) 3D obstacle avoidance paths from the starting position (*S*) to both target positions (*T1* and *T2*)

paths are planar

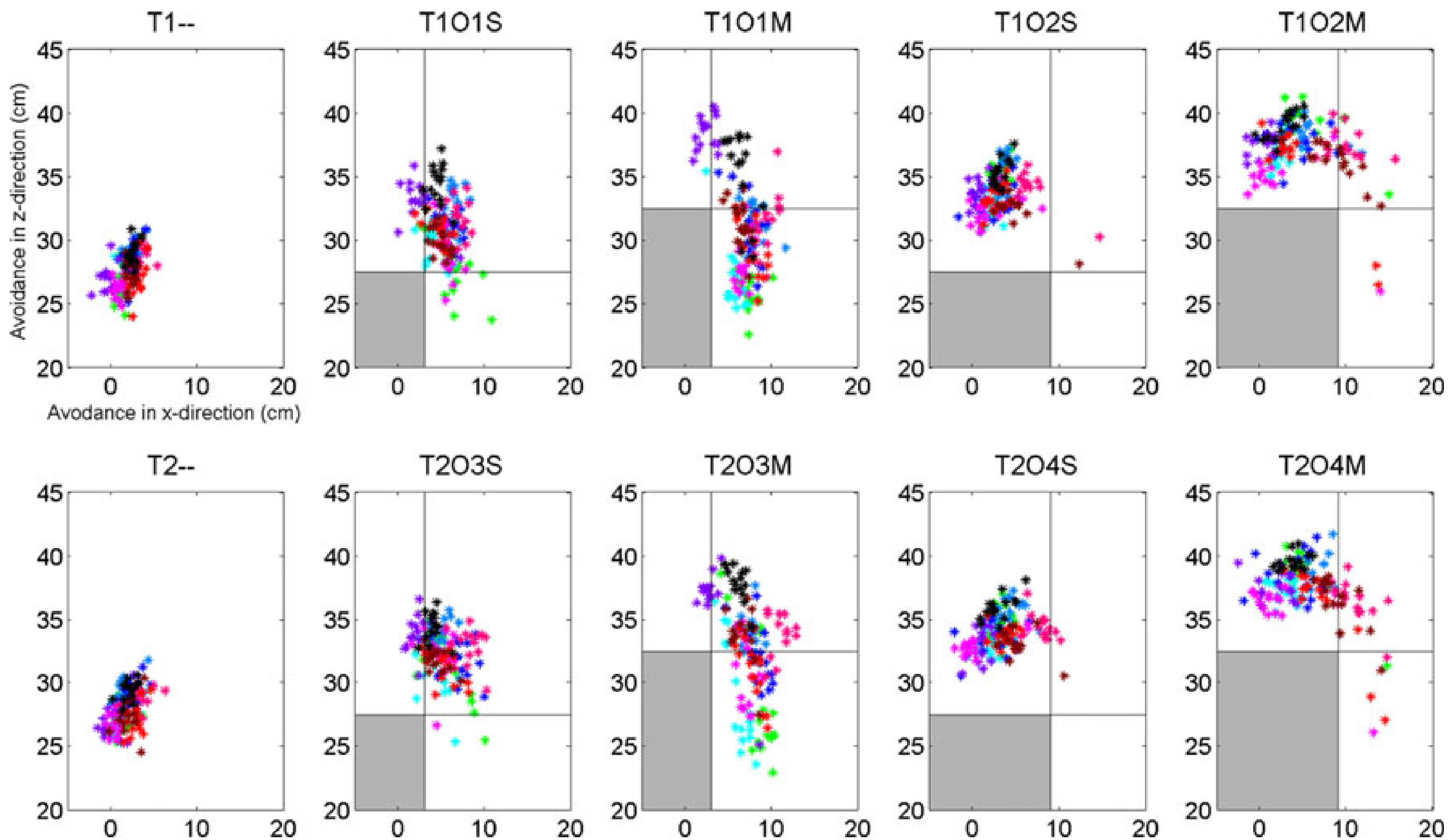


the plane of movement depends on the obstacle height



colors: participants…

the plane of movement depends on the obstacle height

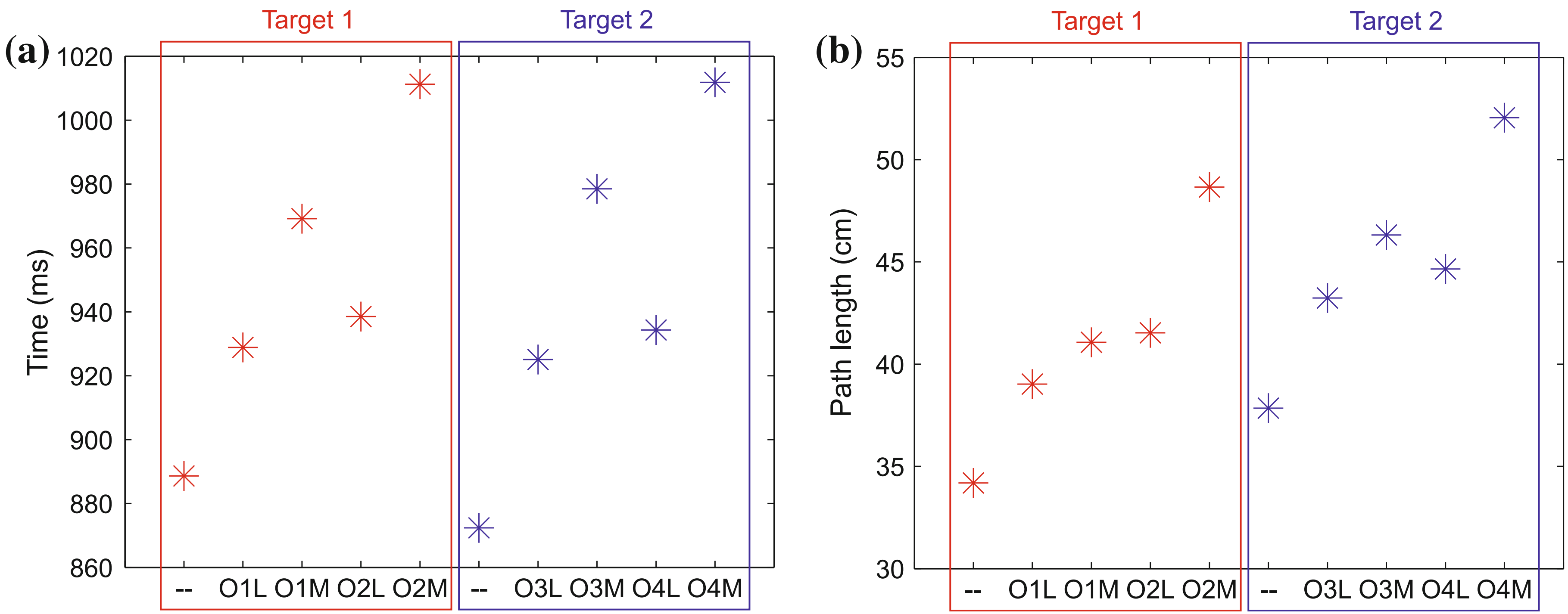


colors: participants…

=> end-effector path

- is simple and invariant…

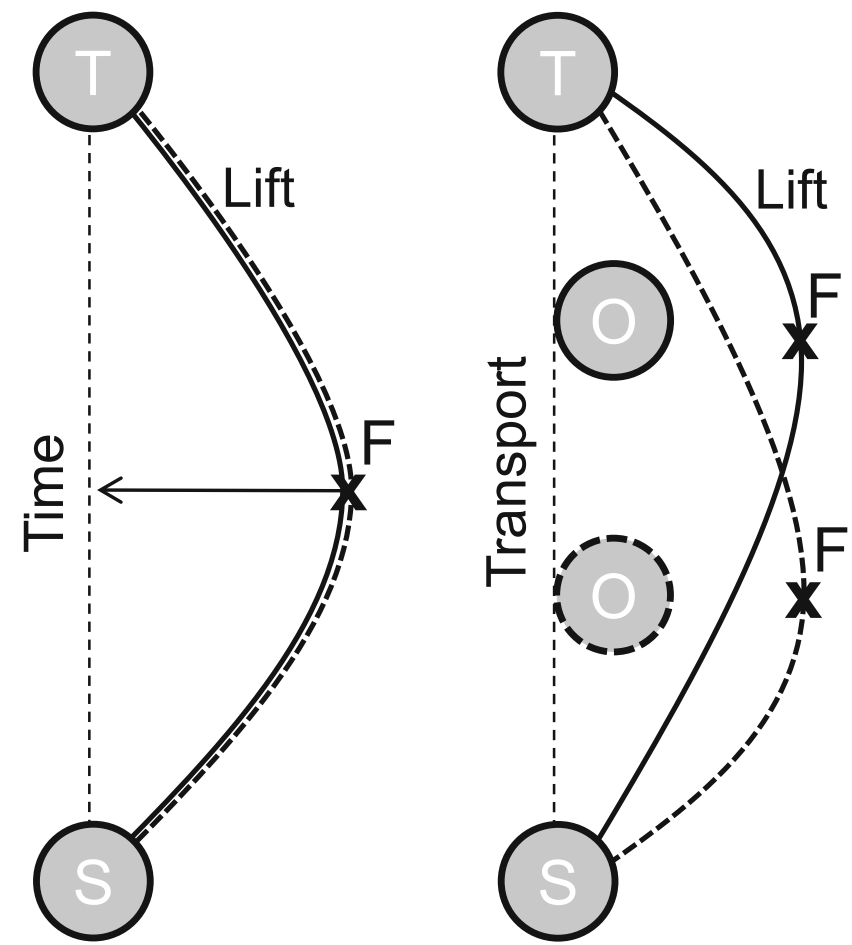
