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Modeling und Simulation

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References

[1] Perl, J.; Uthmann, T. (1997). Modellbildung. In Perl, J., Lames, M. & Miethling, W.-D. (Hg.) Informatik im Sport (S. 43-80). Schorndorf: Hofmann

[2] Bossel, H. (1994). Modellbildung und Simulation. Braunschweig: Vieweg

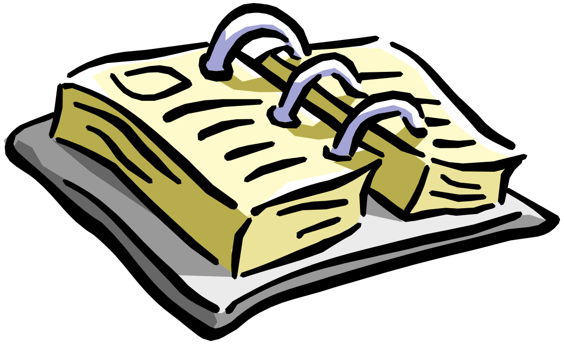
[3] Perl, J.; Lames, M.; Glitsch, U. (2002). Modellbildung in der Sportwissenschaft. Schorndorf: Hofmann

[4] Stachowiak, H. (1973). Allgemeine Modelltheorie. Springer: Wien

[5] Baca, A. & Perl, J. (Eds.) (2019). Modelling and Simulation in Sport and Exercise. Routledge: London and New York

Survey

- Fundamentals of Modeling
- Markov Chains
- Neural Networks
- Models in Biomechanics
  - Example: Rowing
    - Physical and Mathematical Models
    - Data Driven Models



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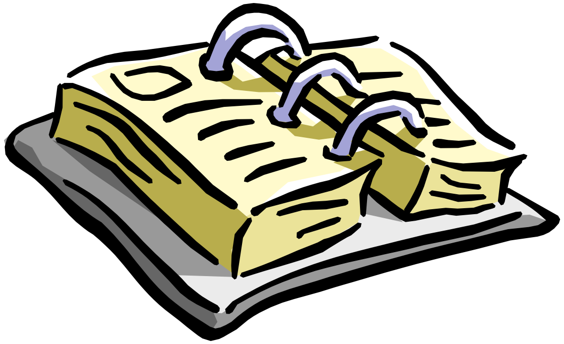


Concept of model ([3], S. 15)

A model is an abstract representation of a system. It is used to diagnose the system state and to predict the system behavior.

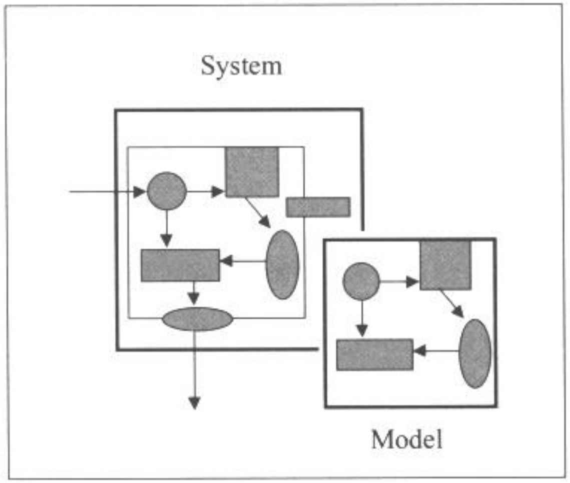
System means a real construct of interacting components, which in turn interacts with the system environment, and whose state or behavior description is of interest.

Modeling serves, among other things, to represent the essential aspects of the structure and behavior of the system in the model in order to be able to examine the model as an alternative.

Abstraction

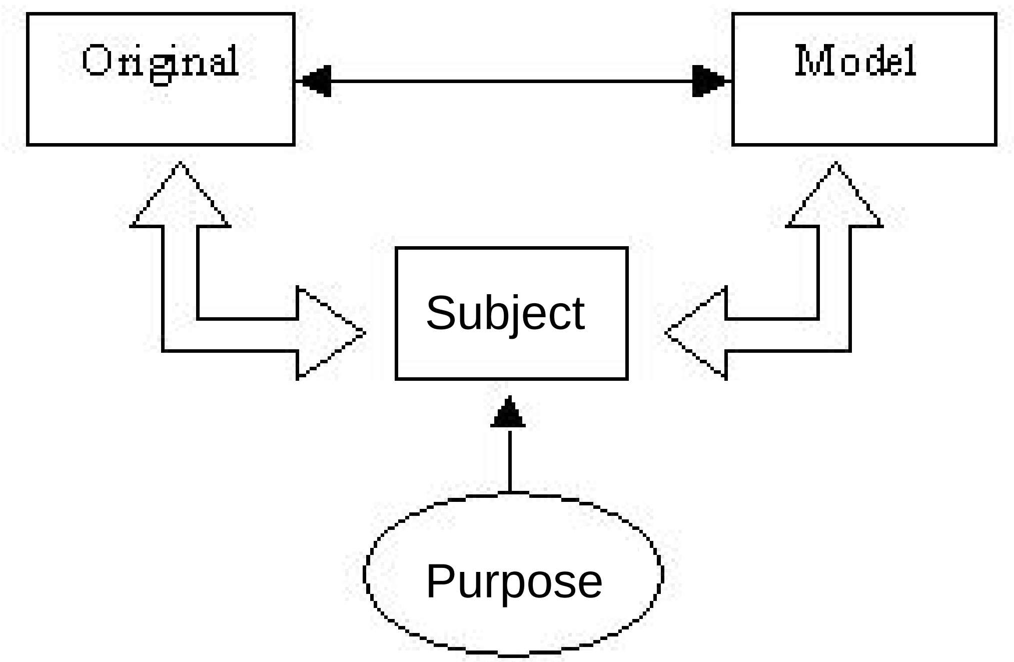
Limitation to essential aspects of the system

Components and relationships with the outside world, for example, are neglected



System and Model; from [3]

Characteristics of models [4]



Models are not per se assigned to their originals, they fulfill their function only for a specific purpose

Characteristics of models

A model for an original can be spoken of if an original is reproduced in a shortened manner, i.e.

- some original attributes are omitted (preterition) or
- some model attributes are introduced additionally (abundance),
- some original attributes are assigned other meanings (transcoding) or
- some original attributes are highlighted (contrasting).

Types of models [3]

White box vs. black box-Models

White box: Systems whose components and interactions are known are mapped to models under the conscious application of abstraction, reduction and modification – *structurally*

Black box: Only the behavior of the system, the interaction with the environment is modeled - *pragmatic*

Types of models [[2]

White box vs. black box-Models

Hybrid

In practice, often; The structure of the system's effect is presented to the best of its knowledge in such a way that "qualitatively" correct behaviour results; unknown model parameters are then adjusted in such a way that the model behavior also numerically corresponds to the observed behavior of the original as far as possible ("empirical validity") "grey box"

Types of models [3]

Quantitative vs qualitative models

Quantitative: measurable

Qualitative: descriptive

Advantageous: quantitative evaluation of qualitative process types – for example, processes can be qualitatively modeled by state transitions, then state transition models are used for quantitative evaluation (e.g. Markov chains)

Types of models [1, 3]

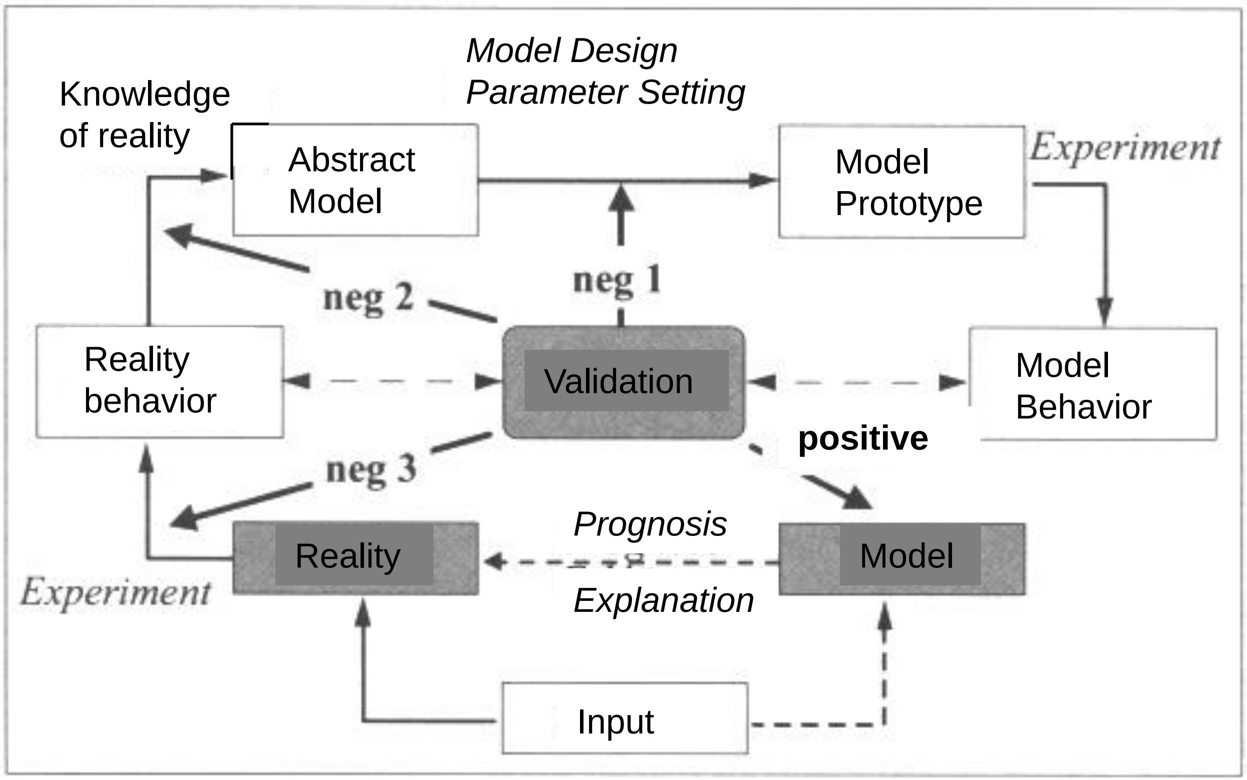
Continuous vs Discrete Modeling

- Differential / Difference Equations
- Time/State Event Oriented

Structure-oriented vs process-oriented modeling

- Structure-oriented: Model consists of action/situation structures ("consists of" description); e.g.: frequency distributions; *static*
- Process-oriented: Model consists of state-event transitions (procedural "passes in" description); *dynamic*

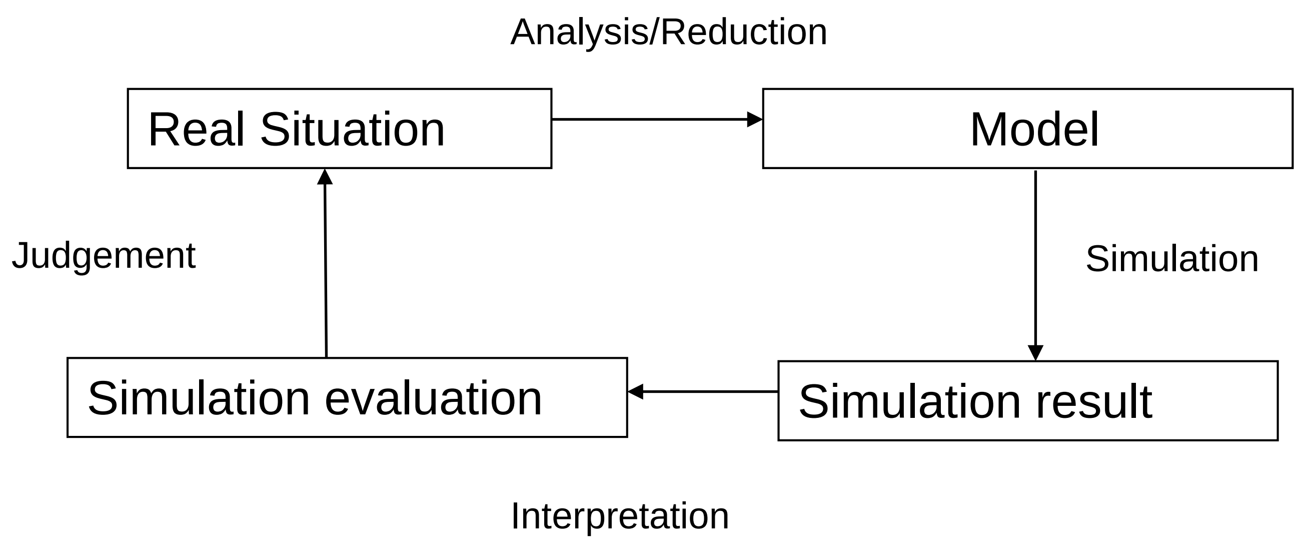
Modeling [3]



