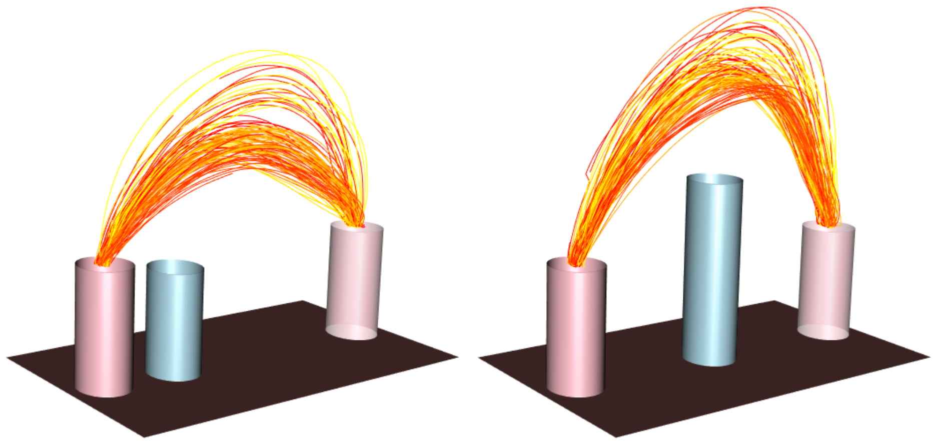
HUMAN ARM TRAJECTORIES IN OBSTACLE AVOIDANCE

LARS LAU RAKET[☽] & BRITTA GRIMME[☼]



(a) Experiment 1 (b) Experiment 9

Figure 1: Recorded movement trajectories from two obstacle-avoidance experiments.

Introduction

A major challenge in the study of human movement is to determine systematic patterns and differences in movements between subjects. From a neuroscience perspective, identification of consistent patterns can help us better understand the movement generating mechanisms in the central nervous system. In applications, identification of systematic motion traits finds many uses, for example access control, gesture recognition, and threat detection.

The present data set consists of observed motion trajectories in a designed single-obstacle avoidance experiment recorded in a motion laboratory, see Figure 2.

When using this data set please cite Grimme (2014).

Experimental setup

Ten participants performed a series of simple obstacle avoidance tasks on a table by relocating a cylindrical object from a starting position to a target position. Between the starting position and target, obstacles of varying heights and positions were placed. The participants were instructed to avoid the obstacles by lifting the cylindric object over them, see Figure 2.

The movements were recorded with the Visualeyez (Phoenix Technologies Inc.) motion capture system VZ 4000. A wireless infrared light-emitting diode (IRED) was attached to the object. The trajectories of markers were recorded in three Cartesian dimensions at a sampling rate of 110 Hz based on a reference frame anchored on the table. The starting position projected to the table was taken as the origin of each trajectory in three-dimensional Cartesian space. The recorded trajectories for two experimental setups are shown in Figure 1. For an elaborate description of a similar experimental setup we refer to Grimme et al. (2012).

Fifteen obstacle avoidance tasks were performed (one for every combination of obstacle height S, M, or T and obstacle distance from starting position $d \in \{15, 22.5, 30, 37.5, 45\}$) as well as a control experiment with no obstacle. The participants repeated each task ten times, giving $n = 100$ functional samples per experiment, and a total of $n_f = 1600$ functional samples in the dataset, with a total data size of $m_f = 174,160$ three-dimensional observation points.

[☽]Department of Mathematical Sciences, University of Copenhagen
[☼]Institut für Neuroinformatik, Ruhr-University Bochum