isochrony



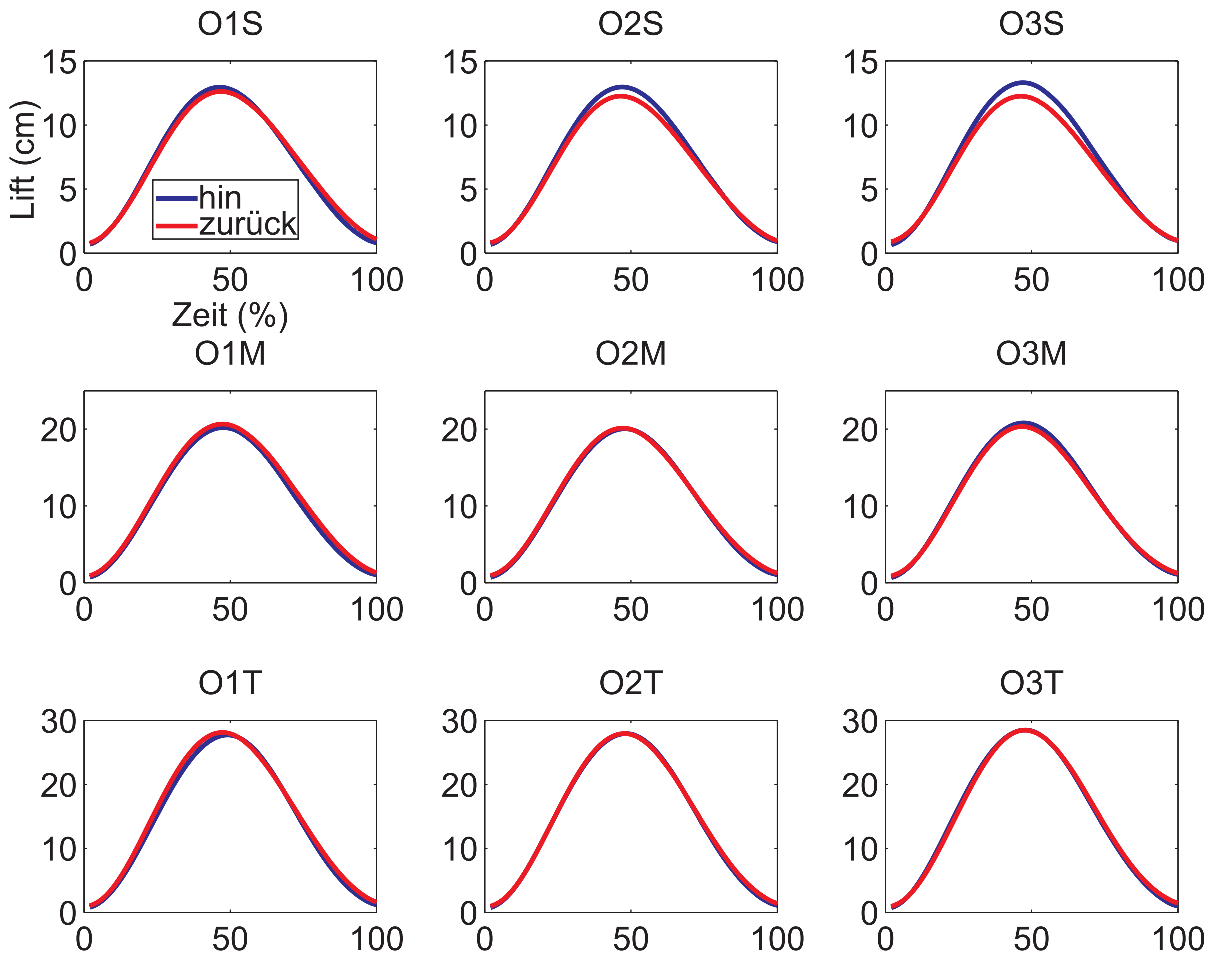
same movement time

different path length

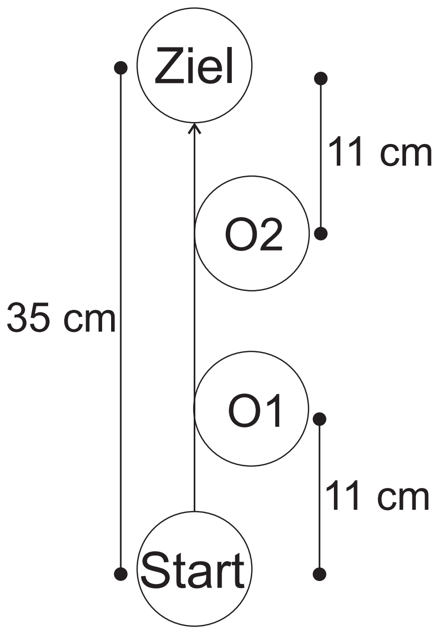
local isochrony

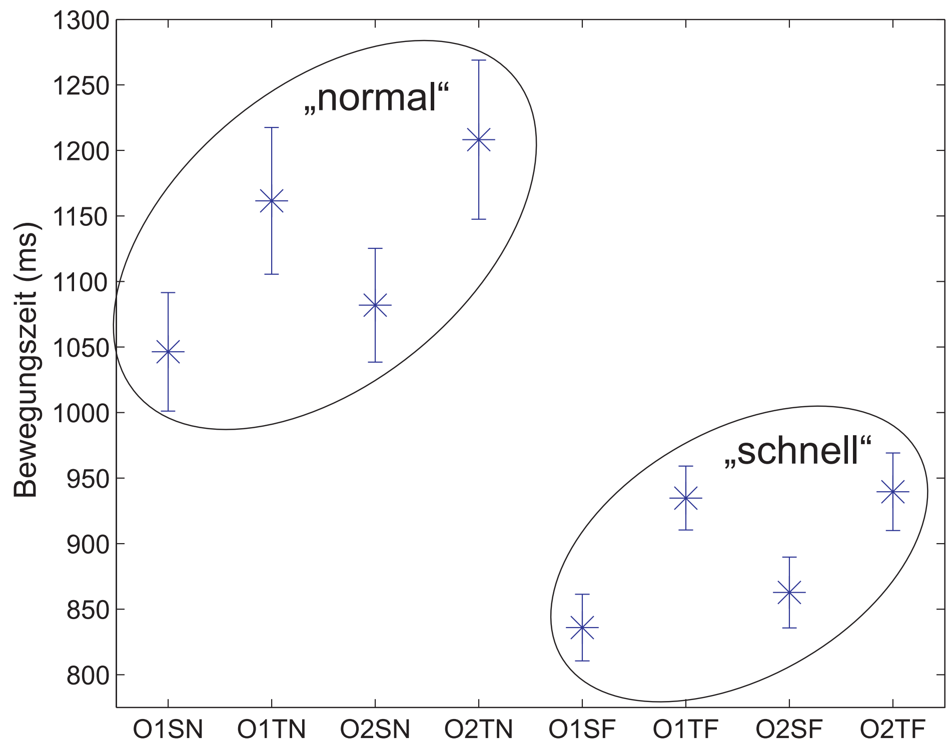


invariance of lift across space

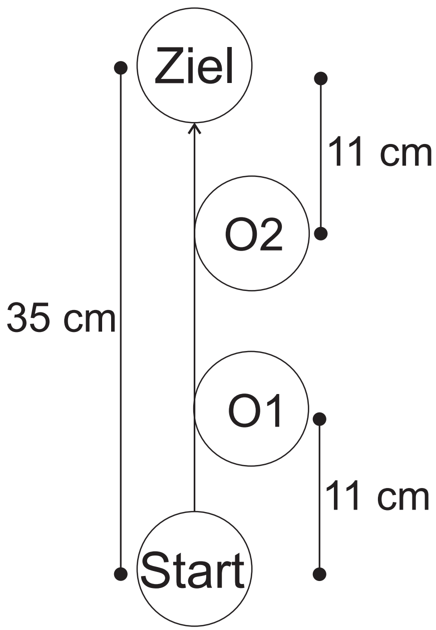


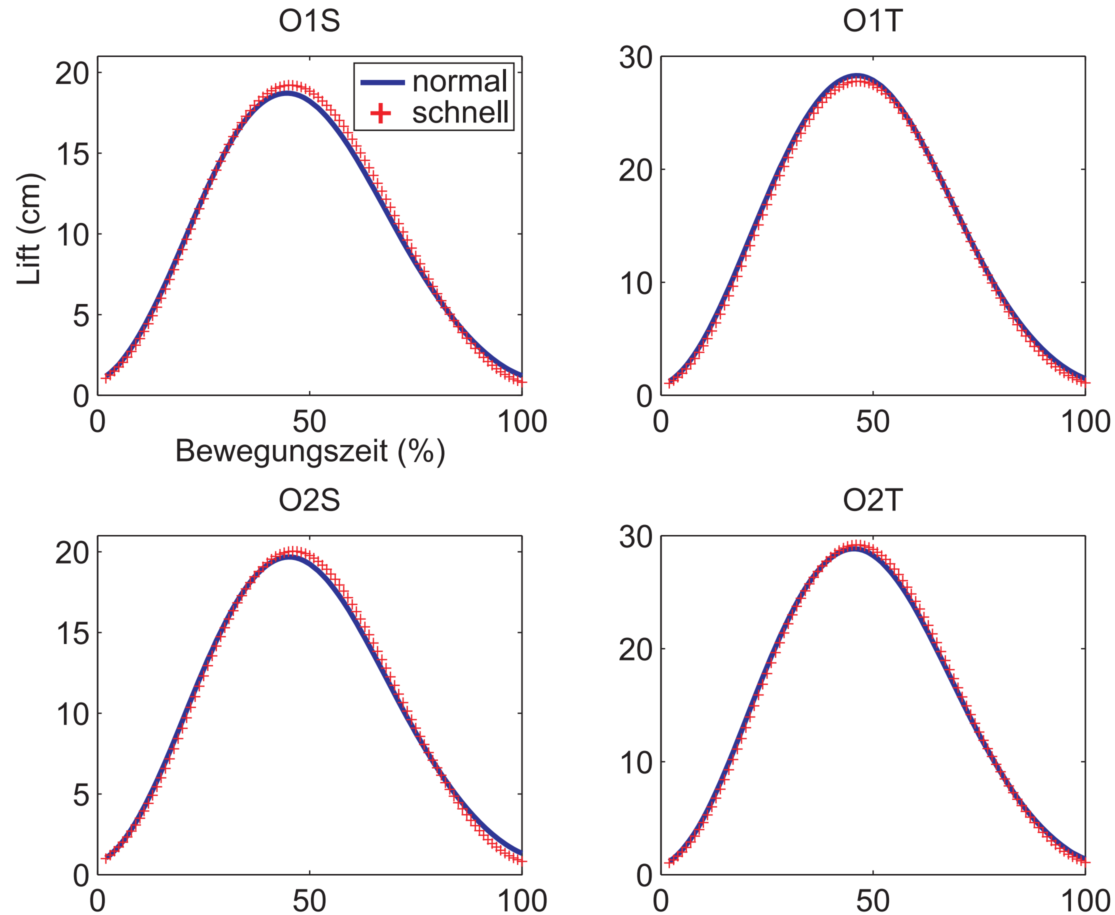
scaling with movement time



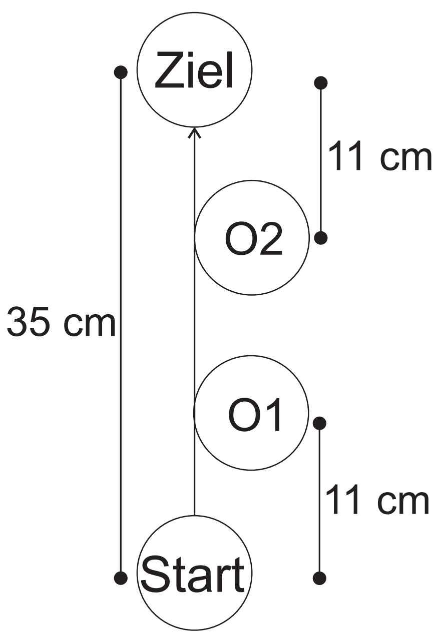


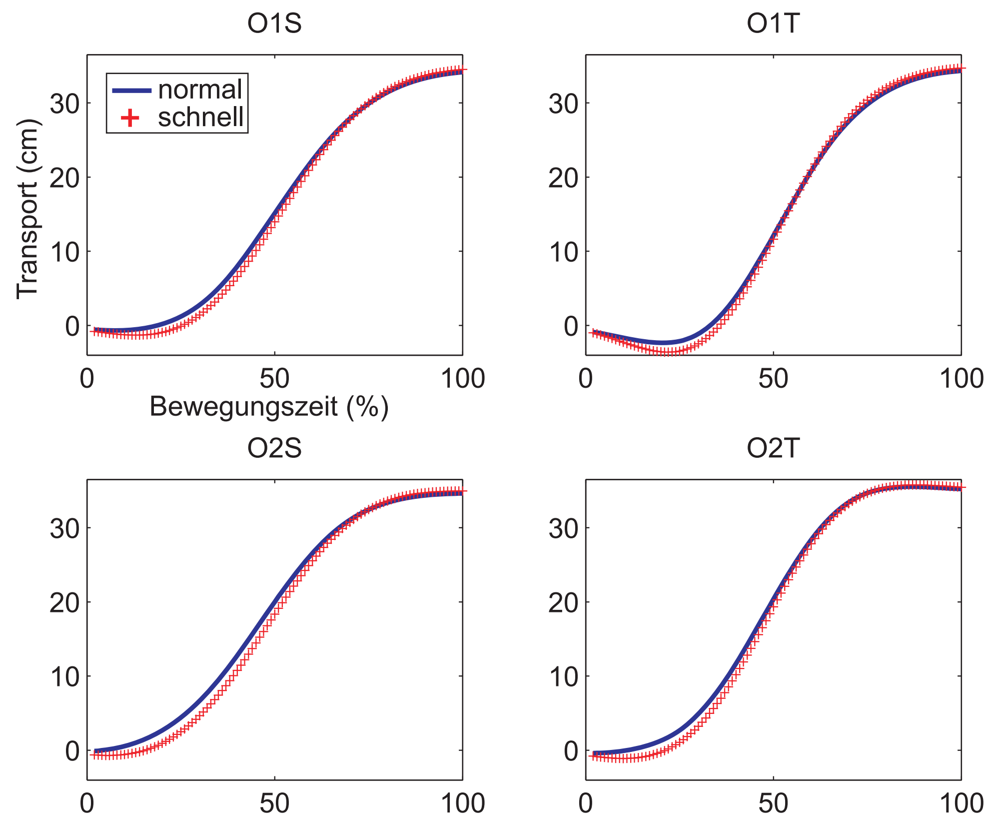
scaling with movement time