Modeling as iterative process; from [3]

Simulation

The main goal is to predict the behavior of the modeled system



Unconventional modeling paradigms

Neural networks

Fuzzy Modeling

Genetic algorithms

Chaos Theory

Data Driven Modelling

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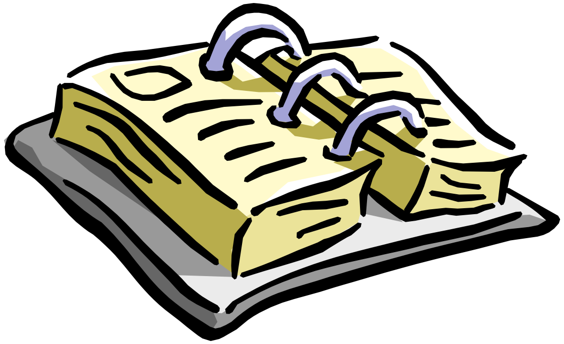


Markov Chains

The game/competition is described by a transition matrix

Transition probabilities are determined on the basis of states

In the i-th row and j-th column of the matrix, the probability of transition from state i to state j is given

Markov Chains

If one assumes the state transition probabilities of the following property, one can understand the matrix as a description of a stochastic process; you can then calculate different quantities (e.g. probabilities of success)

„Markov“-Property: The subsequent state (the transition probability to this state) depends only on the present state and not on the prehistory

Markov Chains Example Table Tennis

	A-Serve	B-Forehand	B-Backhand	A-Defensive	A-Offensive	A-Error	A-Point
A-Serve	0	0.7	0.1	0	0	0.1	0.1
B-Forehand	0	0	0	0.27	0.27	0.27	0.18
B-Backhand	0	0	0	0.3	0.3	0.1	0.3
A-Defensive	0	0.4	0.2	0	0	0.2	0.2
A-Offensive	0	0.4	0.3	0	0	0.2	0.1
A-Error	0	0	0	0	0	0	0
A-Point	0	0	0	0	0	0	0

Matrix **M**

Markov Chains Example Table Tennis

	A-Serve	B-Forehand	B-Backhand	A-Defensive	A-Offensive	A-Error	A-Point
A-Serve	0	0.7	0.1	0	0	0.1	0.1
B-Forehand	0	0	0	0.27	0.27	0.27	0.18
B-Backhand	0	0	0	0.3	0.3	0.1	0.3
A-Defensive	0	0.4	0.2	0	0	0.2	0.2
A-Offensive	0	0.4	0.3	0	0	0.2	0.1
A-Error	0	0	0	0	0	0	0
A-Point	0	0	0	0	0	0	0

Probability of Point for A after 1, 2 or 3 strokes?

Markov Chains Example Table Tennis

In the i-th row and j-th column of the matrix **M·M**, the probability of transition from state i to state j in 2 steps is given

	A-Serve	B-Forehand	B-Backhand	A-Defensive	A-Offensive	A-Error	A-Point
A-Serve	0	0	0	0.219	0.219	0.199	0.156
B-Forehand	0	0.216	0.135	0	0	108	0.054
B-Backhand	0	0.24	0.15	0	0	0.12	0.06
A-Defensive	0	0	0	0.168	0.168	0.128	0.132
A-Offensive	0	0	0	0.198	0.198	0.138	0.162
A-Error	0	0	0	0	0	0	0
A-Point	0	0	0	0	0	0	0

Markov Chains Example Table Tennis

In the i-th row and j-th column of the matrix $\mathbf{M}^n$, the probability of transition from state i to state j in n steps is given

How can the probability of A making the point be calculated?

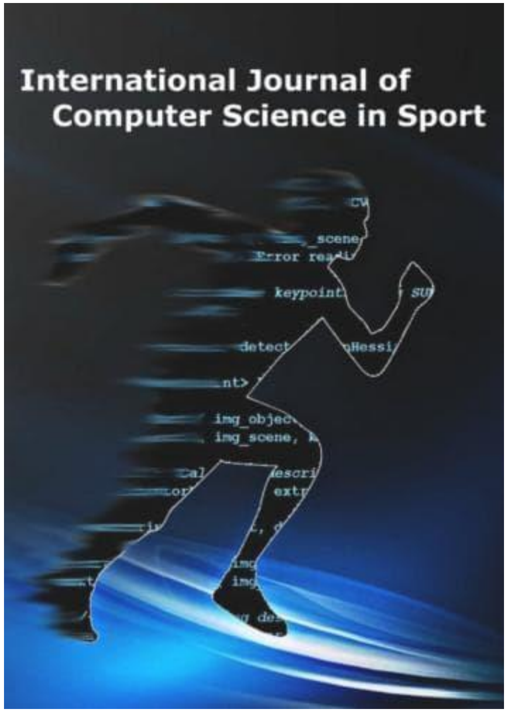
Markov Chains Example Table Tennis

	A-Serve	B-Forehand	B-Backhand	A-Defensive	A-Offensive	A-Error	A-Point
A-Serve	0	0.7	0.1	0	0	0.1	0.1
B-Forehand	0	0	0	0.22	0.32	0.27	0.18
B-Backhand	0	0	0	0.3	0.3	0.1	0.3
A-Defensive	0	0.4	0.2	0	0	0.2	0.2
A-Offensive	0	0.4	0.3	0	0	0.2	0.1
A-Error	0	0	0	0	0	0	0
A-Point	0	0	0	0	0	0	0

Simulation

How to identify the most influencing game situation?

Wenninger, S. & Lames, M. (2016). Performance Analysis in Table Tennis - Stochastic Simulation by Numerical Derivation, International Journal of Computer Science in Sport 15 (1), 22-6



Hidden Markov Models

Markov chain/process with unobservable states

There are a finite number of states, each of which is associated with a transitionxprobability to other states. At each time one specific state is taken. The state at a specific time is directly and solely influenced by the state at the previous time.

After each transition from one state to the next, an output observation is generated based on an observation probability distribution associated with the current state (cf. Jiang, 2010). From the observable output the underlying process shall be deduced.

Baca, A. (2013) Mathematical Modelling 7 (1), 55-61

Hidden Markov Models - Example

„If, for instance, different exercises shall be classified, separate HMMs may be trained for each individual exercise. When evaluating a given sequence, likelihoods from each trained HMM may be calculated. The sequence can then be assigned to that HMM with the largest likelihood.“

Baca, A. (2013) Mathematical Modelling 7 (1), 55-61

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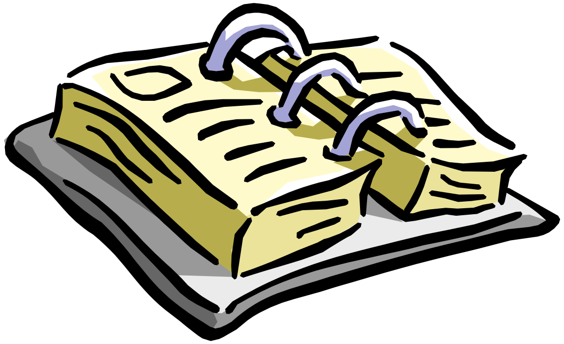
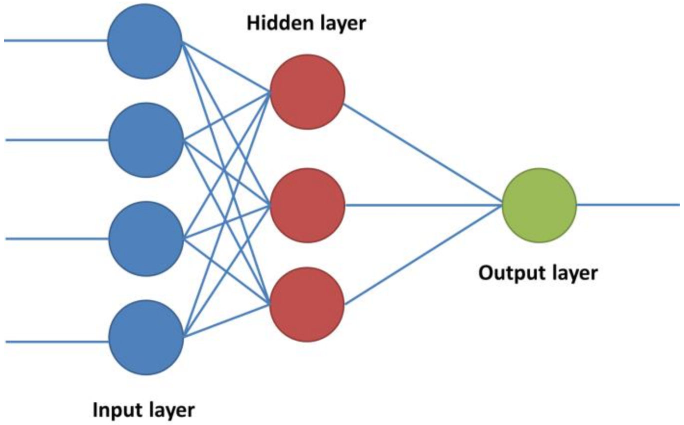


Methods of artificial intelligence

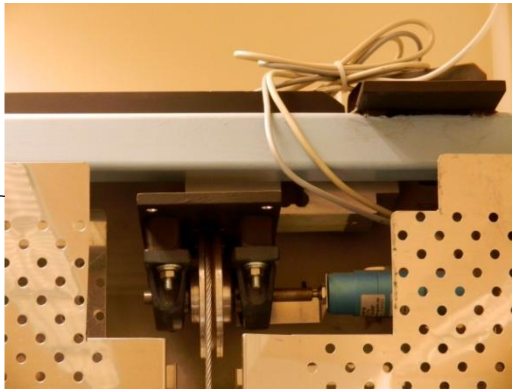
Neuronal Networks

Supervised Learning



MMA: Leg press machine

Sensor-equipped leg press machine



Attached force (load cell) and way (rotary encoder) sensors

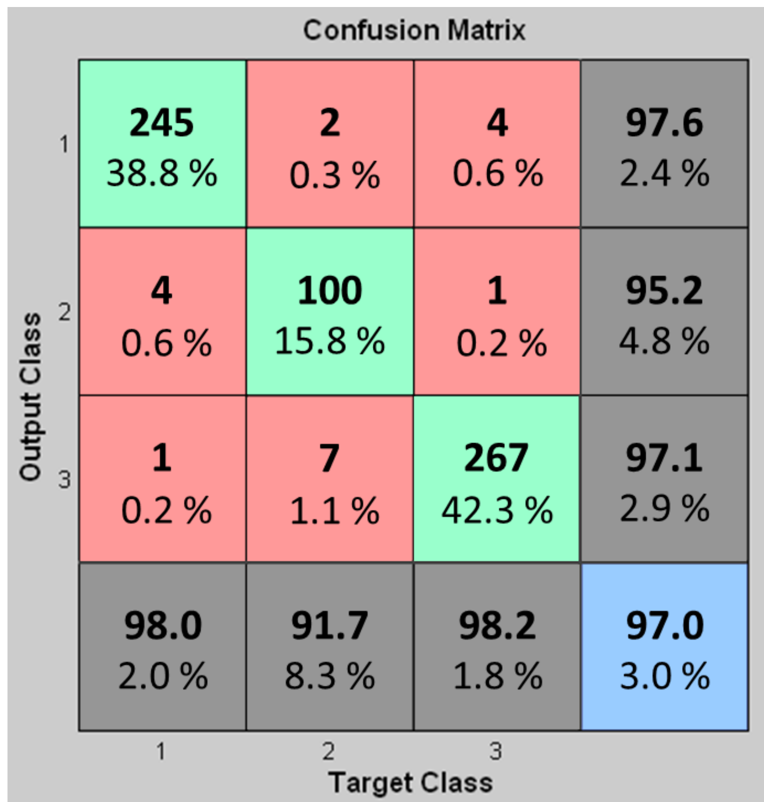
MMA – Weight training machine:
Classification by MLP