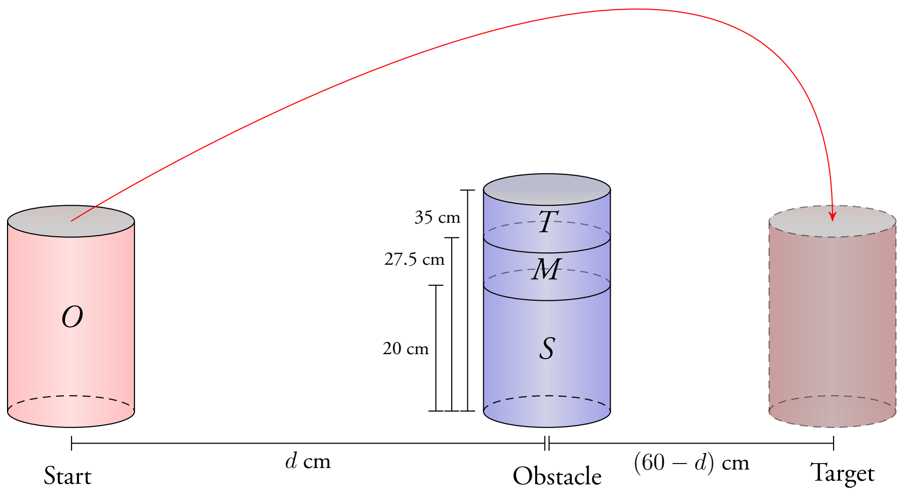


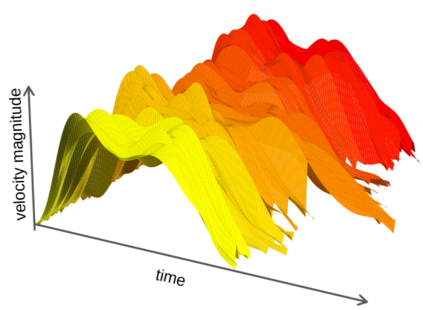
Figure 2: Obstacle avoidance setup. Participants have to move the cylindrical object O from the starting position to the target position by lifting it over an obstacle. Obstacles of three different heights, small (S), medium (M), and tall (T), were used in the experiment, and the distance from starting position to obstacle d were varied across the experiments.

Data

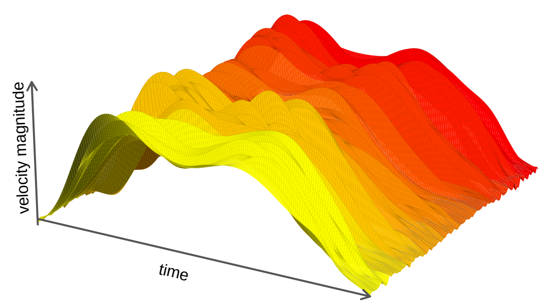
We provide the recorded trajectory data as well as the velocity calculated using symmetric second-order finite differences. The data can be read into R using the code found in Listing 1. The numbering of the experimental setups is given in Table 1.

	S	M	T
15.0 cm	1	2	3
22.5 cm	4	5	6
30.0 cm	7	8	9
37.5 cm	10	11	12
45.0 cm	13	14	15

Table 1: Numbering of experiments. Experiment 16 has no obstacle.



(a) Smoothed velocity



(b) Smoothed velocity, procentual time

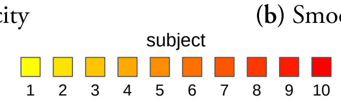


Figure 3: Surface plots of velocity magnitudes over time ordered by repetition and subject in experiment 9.

Data challenges

The data contain systematic amplitude variability, as can be seen in Figure 1. What cannot be seen in this figure is that the data also contains phase variability—variability in movement timing. In Figure 3 (a) we have plotted smoothed velocity magnitude as surfaces by ordering the curves after repetition and participant along the y-axis. These clearly show the phase variability, and we can see that the intrasubject phase variability is smaller than intersubject variability. Figure 3 (b) shows the same data plotted using procentual time (i.e. time 0 at the start of the experiment and time 1 when the target is reached). This results in better alignment across the samples, but the samples are still not perfectly aligned.

This data contains numerous challenges, among others:

Warping of time-dependent values If we warp time-dependent signals such as velocity and acceleration, we should in principle adjust the values accordingly; if we squeeze a velocity signal from $[0, 1/2]$ to $[0, 1]$ the velocity values should be halved in order to retain comparable spatial positions. The result of allowing value modification is however a model that is so flexible that samples can be matched perfectly. How can we handle such flexibility?

Classification Given a movement trajectory can we find out who performed the movement? And can we find out which experiment he/she performed?

Influence of the experimental setup Can we identify simple models that describe the effect of the position and height of the obstacle on the movement path?

Existing work on data

We have analyzed the derivatives of the velocity magnitude curves from this data in the paper Raket et al. (2015) using a hierarchical version of the model proposed by Raket et al. (2014). This hierarchical model simultaneously models movement timing and variation in (acceleration) trajectory. The model is applied in a classification setup, where we seek to identify the participant performing a given movement using the observed acceleration signal.

Listing 1: Loading the data into R

```
repetitions <- 10
participants <- 10
experiments <- 16

y <- as.matrix(read.table('armTrajectories.dat'))
dim(y) <- c(nrow(y), 3, repetitions, participants, experiments)

yvelo <- as.matrix(read.table('armVelocity.dat'))
dim(yvelo) <- c(nrow(yvelo), 3, repetitions, participants, experiments)
```

References

Grimme, B. (2014). *Analysis and identification of elementary invariants as building blocks of human arm movements*. PhD thesis, International Graduate School of Biosciences, Ruhr-Universität Bochum. (In German).

Grimme, B., Lipinski, J., and Schöner, G. (2012). Naturalistic arm movements during obstacle avoidance in 3D and the identification of movement primitives. *Experimental Brain Research*, 222(3):185–200.

Raket, L. L., Grimme, B., Schöner, G., Markussen, B., and Igel, C. (2015). Statistical analysis of human arm movements using timing and motion separation. (Working paper, available on request).

Raket, L. L., Sommer, S., and Markussen, B. (2014). A nonlinear mixed-effects model for simultaneous smoothing and registration of functional data. *Pattern Recognition Letters*, 38:1–7.