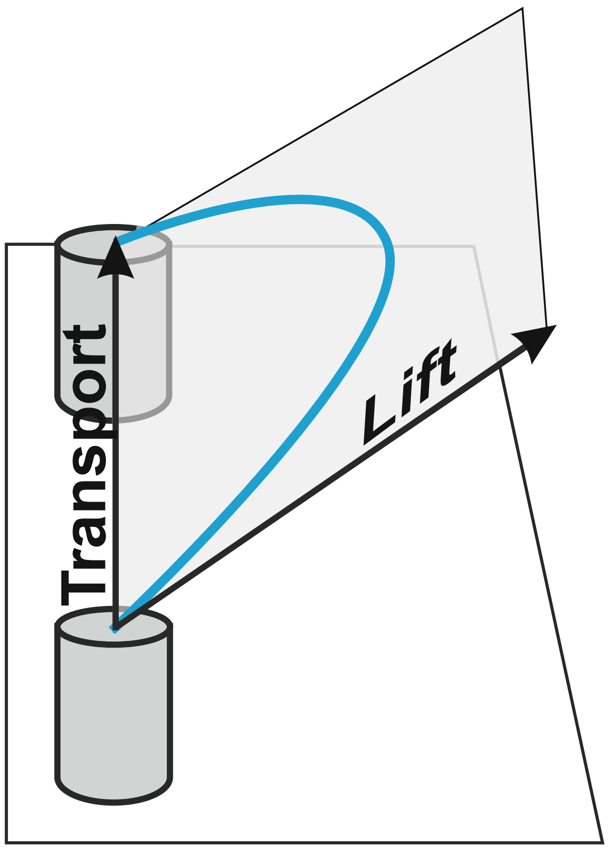
scaling with movement time



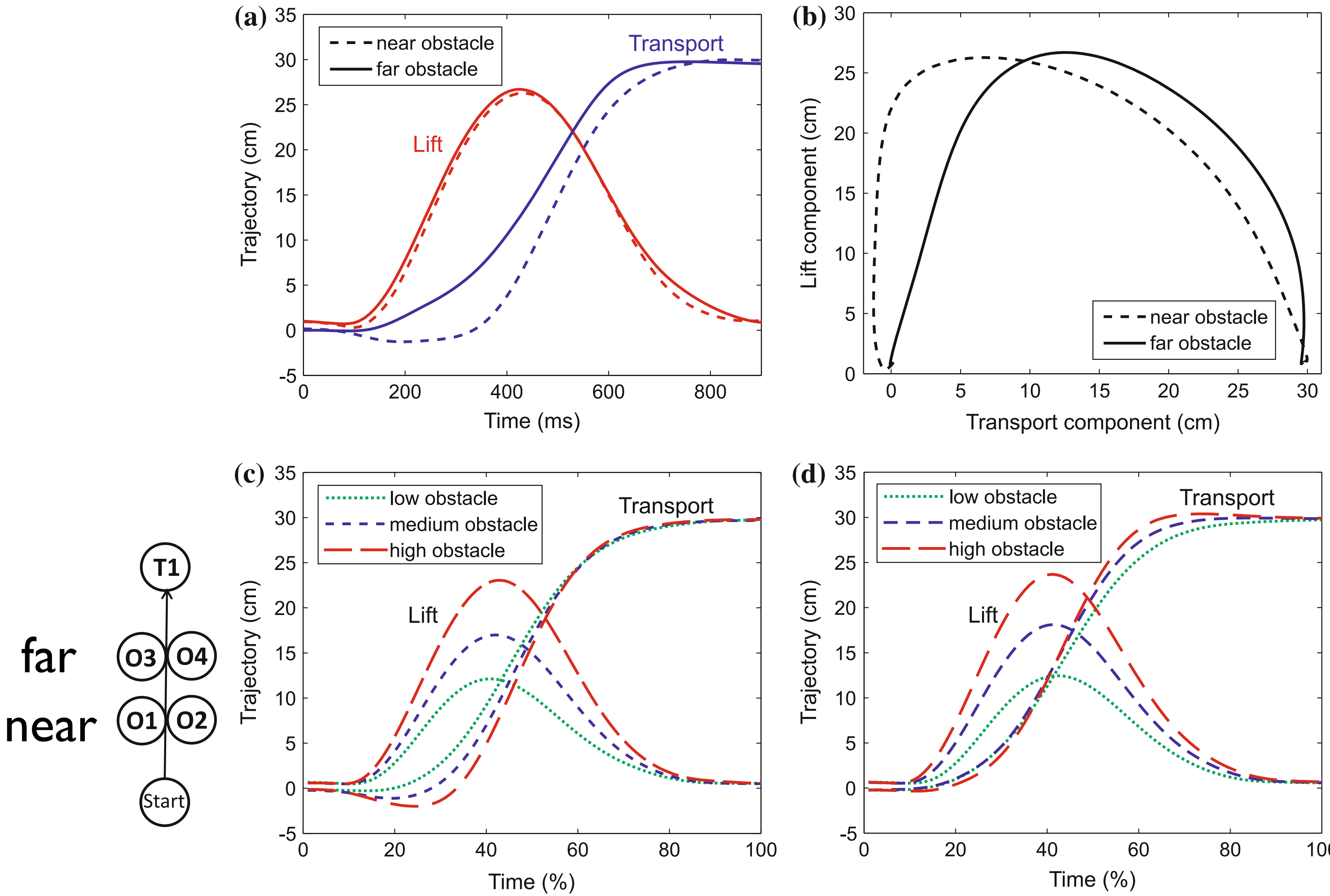


elementary behaviors

- based on planarity
- decompose movement into transport and lift component



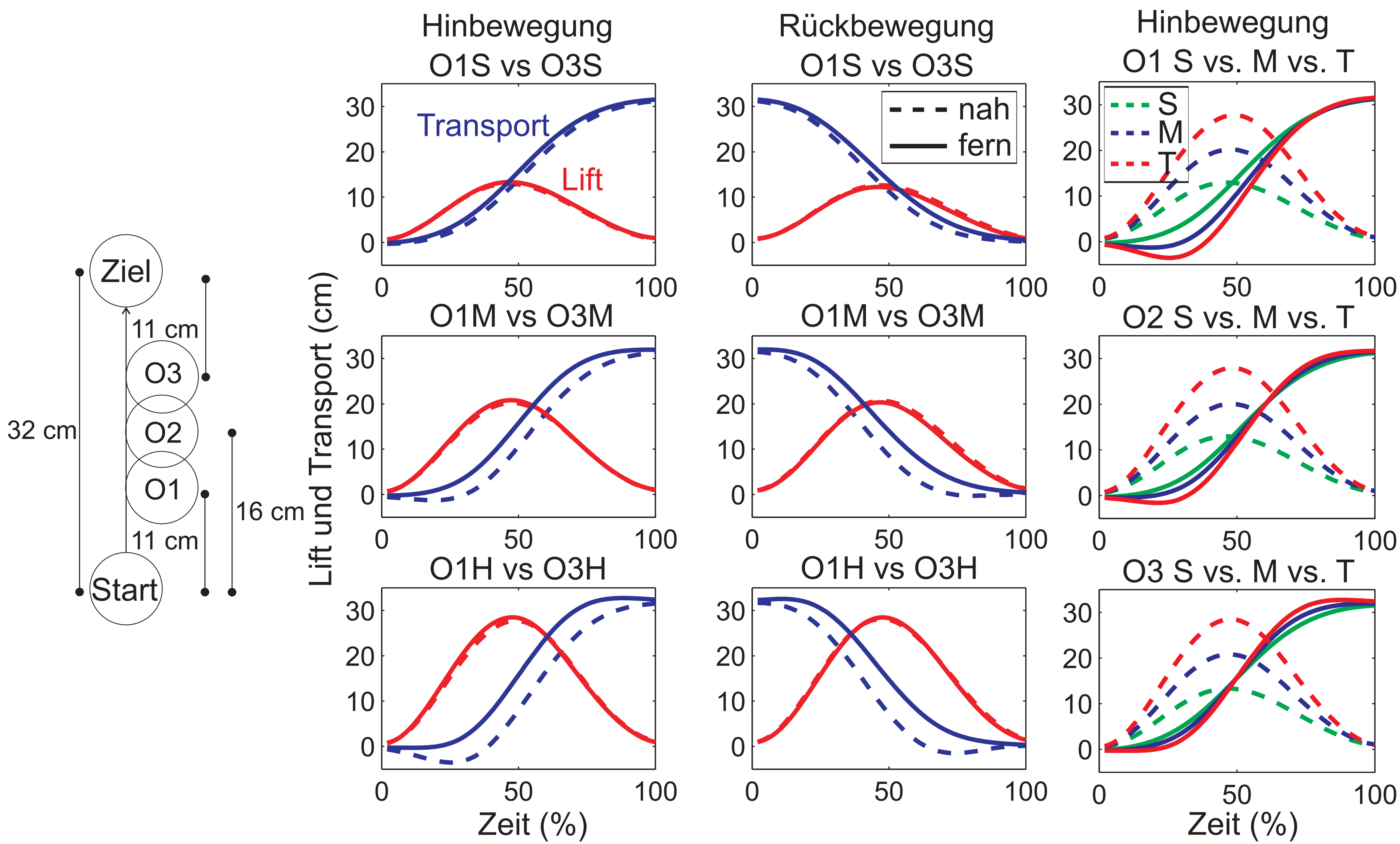
lift vs. transport



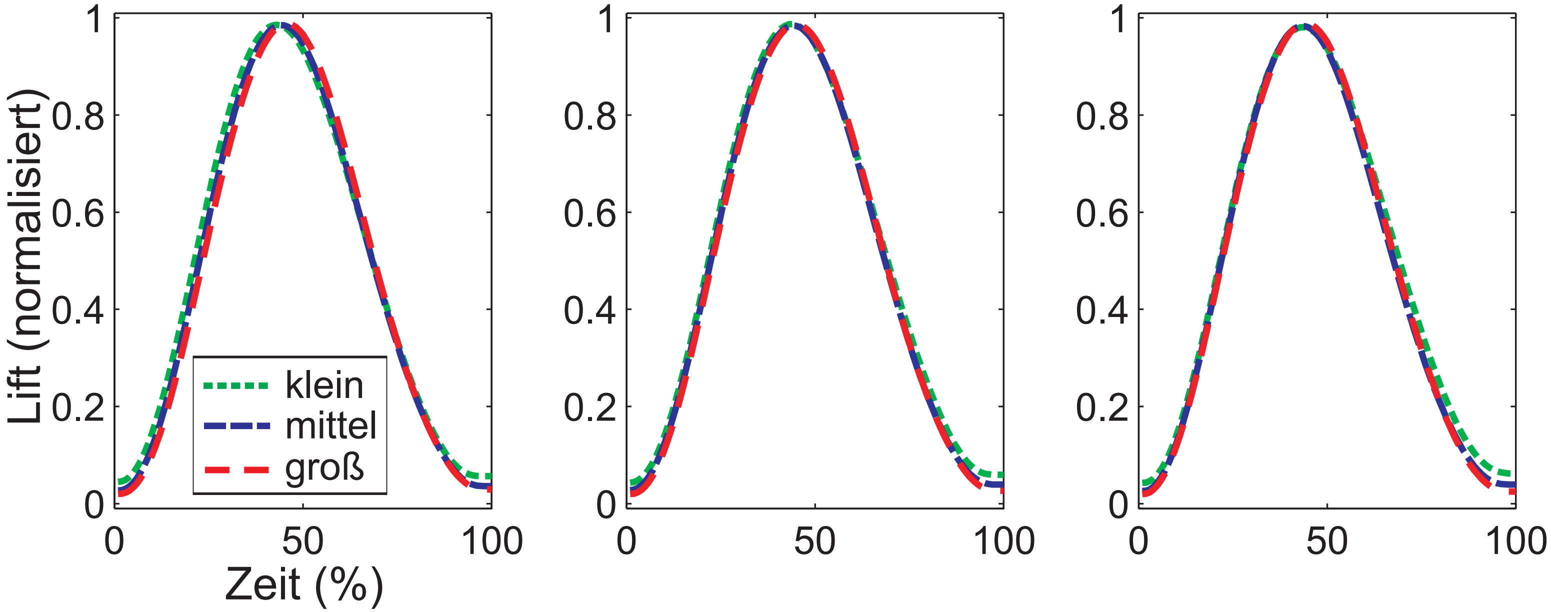
near

far

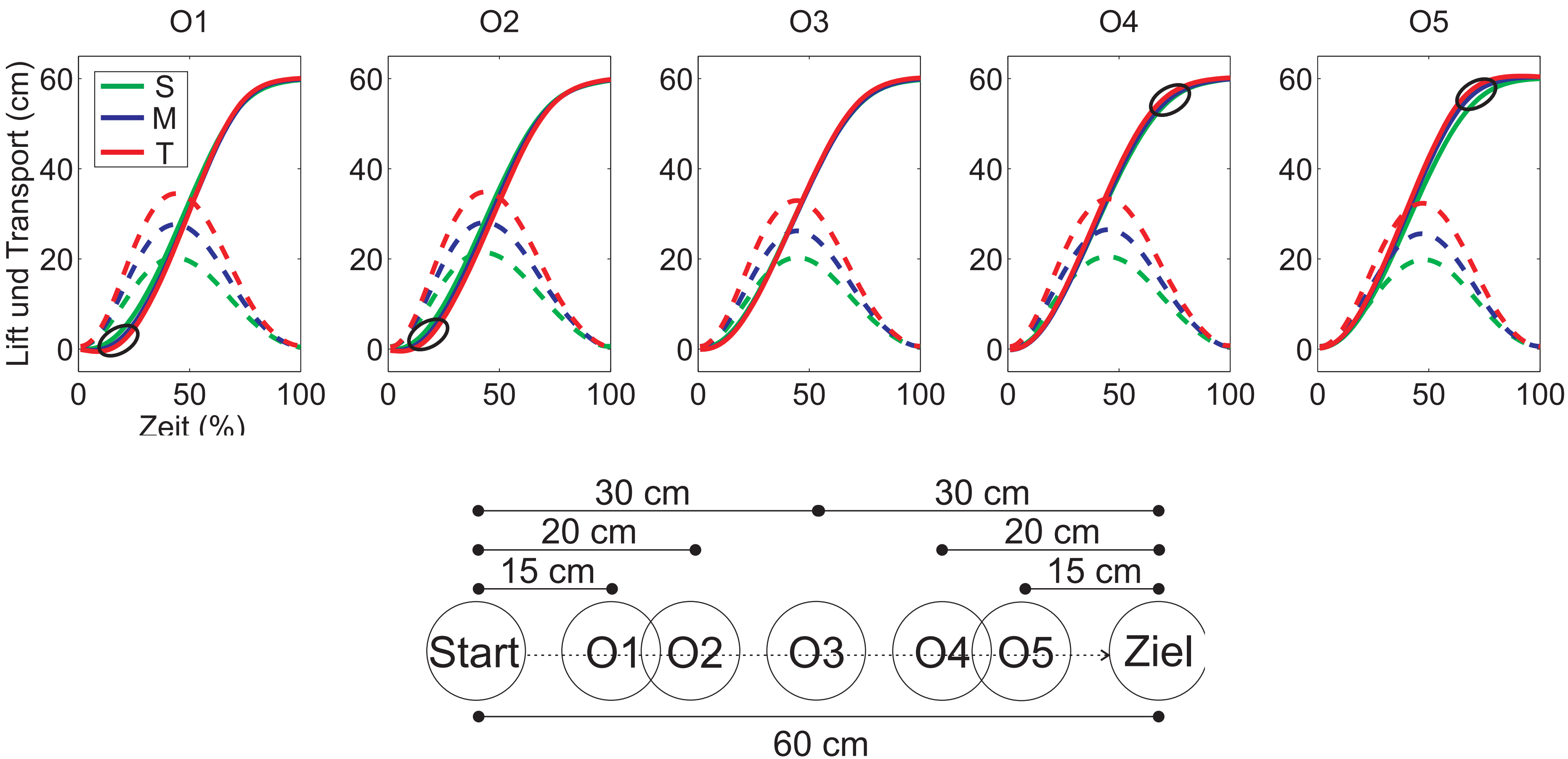
lift vs. transport



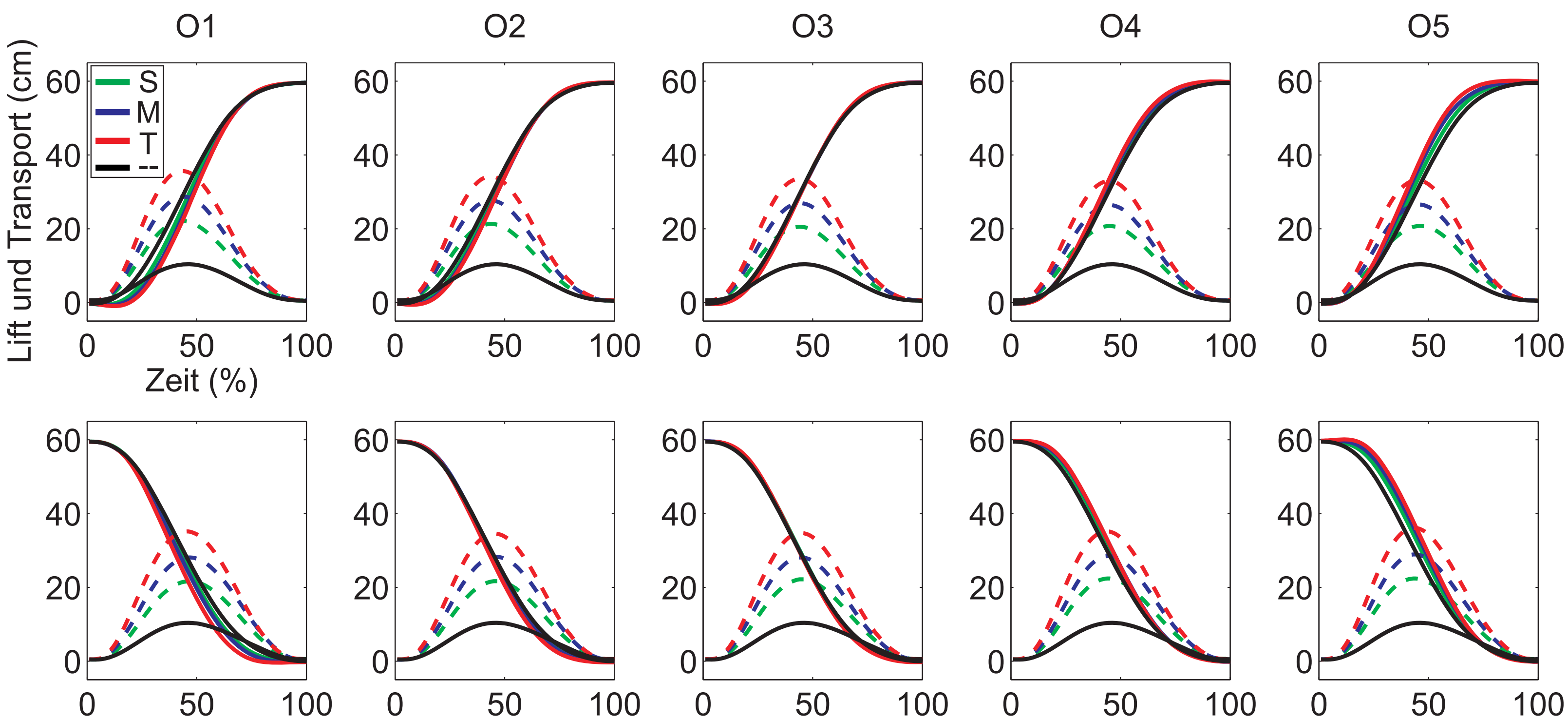
scaling lift to amplitude and time