- Features based on time and velocity dependent characteristics
- 3 classes:

well-performed execution

improper/ inconstant flexion phase

improper/ inconstant extension phase



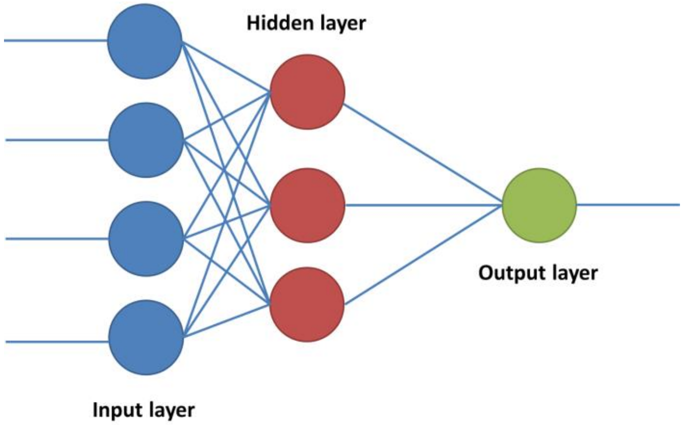
Confusion matrix of entire data set

Novatchkov & Baca,
JSSM, 2013

Methods of artificial intelligence

Neuronal Networks

Supervised Learning



Unsupervised Learning

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Criteria

Training set consists only of input patterns

Learning algorithm attempts to identify groups (clusters) of similar input vectors and map them to groups of similar or adjacent neurons

Best known: Self-organizing maps according to Kohonen (1984) - SOM

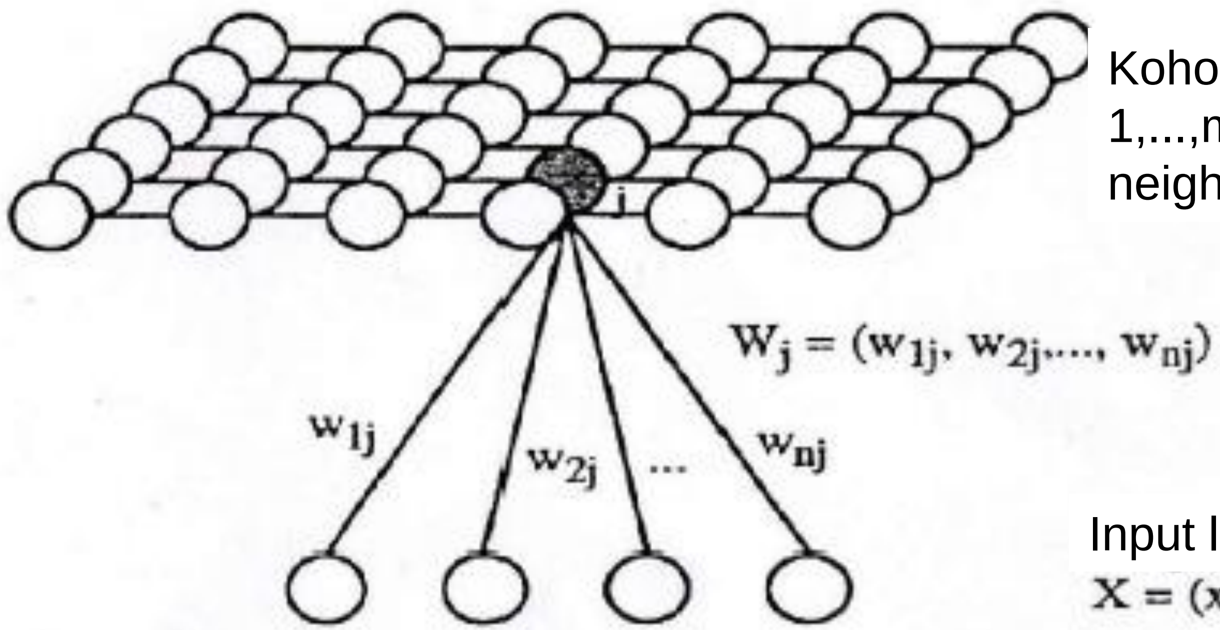
SOMs

The learning method makes the weighting factors of the neuron that is most similar to the input vector ("winner neuron") to the input vector and those of its neighboring neurons more similar to the input vector

Biologically the most plausible; it is assumed that parts of the brain realize a topology-preserving image

Very suitable for classification problems

Architecture of a SOM



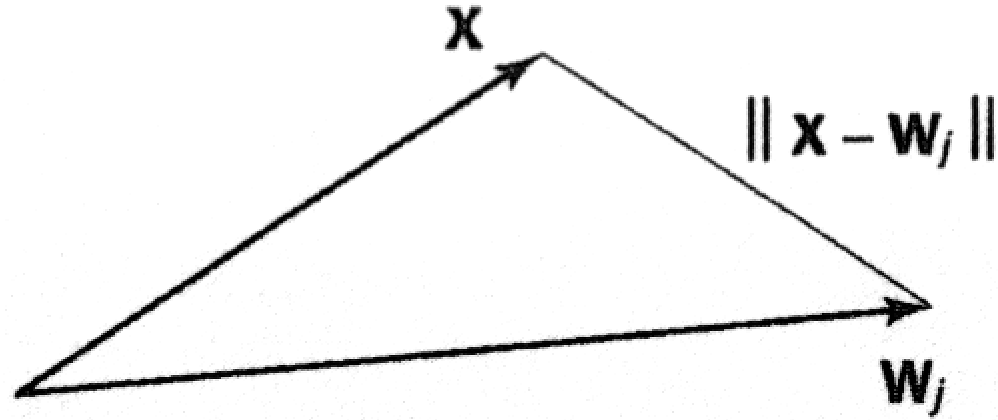
Kohonen neurons 1,...,m with neighborhood grid

Input layer
$X = (x_1, \ldots, x_n)$

Determination of the "winner neuron"

Use of the "Euclidean Norm" – determination of the distance of the vector X to the individual weighting vectors. Winnerneuron W_c is the one for which:

$$\| X - W_c \| = \min_j (\| X - W_j \|)$$



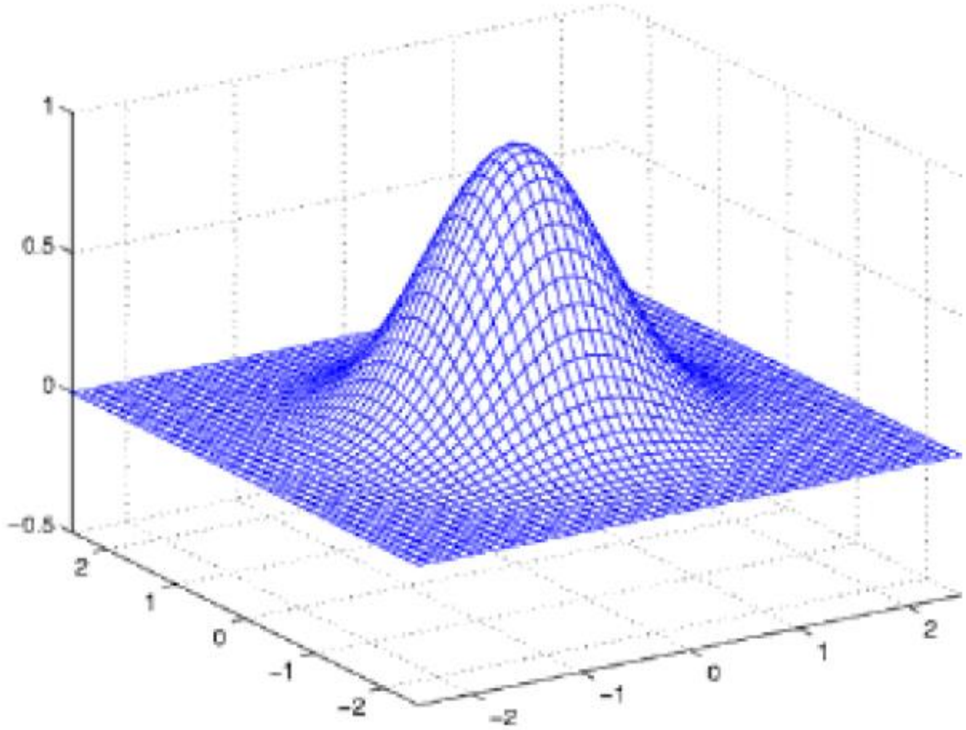
Minimal Euclidean Distance

Training: Neighborhood & Learning Rate Function (= training function)

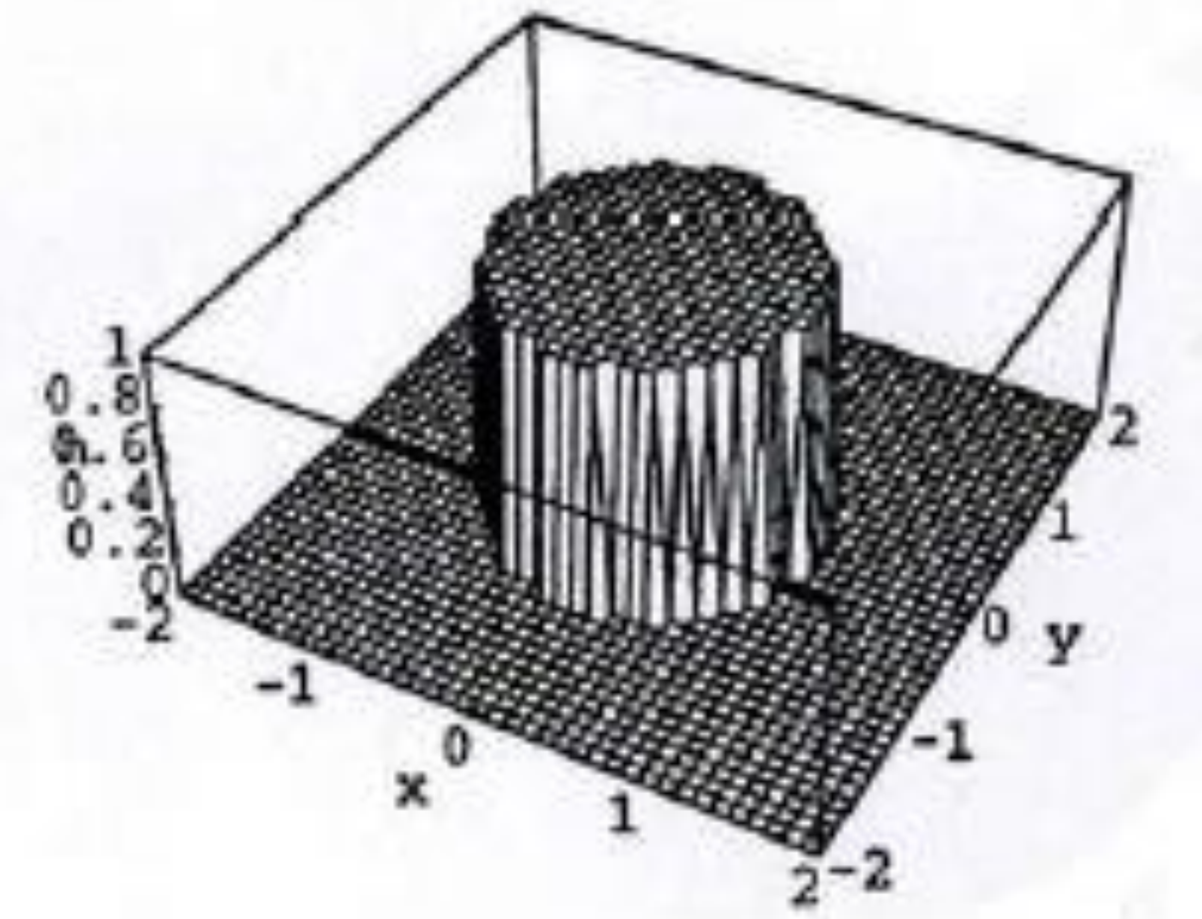
The actual training of the map is to adapt the weight vectors of the winning neuron and those of its surrounding neurons to the input vector using a learning rule. The degree of proximity to the winning neuron plays a major role. The training function consists of the so-called neighborhood or distance function and the learning rate function (see below).

The speed and accuracy of a learning process is always controllable by and proportional to a learning rate written as η or α. The learning rate is reduced after each epoch to reduce the learning progress of the card over the course of the training.
Good value range: 0.01 - 0.9

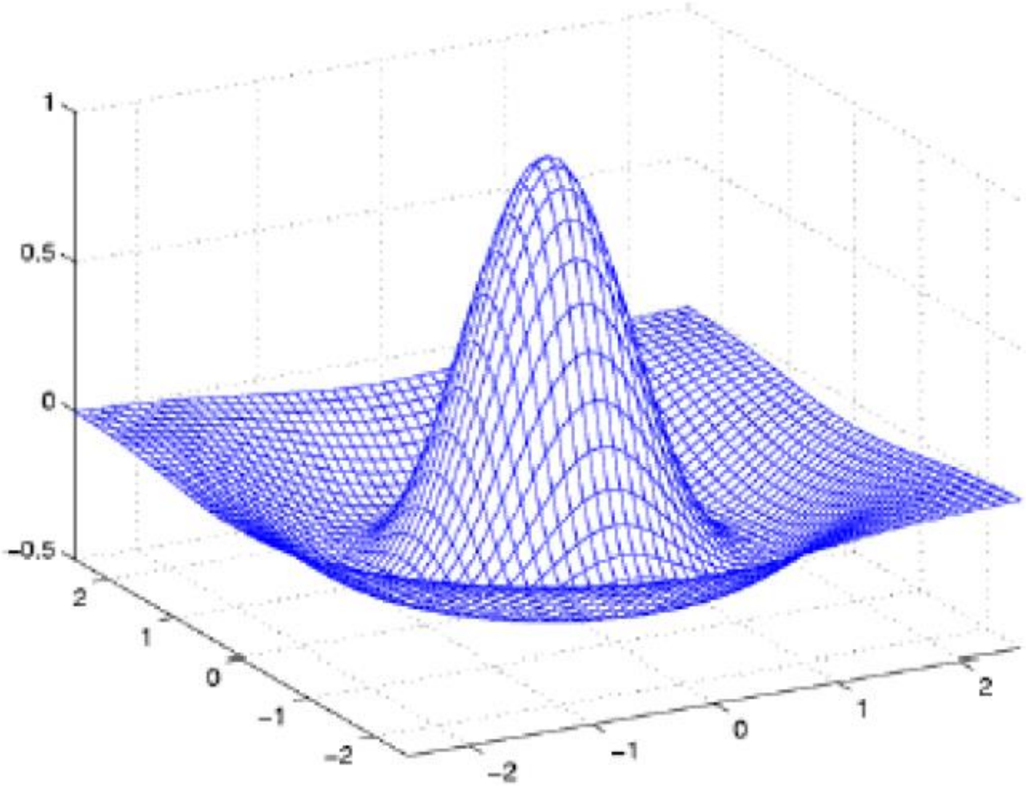
Gaussian Bell Curve



Cylinder function



Mexican-Hat-Function



Divergence possible

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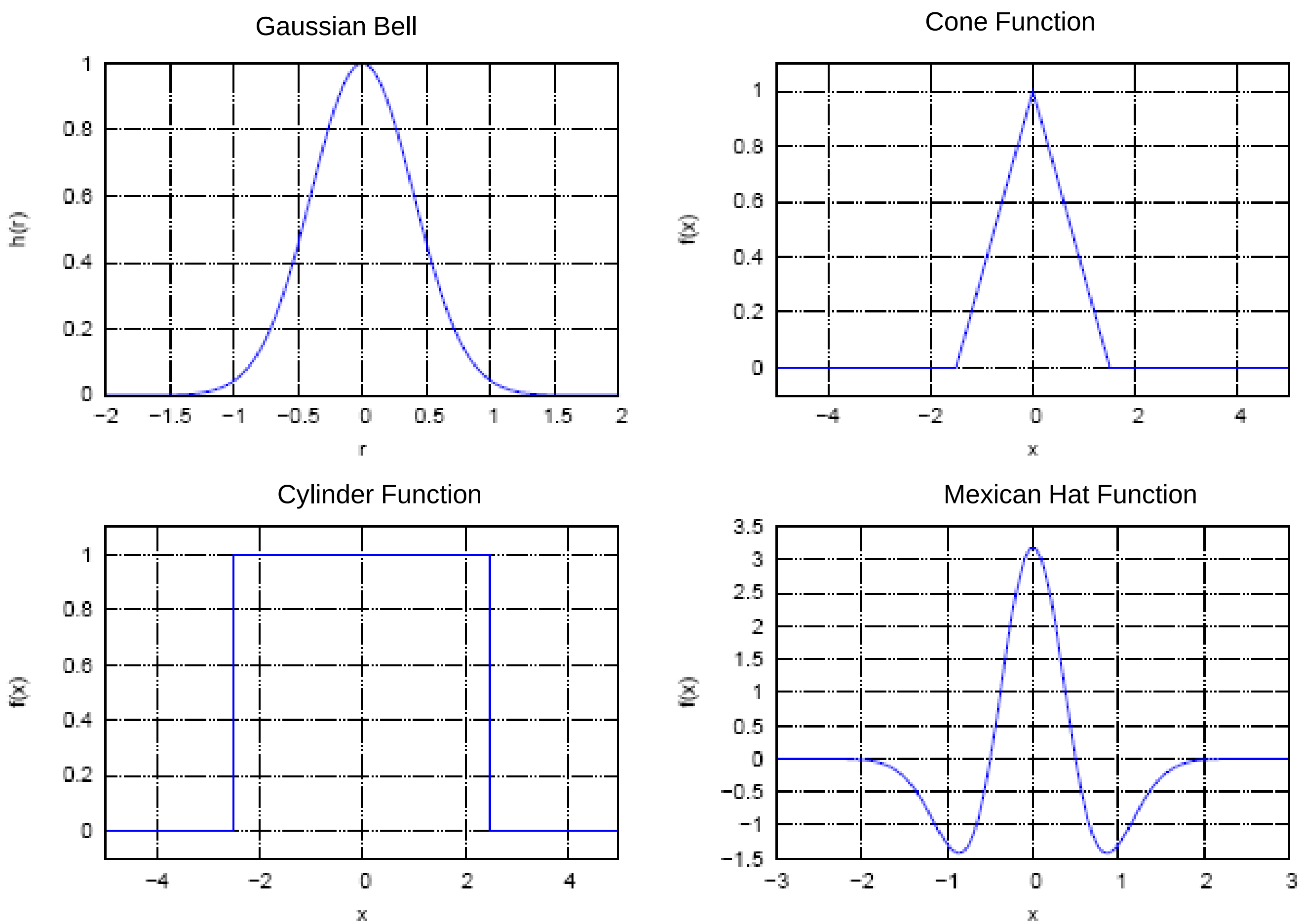


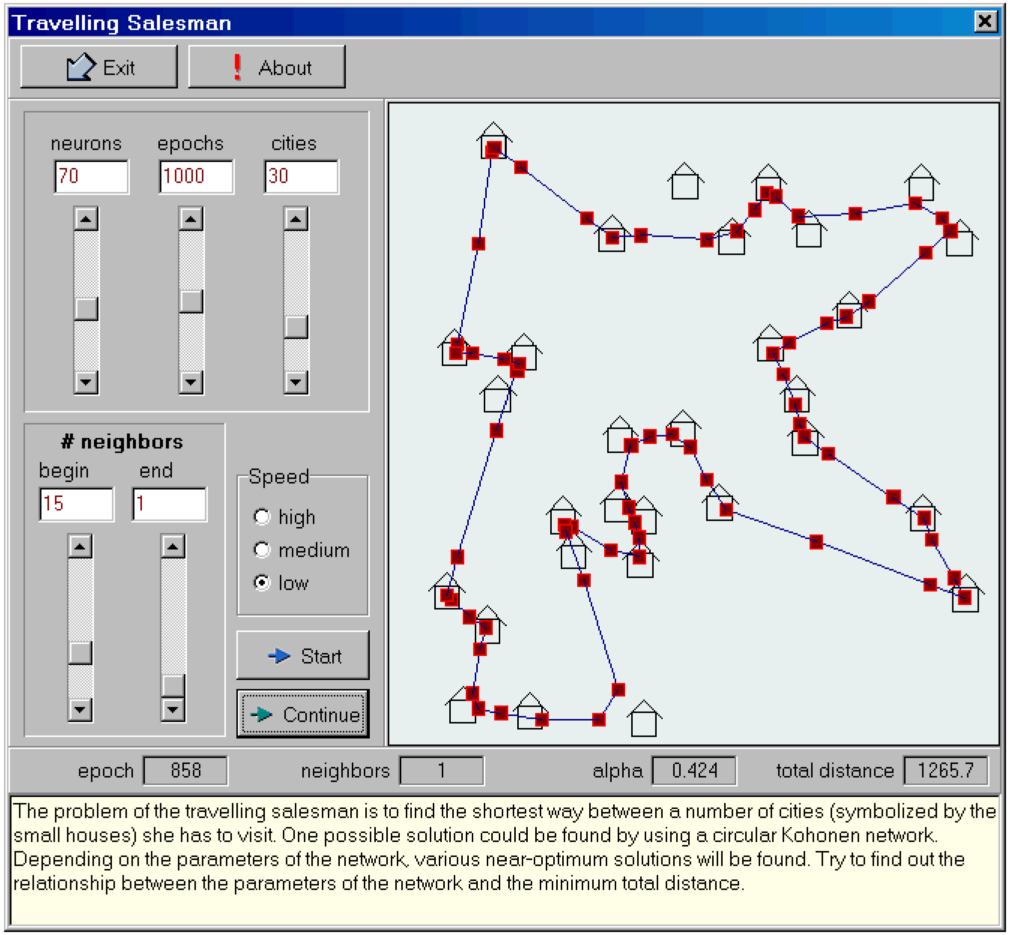
Learning algorithm:

In the case of self-organizing maps, a distinction is made between two different learning methods, pattern and epochal learning. In pattern learning, the weight vectors are adapted according to each input pattern that has been applied to the input layer, whereas in epochal learning, the weight adjustment is only made after passing through a complete epoch, i.e. after entering all existing input patterns. However, the most common is pattern learning.