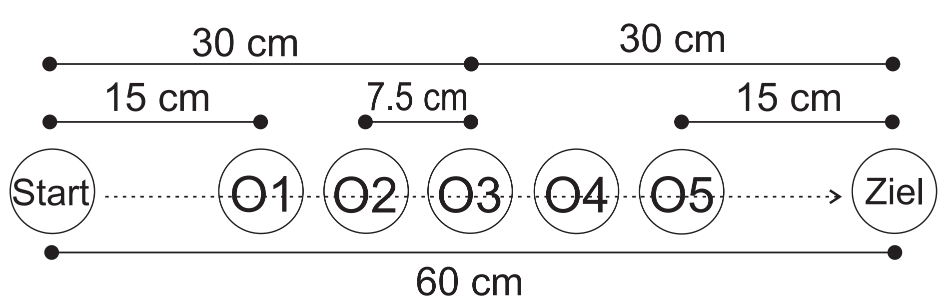


lift vs. transport



lift vs. transport

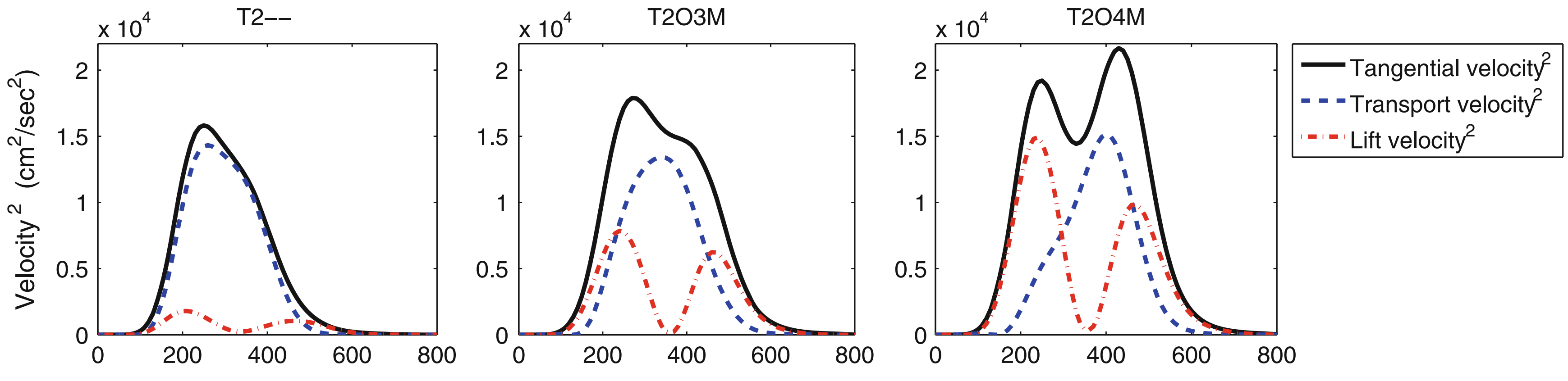


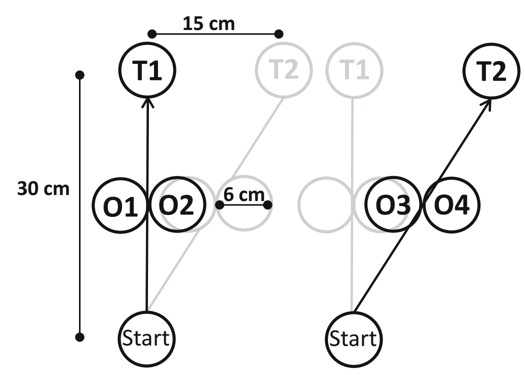


lift vs. transport

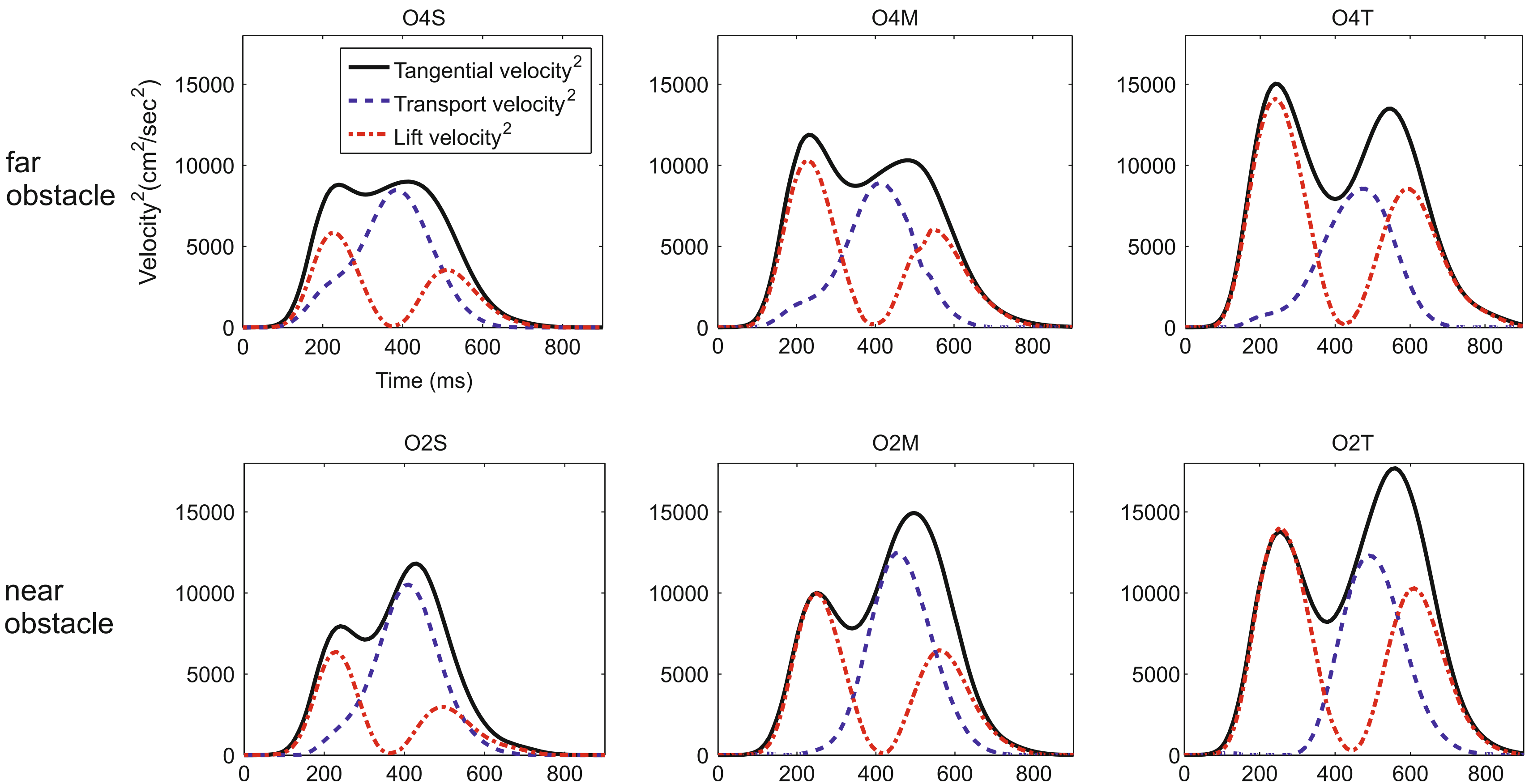
- invariance of lift under location of obstacle along transport
- approximate invariance of transport under height of obstacle
  - exact if obstacle is symmetrically half-way between start and target position of transport

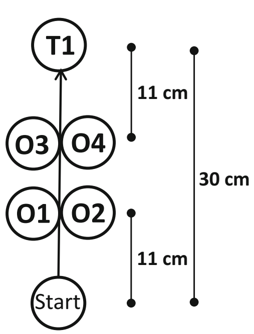
complexity from simple components



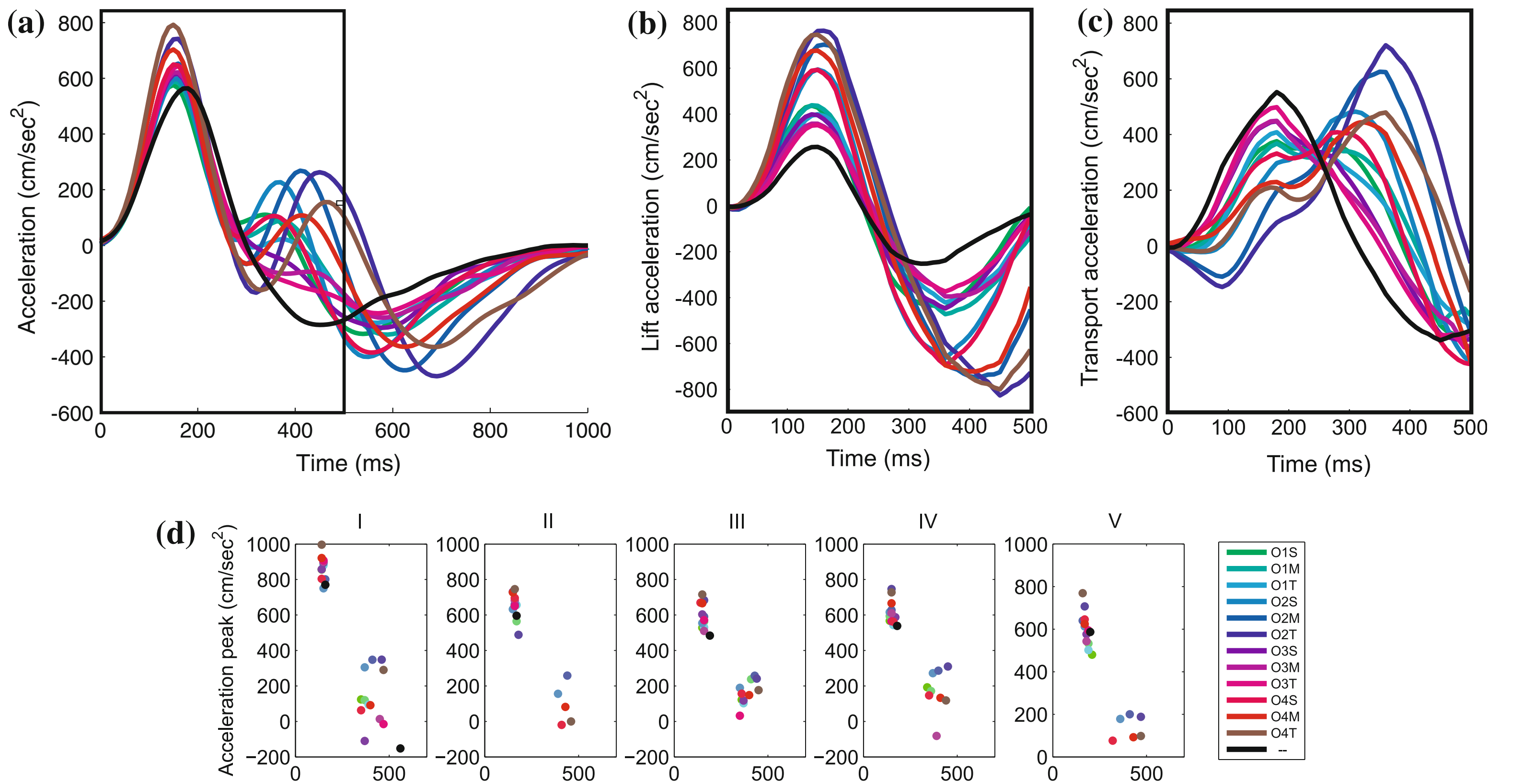


complexity from simple components

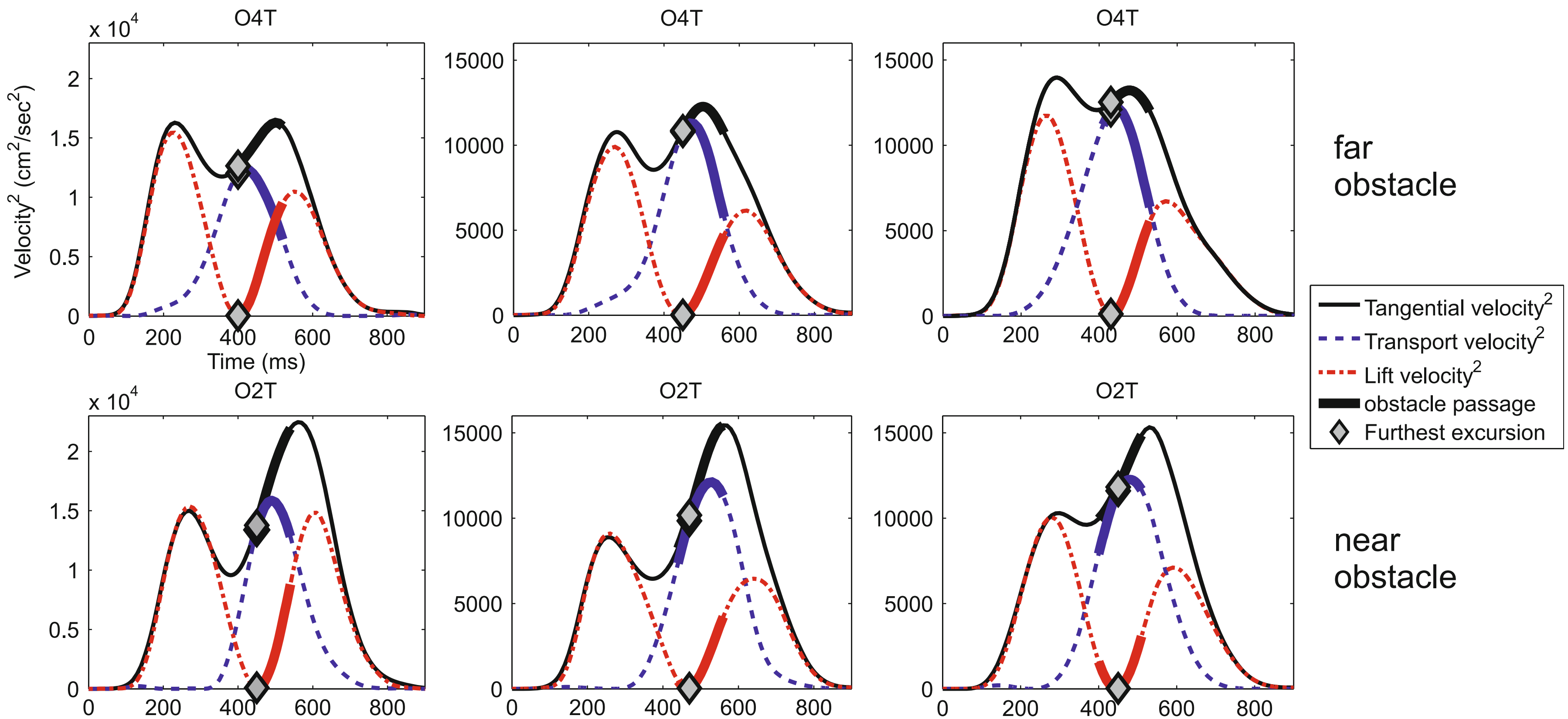


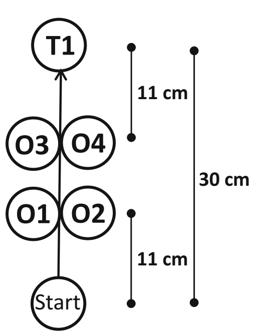


complexity from simple components

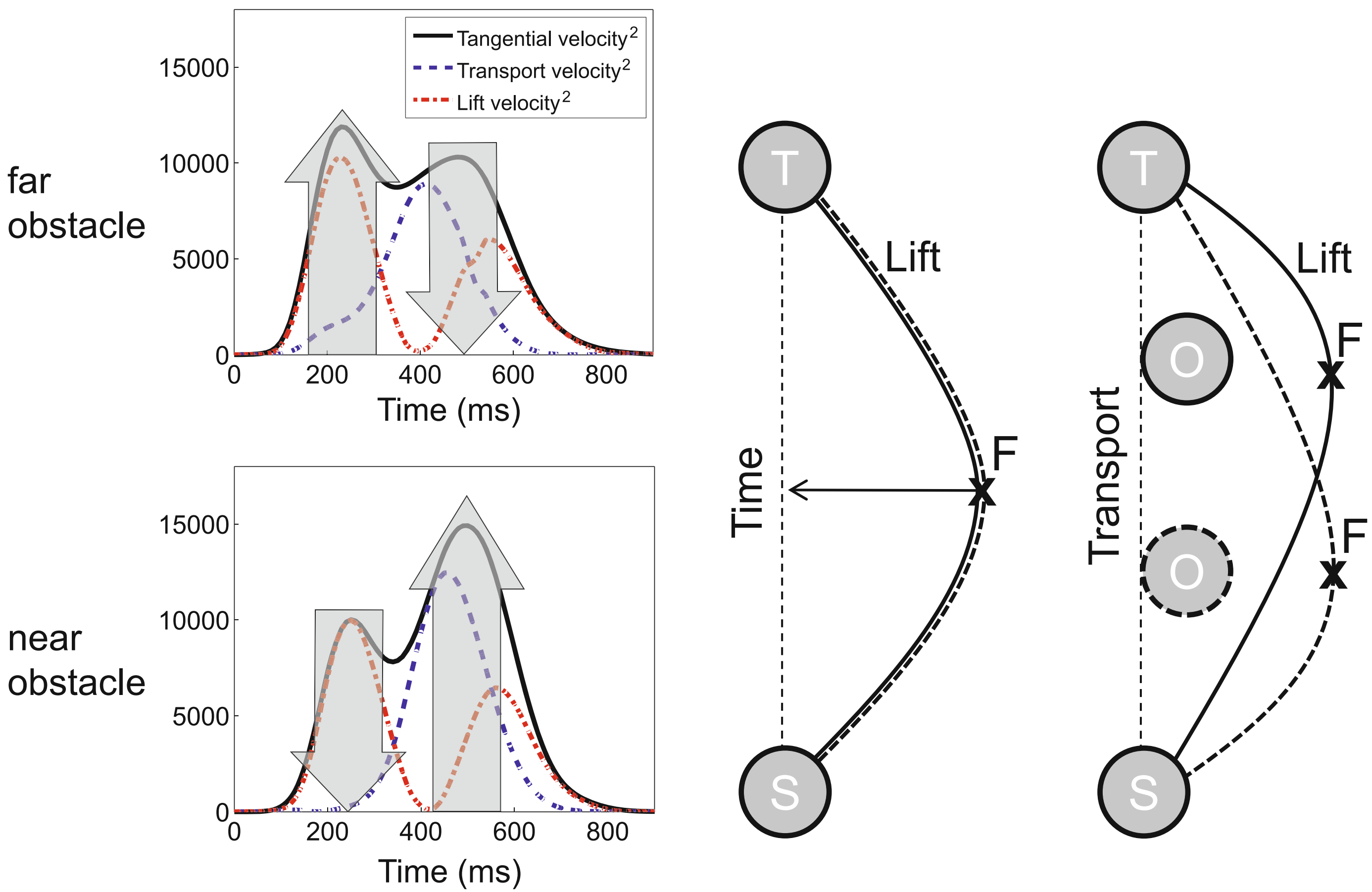


complexity from simple components

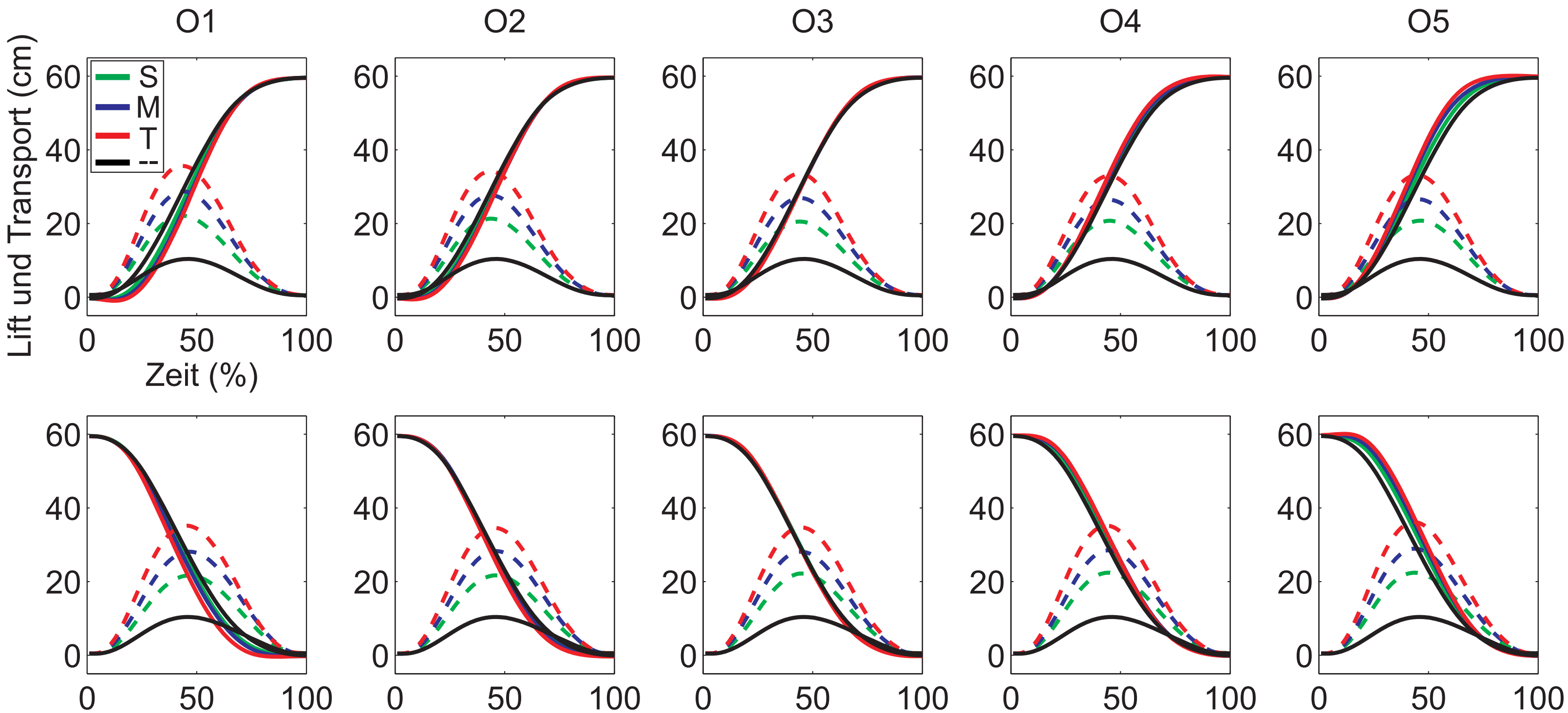


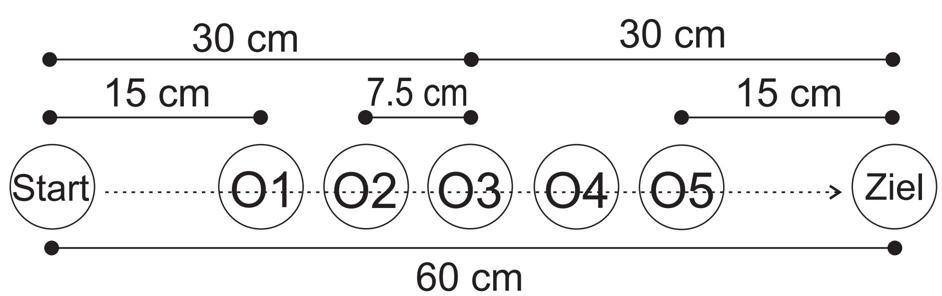


complexity from simple components