$$W_j(t+1) = W_j(t) + \eta(t) * h_{cj}(t) * [\, X(t) - W_j(t) \,]$$

Example Travelling Salesman

Ring topology



http://www.vias.org/simulations/simusoft_travsalm.html

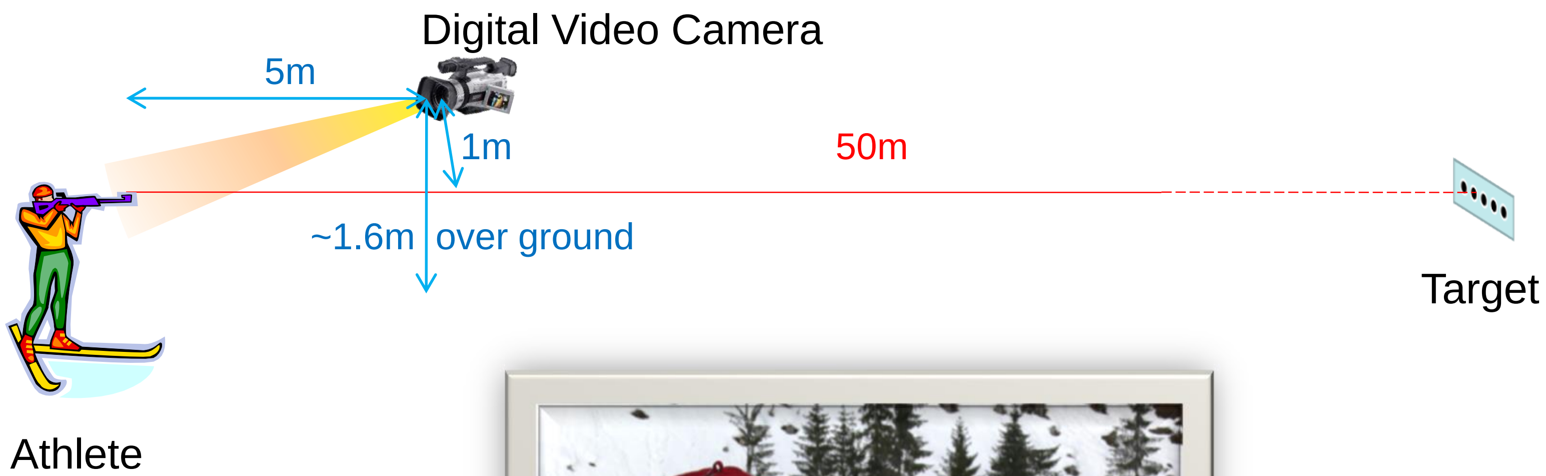
Applications in Sport

Motion Analysis – Clustering/Classification

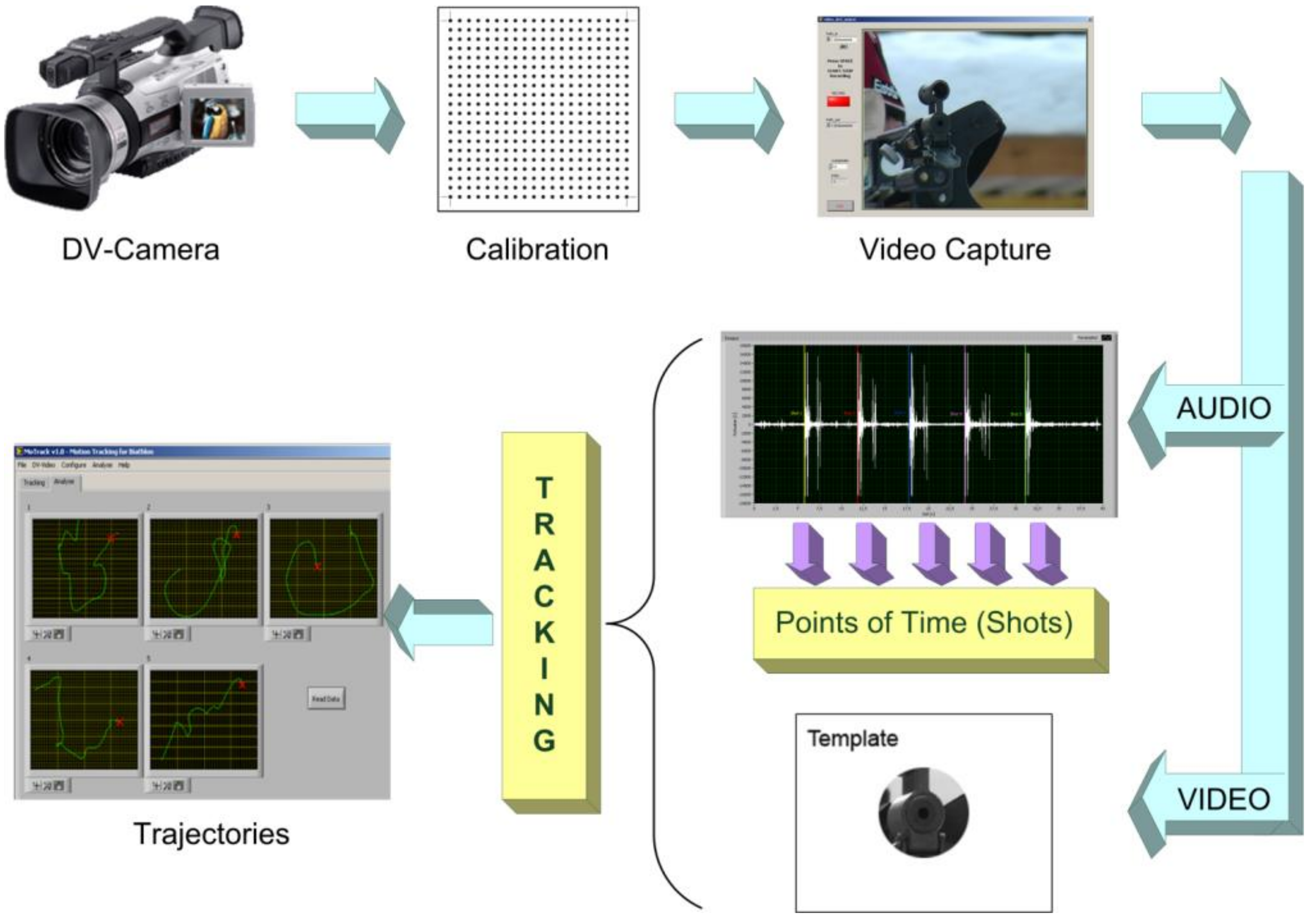
Match and competition analysis

E.g. position sequences in squash

Example – Biathlon shooting



Data acquisition



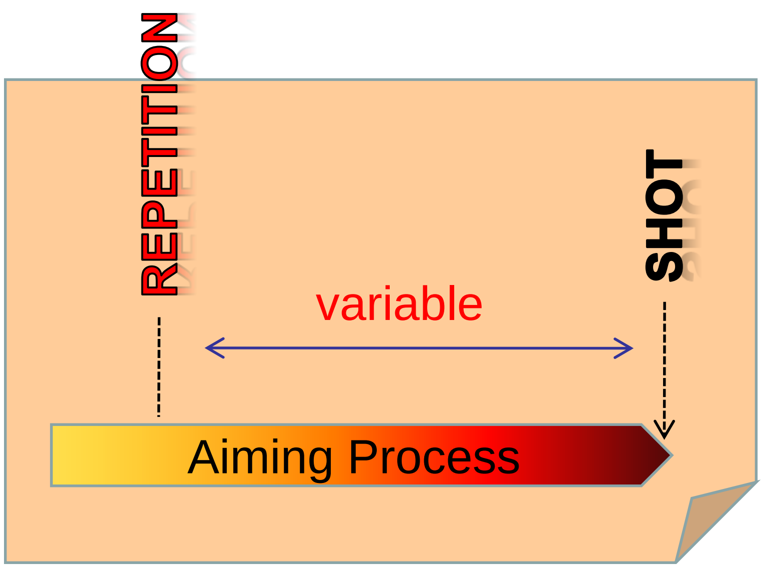
Example of muzzle trajectories (object space coordinates) of a series of five shots

Data Sets

Raw Data
(50Hz)

9 **athletes** each one with:	
8	Sessions
4	Same target
4	Targets next to each other

Calculation of Attribute Vectors for 10 time intervals Δt (variable)



Attribute-Vector (8-dimensions)

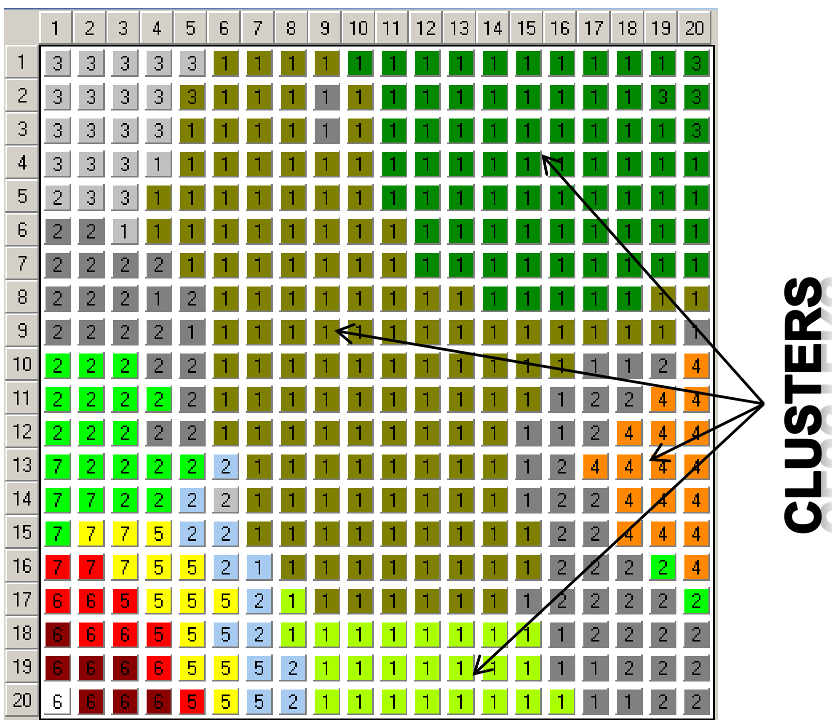
abs. range (x,y) [1]
path length (x,y) [1]
interval difference (x,y) [1]
relative coordinates (x,y)

[1] normalized with regard to Δt

First shot within a series of 5 shots
not further processed

Methods – Neural Network Analysis (*DyCoN*)

Dynamically Controlled Network (self organizing map)



20x20 Neurons

Training

Each neuron represents a unique attribute vector

Clustering (Coloring)