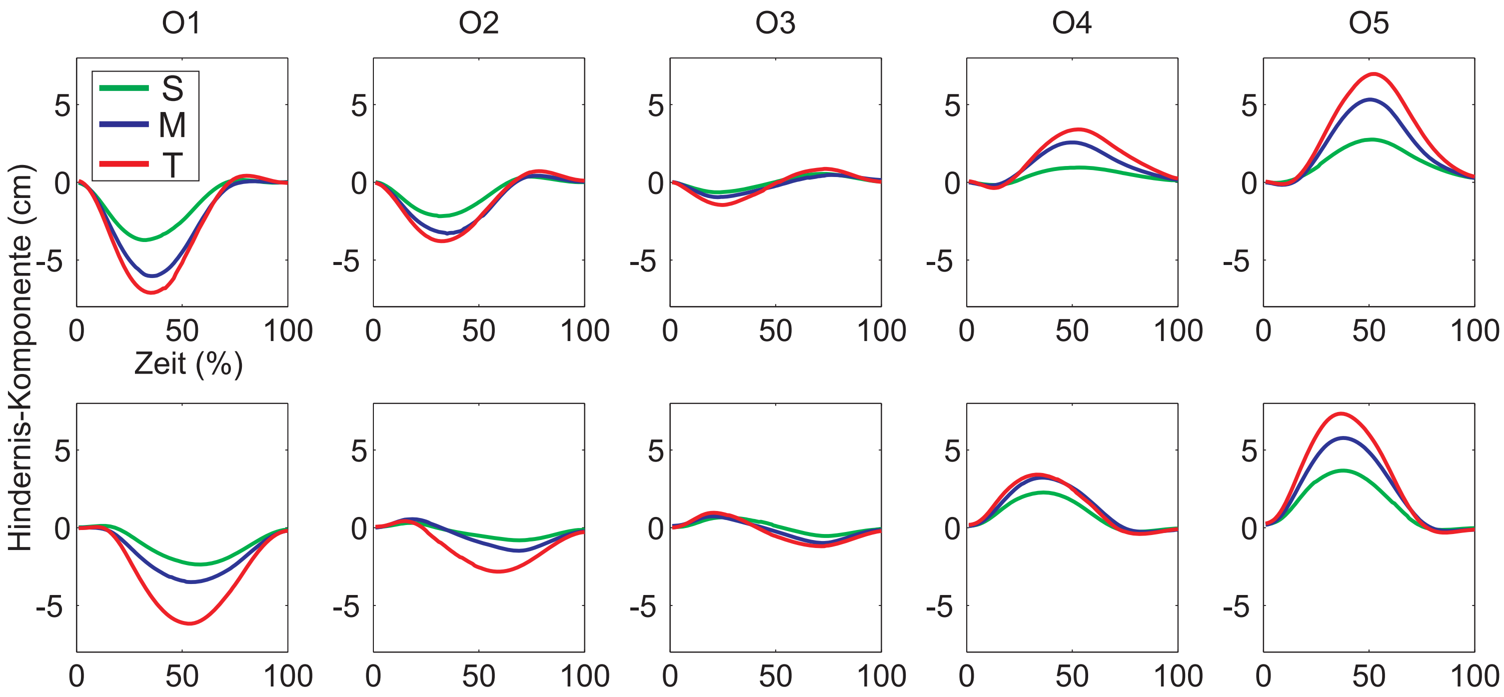


obstacle component



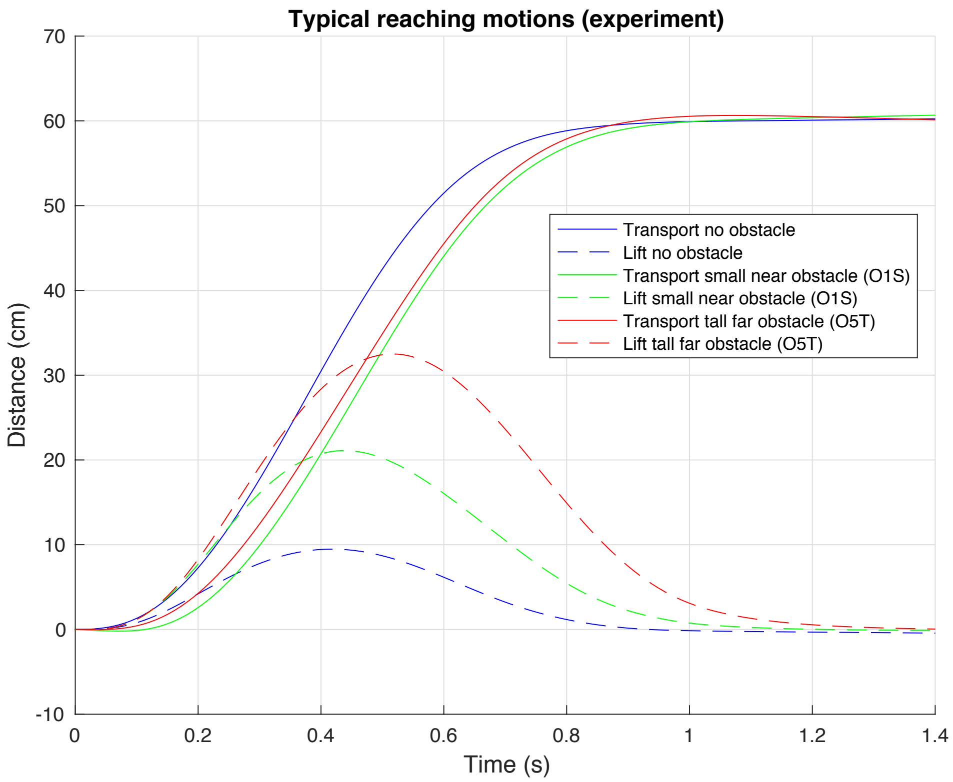


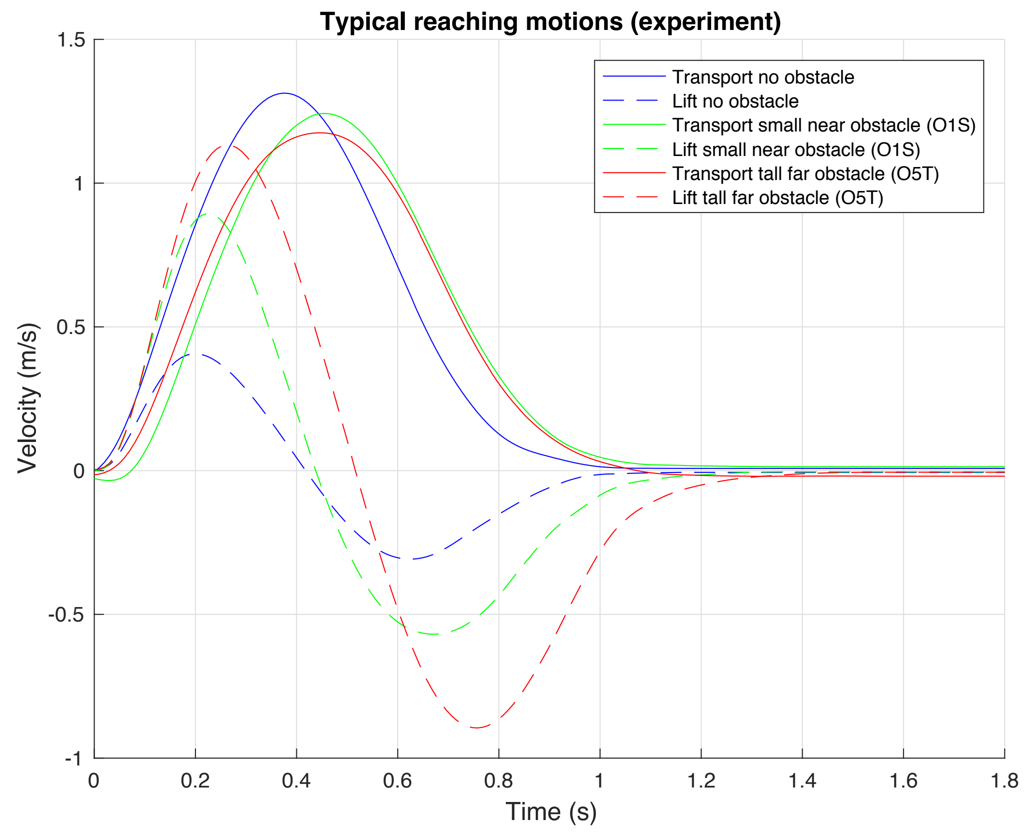
obstacle component



Theoretical account

- Jokeit, Grimme, Schöner, 2018
- unnormalized time experiment:





Primitive “neural oscillator”

- neural oscillator
$$\tau\dot{u} = -u - c\cdot\sigma(v) + h + s_u$$
$$\tau\dot{v} = -v + c\cdot\sigma(u) + h + s_v$$

- solutions
$$u(t) = \tau(h+s)\,C_2\left[\sin(ct/\tau)e^{-t/\tau} + \frac{C_1}{C_2}\left(\cos(ct/\tau)e^{-t/\tau} - 1\right)\right]$$
$$v(t) = C_2 + \tau(h+s)C_1\left[\sin(ct/\tau) + \cos(ct/\tau)\right]e^{-t/\tau}$$

Field of neural oscillators

- of varying frequency, a

$$\tau\dot{u}(a,b) = -u(a,b) - c(a)\cdot\sigma(v(a,b)) + h + s(a,b)$$
$$\tau\dot{v}(a,b) = -v(a,b) + c(a)\cdot\sigma(u(a,b)) + h + s(a,b)$$

- from which velocity profile is composed by projection

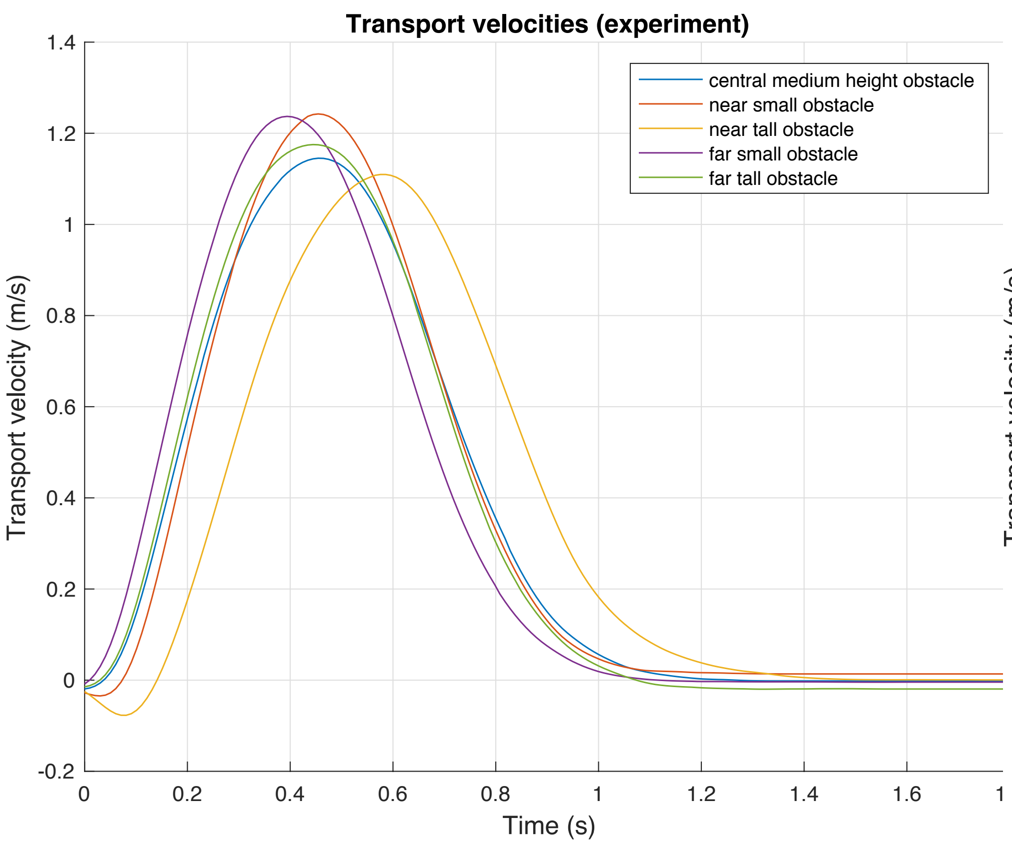
$$V_{\text{bank}}(t) = \frac{1}{N}\int_a\int_b W(a,b)\Theta(u(a,b)(t))\ db\ da$$