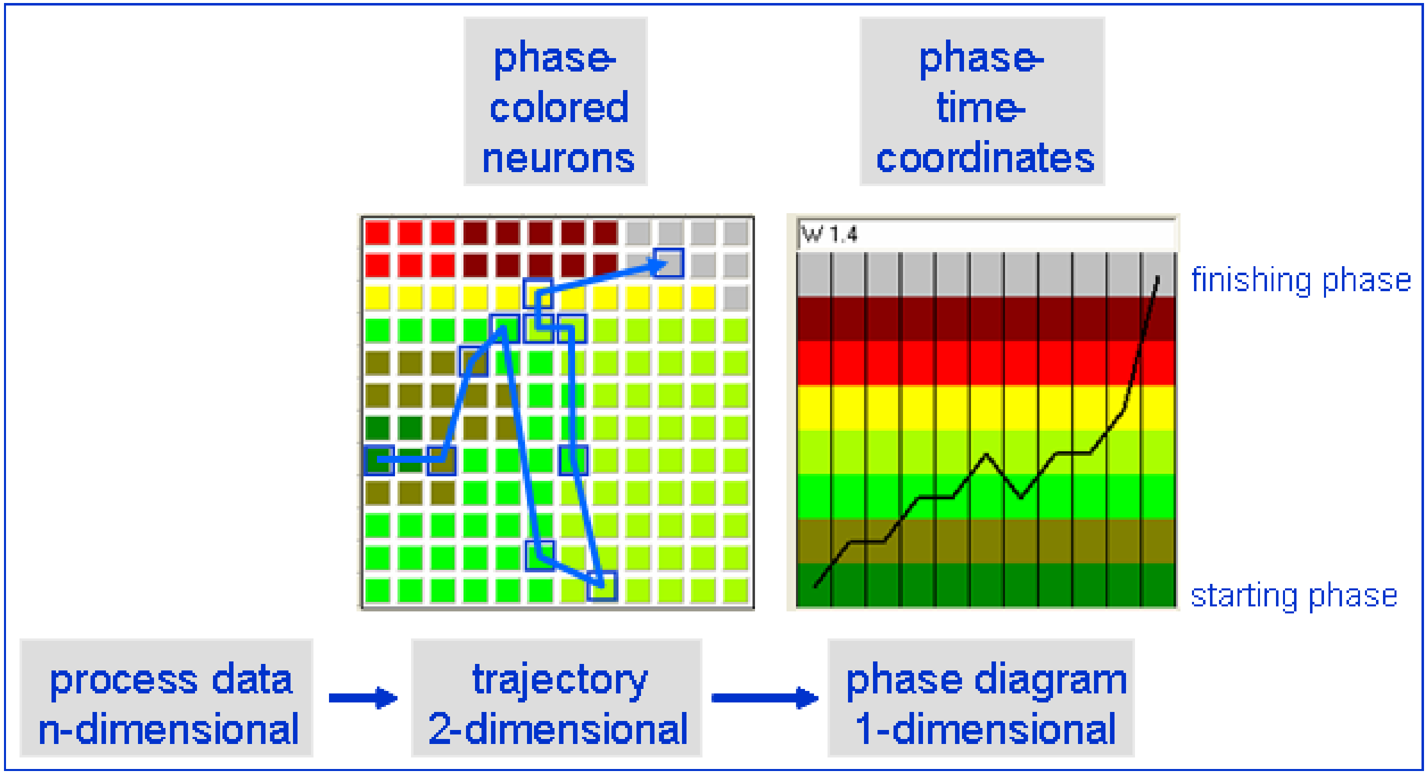
Similar neurons are clustered

Assignment

Each attribute vector is assigned to a cluster

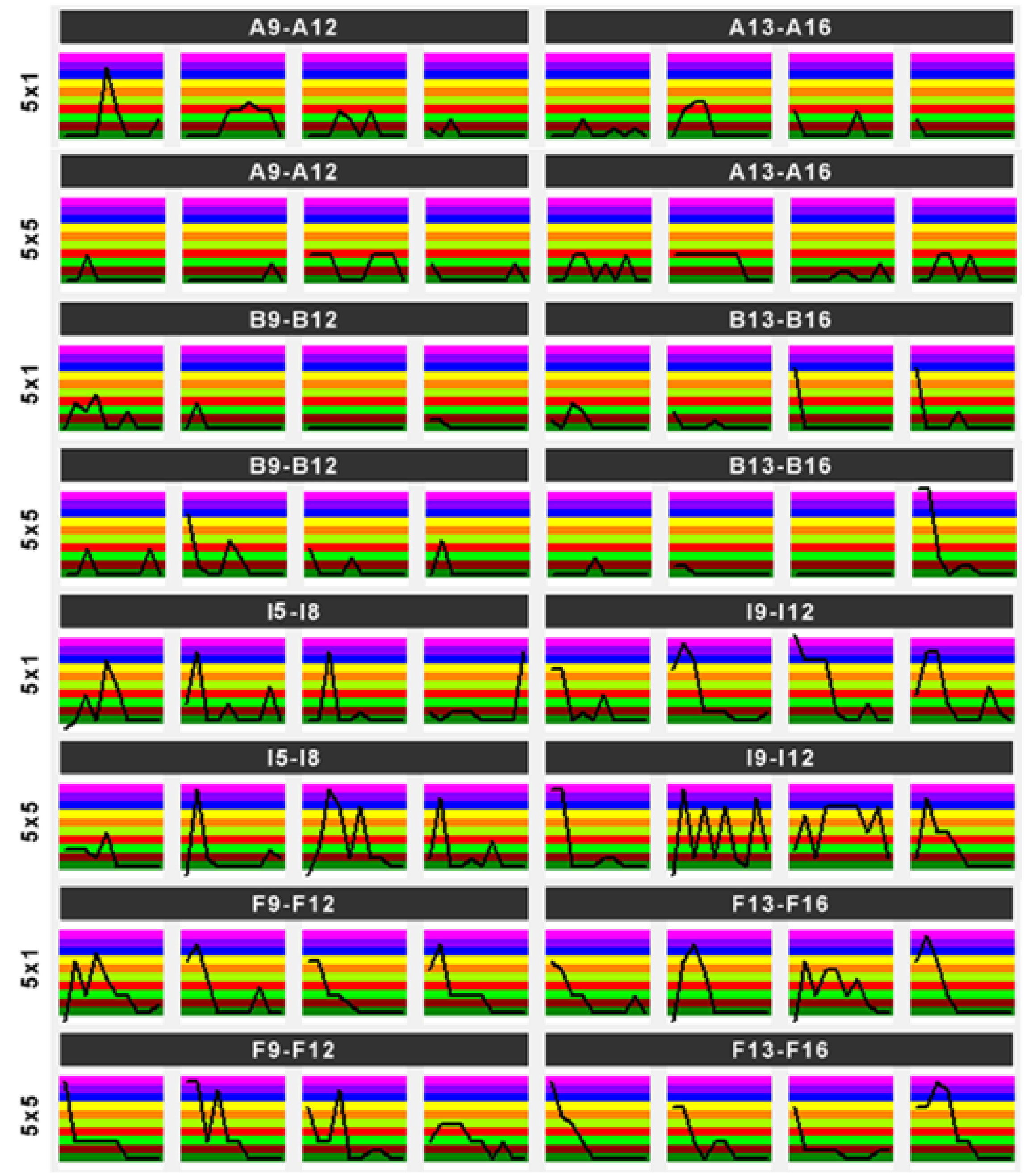
Methods – Neural Networks Analysis *(DyCoN)*

„Phase Diagrams“

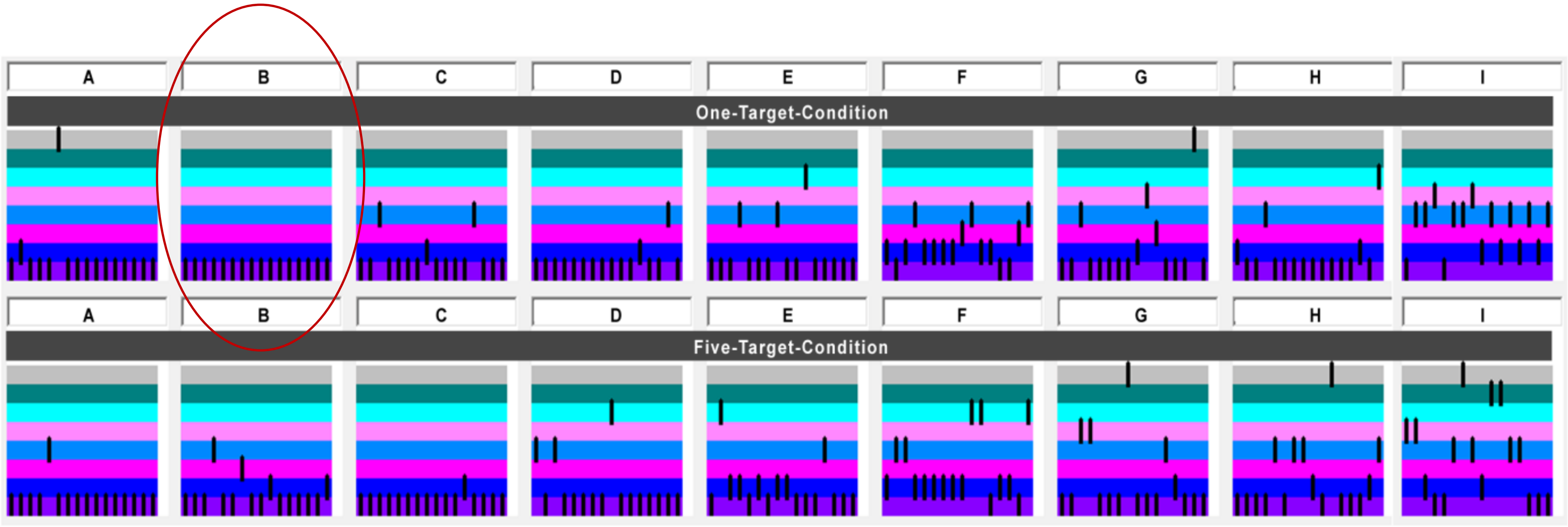


Selected Phase Diagrams

4 series of 4 shots (2-5) for biathletes A and B (national squad) as well as for I and F (A-level). 5×1: one target, 5×5: five targets.



Similarity Analysis



Each bar represents a different type. All shots of B under the one-target-condition, for example, correspond to the same type.

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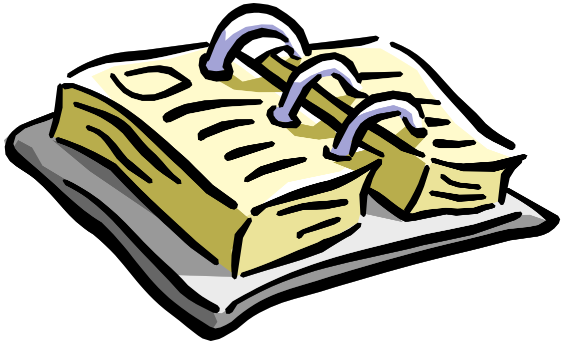

Models in Biomechanics

Physical models

Theoretical models

Anthropometric models

Dynamic Models

    Direct dynamic models

    Invers dynamic models

Data driven models

Deutscher Skiverband, http://rtp-dynamic.ski-online.de/content.php?folder=45

Models in Biomechanics

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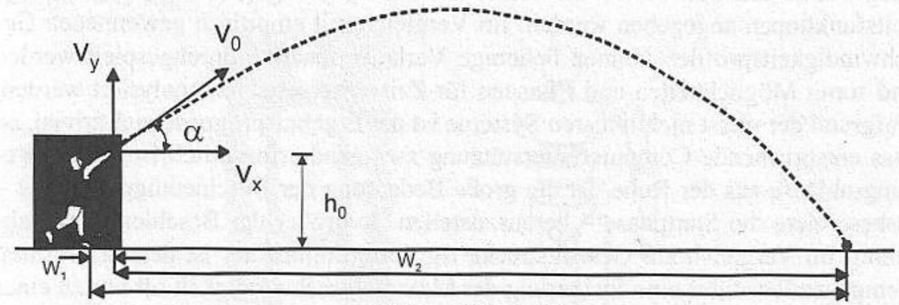


$$W_{ges} = W_1 + W_2$$

$$W_2 = \frac{v_0^2 \cdot \sin 2\alpha}{2g} + v_0 \cdot \cos\alpha \cdot \sqrt{\frac{2}{g} \cdot \left(h_0 + \frac{v_0^2 \cdot \sin^2\alpha}{2g} \right)}$$

Abbildung MN 9 : *Schräger Wurf als mechanisches Modell für die Wettkampfleistung im Kugelstoßen.*

Mathematics & Physics

Models in Biomechanics

Physical models

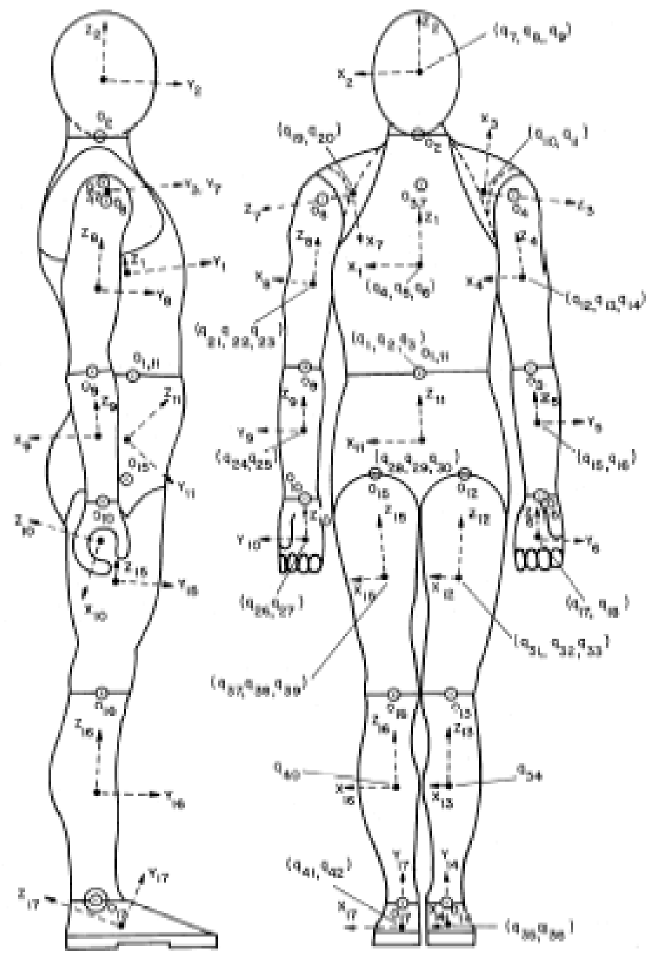
Theoretical models

Anthropometric models

Dynamic Models

- Direct dynamic models
- Invers dynamic models

Data driven models



Models in Biomechanics

Physical models

Theoretical models

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Dynamic Models

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Direct dynamic models

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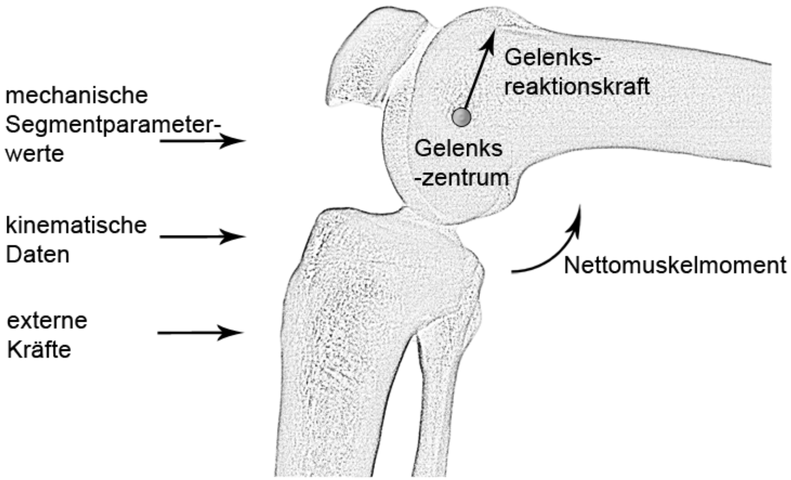