Two fields as primitives for lift and transport

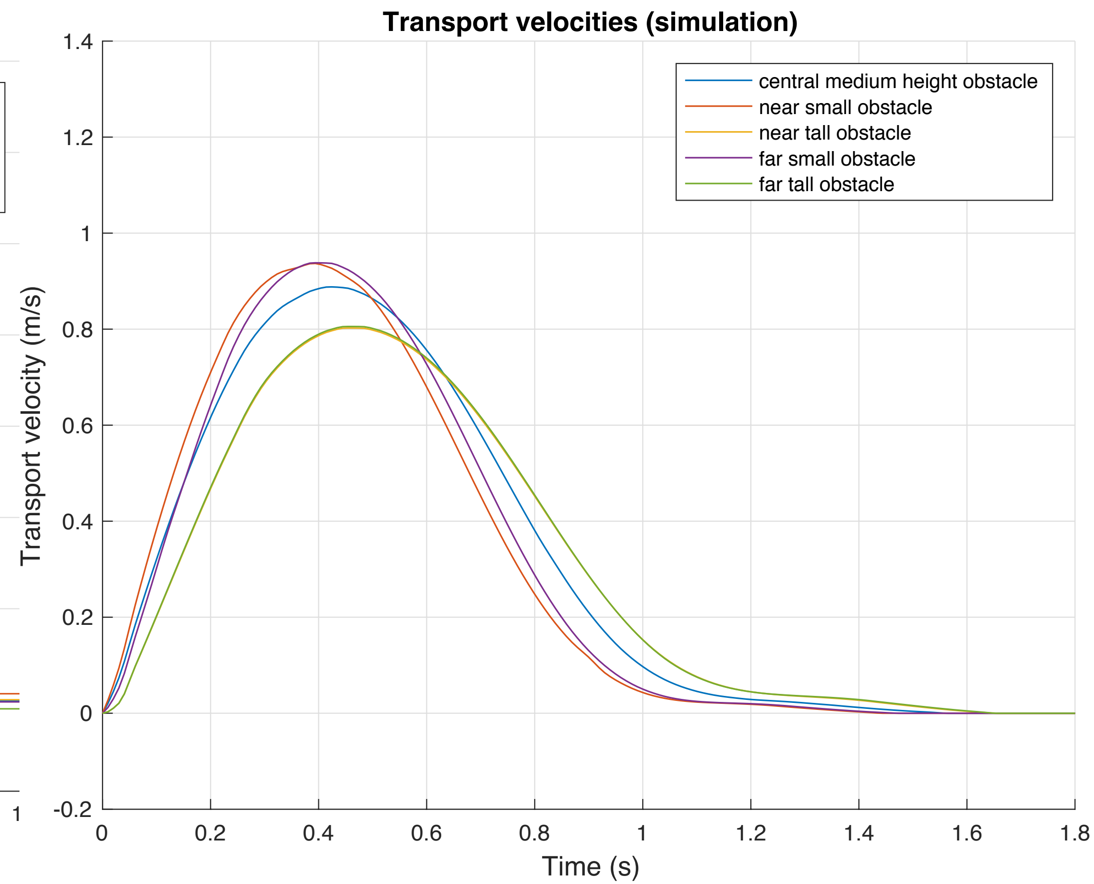
$$v^{\mathrm{LIFT}}(t) = \dot{V}_{\mathrm{slow}}(t)$$

$$\begin{aligned} v^{\mathrm{TRANSPORT}}(t) = V_{\mathrm{fast}}(t) \\ + \alpha_2 H(d_o) W_{\mathrm{slow}}(t_{f_{\mathrm{slow}}}, d_o) \dot{V}_{\mathrm{fast}}(t) \\ - \alpha_1 W_{\mathrm{fast}}(t_{f_{\mathrm{fast}}}, d_o) \dot{V}_{\mathrm{slow}}(t) \end{aligned}$$

Results



Transport velocities (experiment)
central medium height obstacle
near small obstacle
near tall obstacle
far small obstacle
far tall obstacle
Transport velocity (m/s)
Time (s)
1.4
1.2
1
0.8
0.6
0.4
0.2
0
-0.2
0
0.2
0.4
0.6
0.8
1
1.2
1.4
1.6
1



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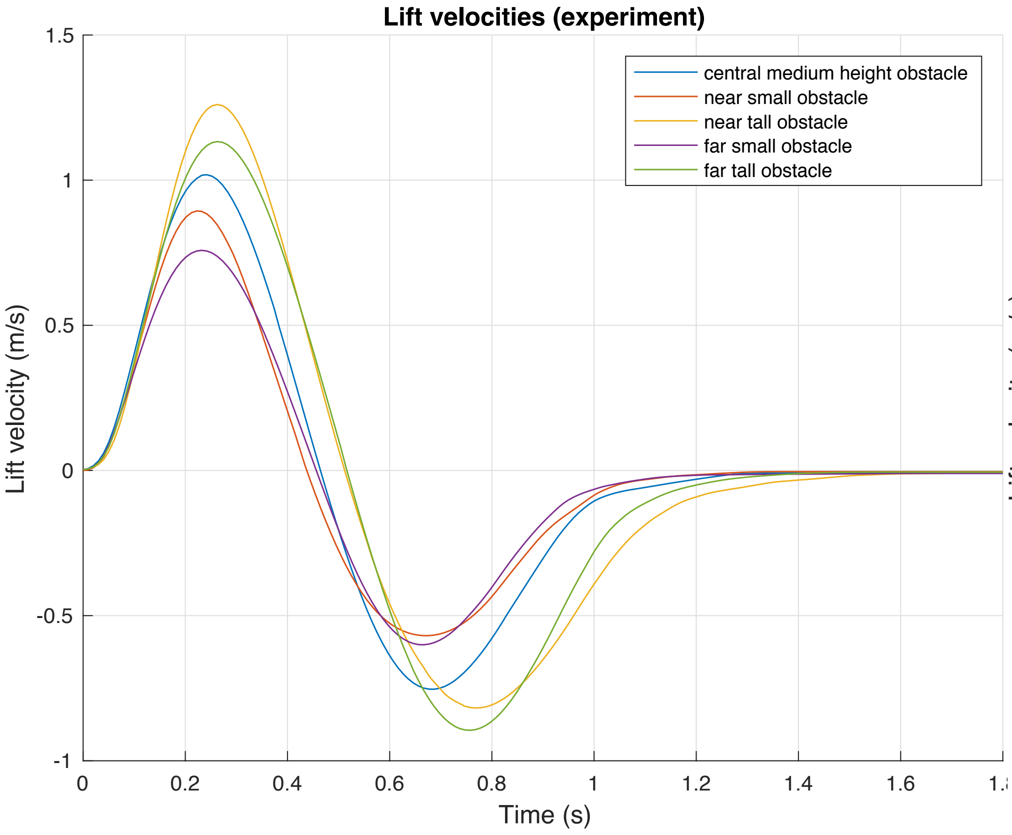
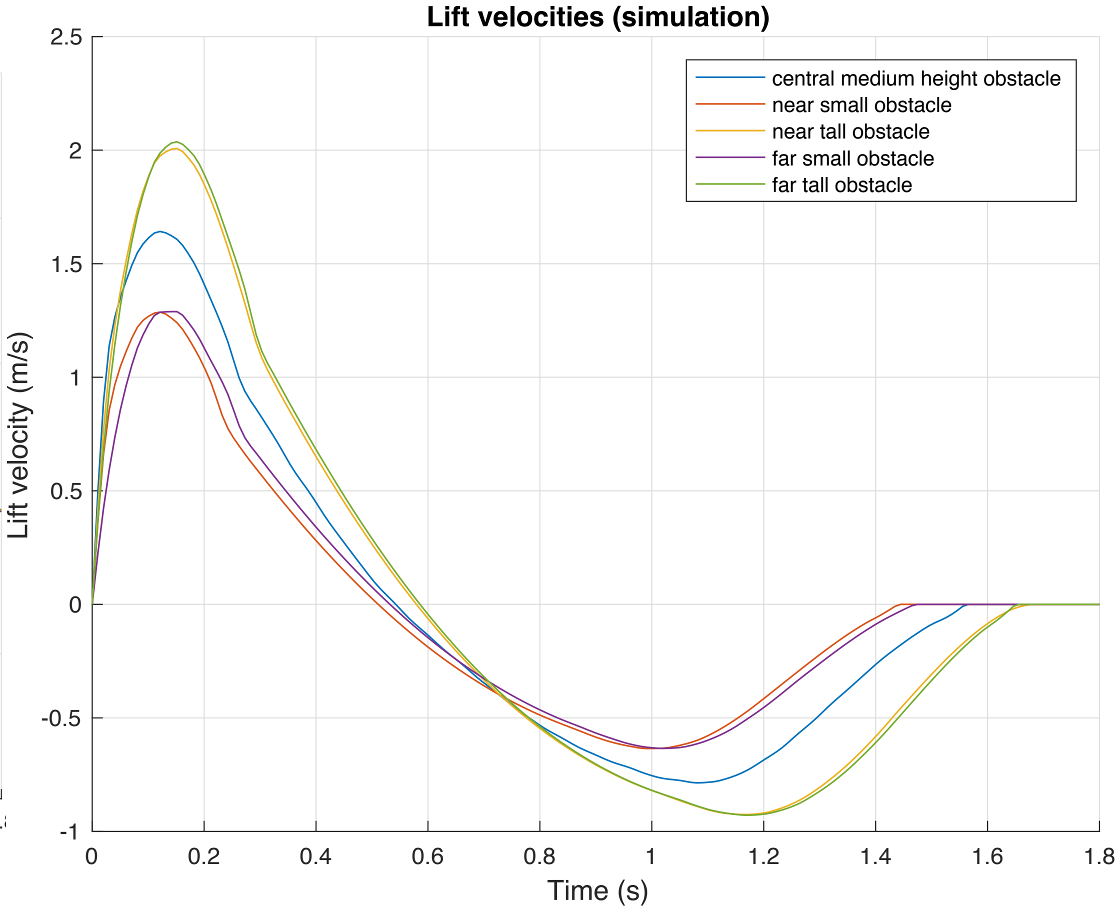
0
-0.2
0
0.2
0.4
0.6
0.8
1
1.2
1.4
1.6
1.8

Results


Lift velocities (experiment)
Lift velocity (m/s)
Time (s)
1.5
1
0.5
0
-0.5
-1
0
0.2
0.4
0.6
0.8
1
1.2
1.4
1.6
central medium height obstacle
near small obstacle
near tall obstacle
far small obstacle
far tall obstacle


Lift velocities (simulation)
Lift velocity (m/s)
Time (s)
2.5
2
1.5
1
0.5
0
-0.5
-1
0
0.2
0.4
0.6
0.8
1
1.2
1.4
1.6
1.8
central medium height obstacle
near small obstacle
near tall obstacle
far small obstacle
far tall obstacle

Conclusion

- Simple DMP approach enables learning while retaining equifinality …
- but does not capture timing as obstacles are avoided.
- New dynamic primitive from multiple oscillators that capture such timing