Models in Biomechanics

Physical models

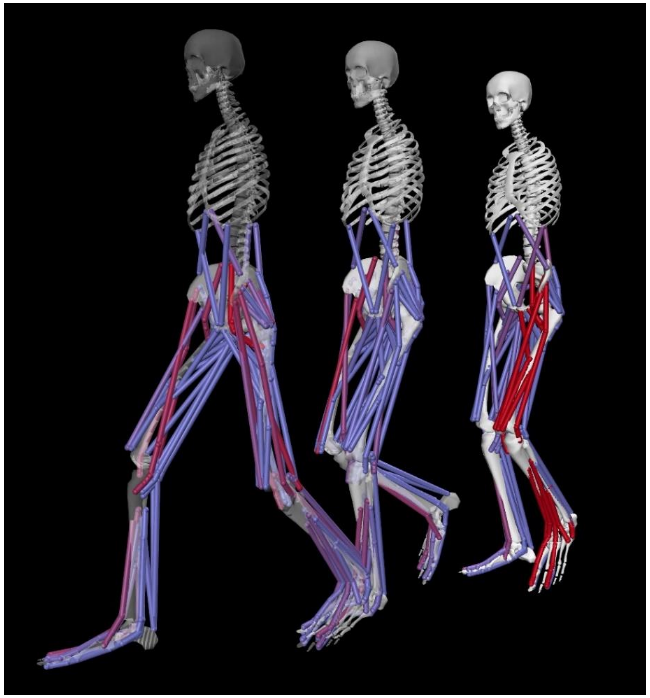
Theoretical models

Anthropometric models

Dynamic Models

- Inverse dynamic models
- Direct dynamic models

Data driven models



$$\ddot{s}=\frac{F}{m}$$

- ➢ Dynamic equations of motion
- ➢ Constraints

→ differential algebraic equation systems

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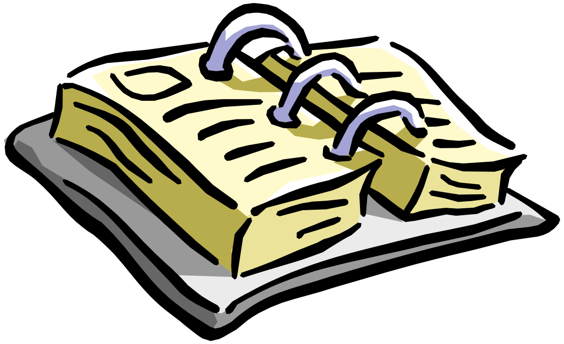
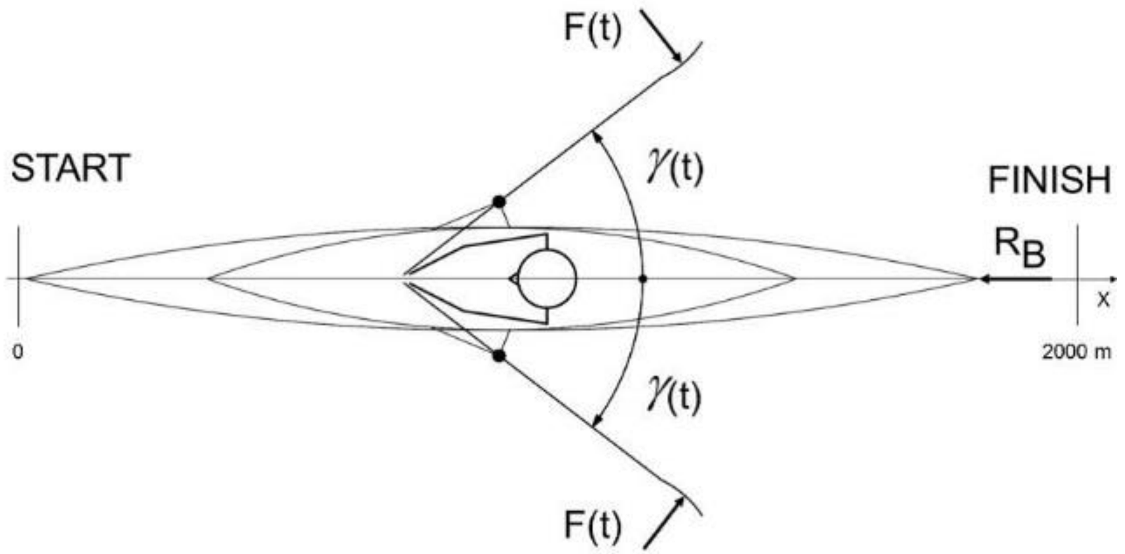


Models in Biomechanics – Example: Rowing



F(t) – scull force,
R_B – boat drag

Wychowański, M., Baca, A, (2018). Rowing. In A. Baca, J. Perl (Eds.), Modelling and Simulation in Sport and Exercise. Routledge, 50-69.

Motion technique

- How movement task is performed
- Analysis by utilizing biomechanical methods

Tactics

- Conscious change of movement technique – changing the paddling method
    - Paddling frequency
    - Times of active phases of paddle‘s blade
    - Times of blade dipping and ascent of paddle
- Phase model of regattas
    - E.g. Start – distance - finish

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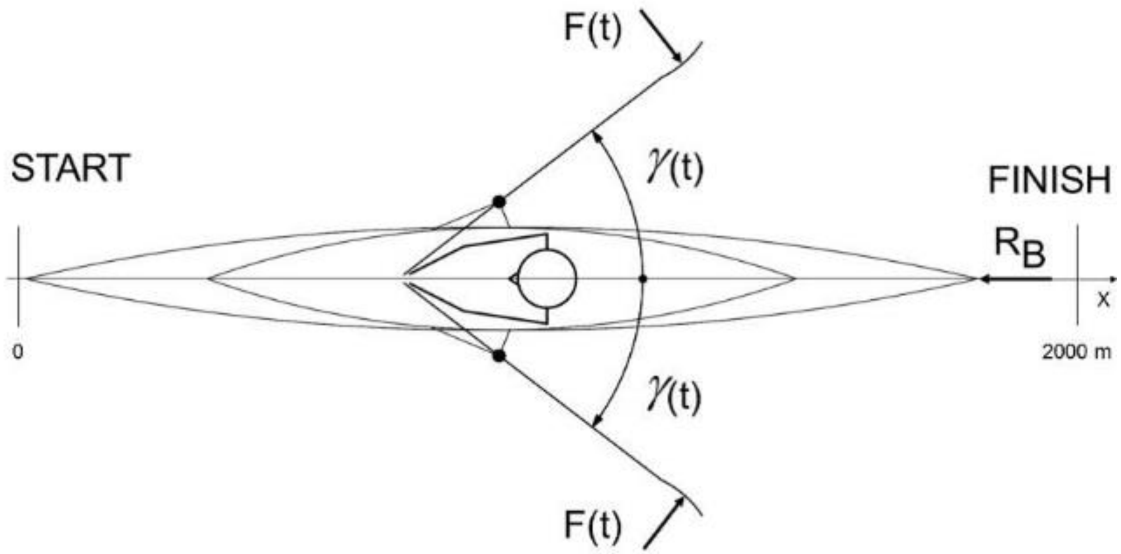
Physical model



F(t) – scull force,
R_B – boat drag

Mathematical model derived from
2nd Newton's dynamics law and
rules describing the hydrodynamic forces

Simple mathematical model

$$m\ddot{x}(t) = T_{OA}(t) - k_B \dot{x}^2(t)$$

$$T_{OA}(t) = 2F(t)\sin\gamma(t)$$

where:

m – mass of the system,

k_B – drag coefficient,

F(t) – force generated by the oar,

T_{OA} – propulsion force.

Oar force – simplified Bollay's model (1939)

$$F(t) = 0.25 c_{DOA} \rho_{H_2O} [1 + \operatorname{sgn} \dot{\gamma}_{OA}(t)] \eta(t) \operatorname{sgn} g(t) \int_{l_{OAMIN}}^{l_{OAMAX}} [l_{OA} \dot{\gamma}_{OA}(t) - \dot{x}(t) \sin \gamma_{OA}(t)]^2 b_{OA} dl_{OA}$$

where:

c_{DOA} – shape coefficient of the oar blade,
F(t) – oar force,
γ(t) – oar angle,
l_{OA} – oar length,
b_{OA} – oar width,
sgn g(t) – braking or propelling function,
η(t) – oar diving control function

Mathematical model of single sculling

PARAMETER	p_i	Value
Total mass	m	100 kg
Drag coeff. boat	k_B	3.8 kg/m
Drag coeff. oar	c_{DOA}	1.13
Water density	ρ_{H2O}	1.0 kg/m³
Dist. oar lock – blade tip	l_{OAmax}	2.04 m
Dist. oar lock – blade root	l_{OAmin}	1.6 m
Blade dipping, ascent	T_{IN}, T_{OUT}	0.1 s
Oar blade width	b_{OA}	0.23 m

Tactics

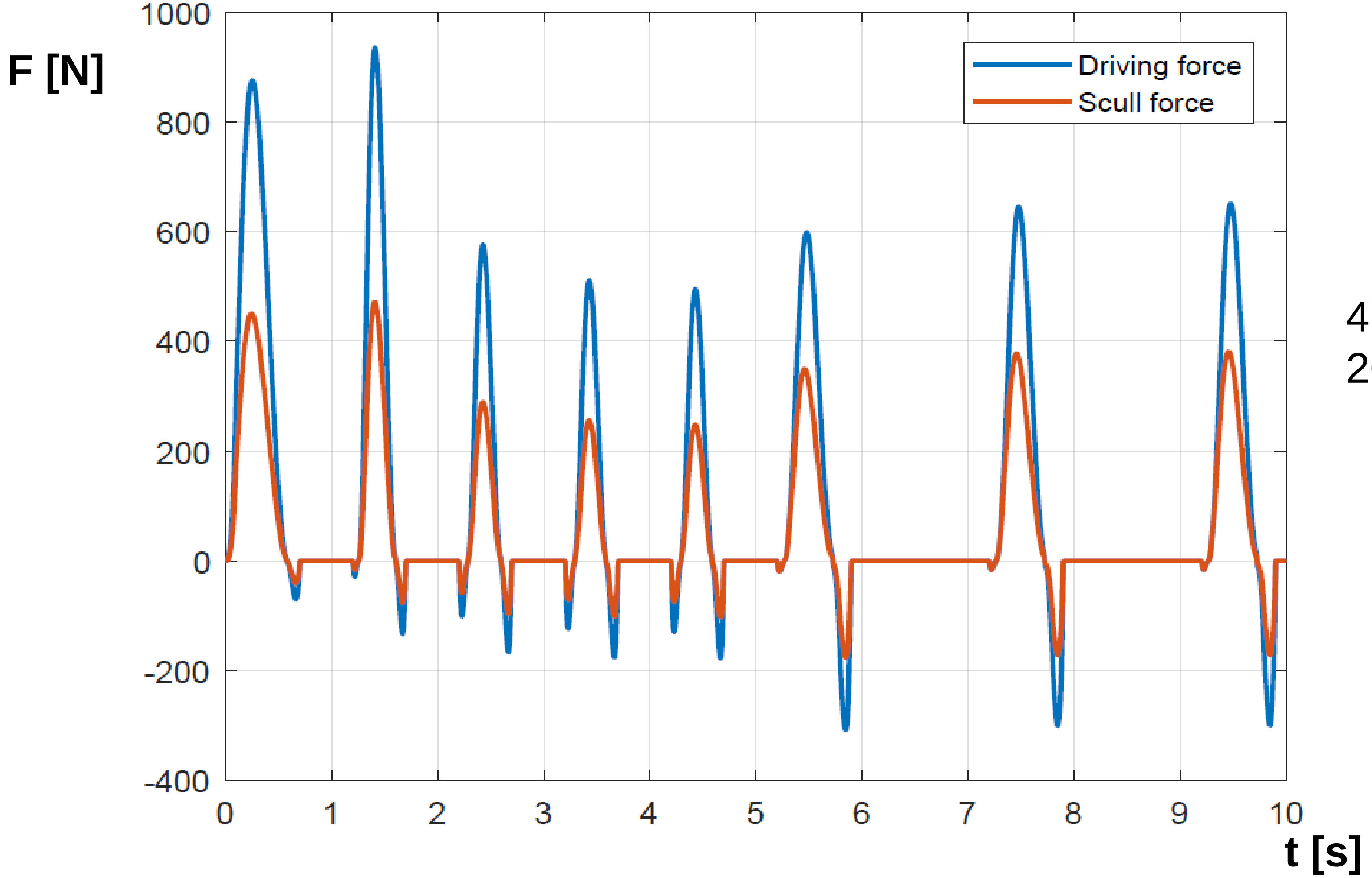
Prestart phase: 1 stroke; $T_A = 0.7$ s; $T_B = 0.5$ s

Start phase: 4 strokes; $T_A = 0.5$ s; $T_B = 0.5$ s

Distance phase: 200 strokes; $T_A = 0.7$ s; $T_B = 1.3$ s

Finish: $T_A = 0.6$ s; $T_B = 1.0$ s

Results - Forces

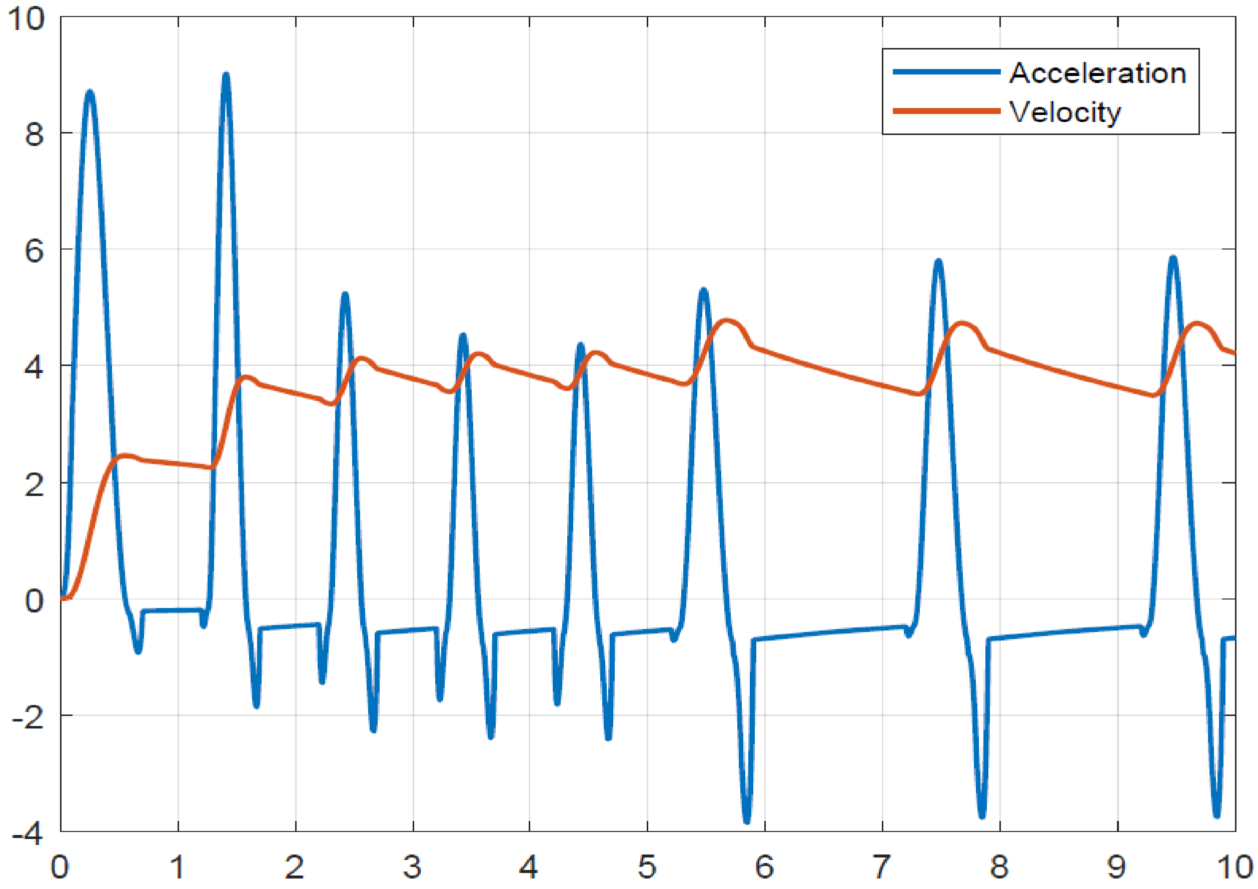


475 s for
2000 m

Results – boat acceleration & velocity

a [m/s²]

v [m/s]



t [s]

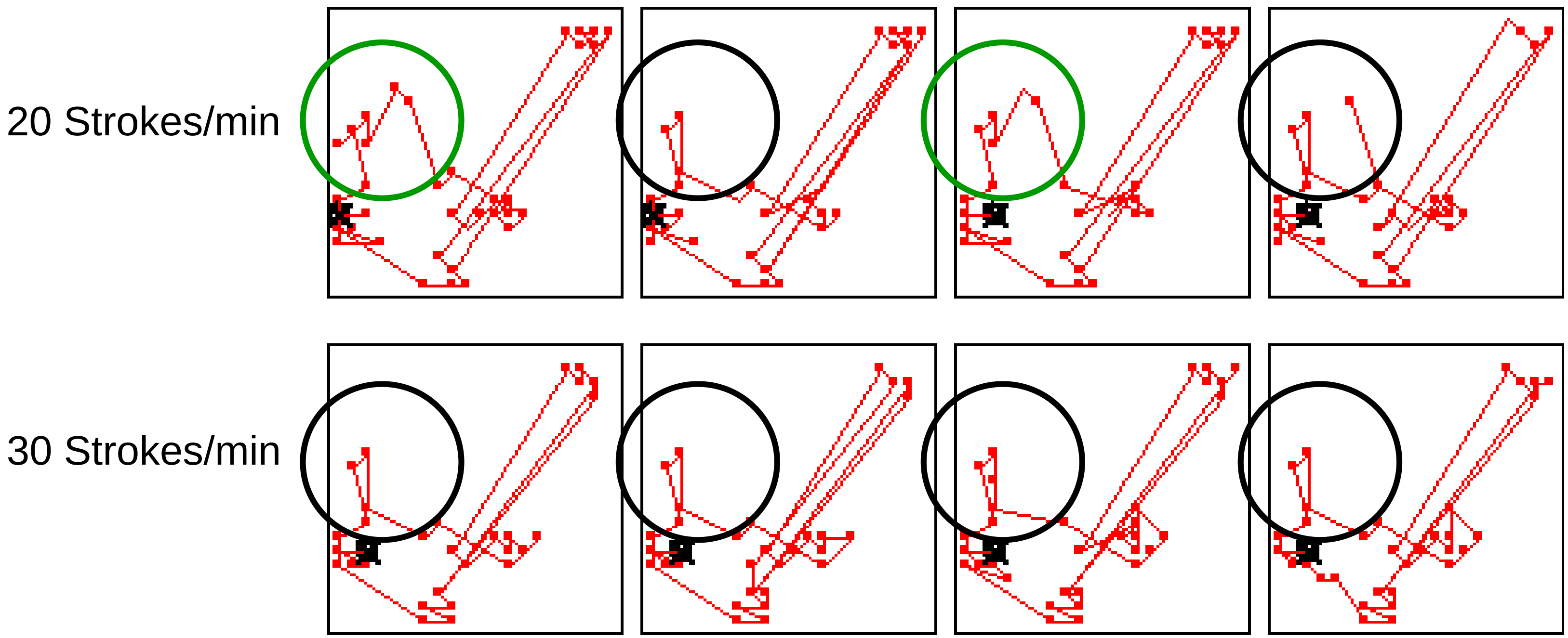
475 s for
2000 m

Data driven models

One main basis of almost any data driven model in human motion related studies is the successful recognition or classification of patterns underlying this motion.

This analysis does not only comprise kinematic parameters, but, moreover, also kinetic and physiological data.

Example: Unsupervised Neural Networks



- 20 strokes/min: two different patterns
- 30 strokes/min: one prevailing pattern

Perl & Baca, 2003.

Team composition

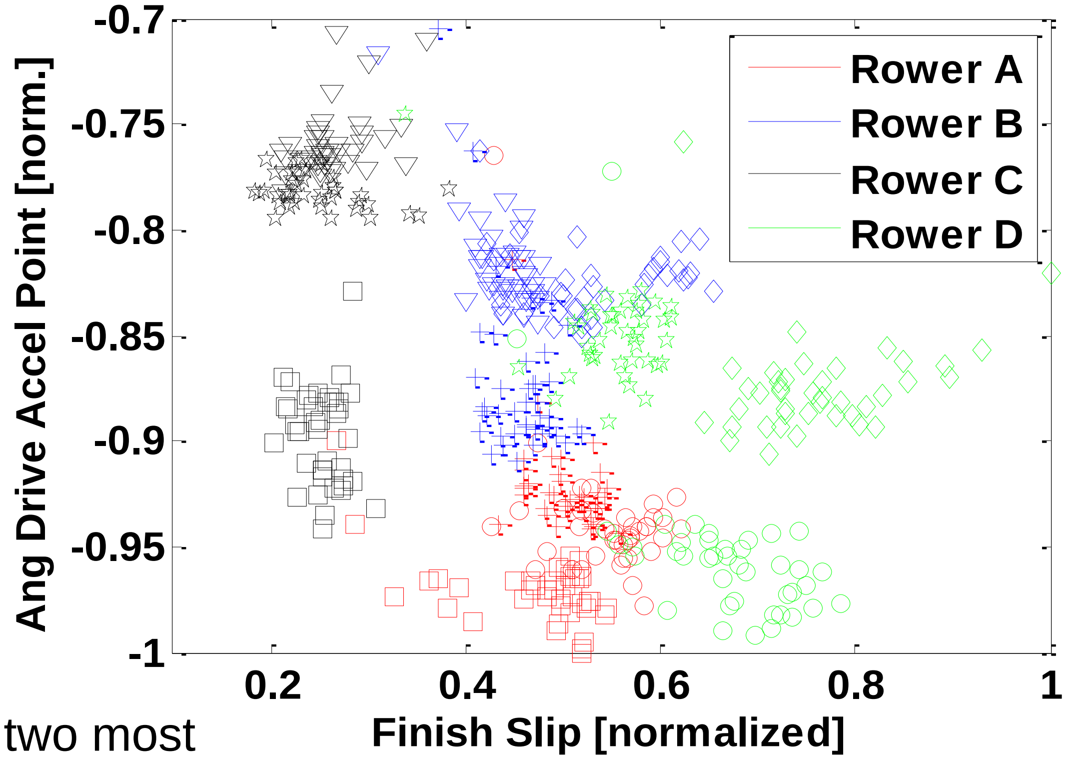
Gravenhorst et al., 2015: Double scull

- ➢ Most relevant features making individual rower‘s technique unique („biomechanical fingerprint“)
- ➢ Selected features allowed them to distinguish technique of four rowers with high accuracy
- ➢ Identification of best-fitting rowers for crews

Gravenhorst, F. et al. (2015). Identifying unique biomechanical fingerprints for rowers and correlations with boat speed. A data-driven approach for rowing performance analysis. *International Journal of Computer Science in Sport*, 14 (1), 4-33.

Data driven model

Oar angle during drive at which boat accererates most



Distribution of two most discriminative features

Angle from end of drive phase until end of stroke

Gravenhorst et al., 2015

Thank you for your attention

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