IDENTIFYING INDIVIDUAL MOVEMENT STYLES IN HIGH PERFORMANCE SPORTS BY MEANS OF SELF-ORGANIZING KOHONEN MAPS

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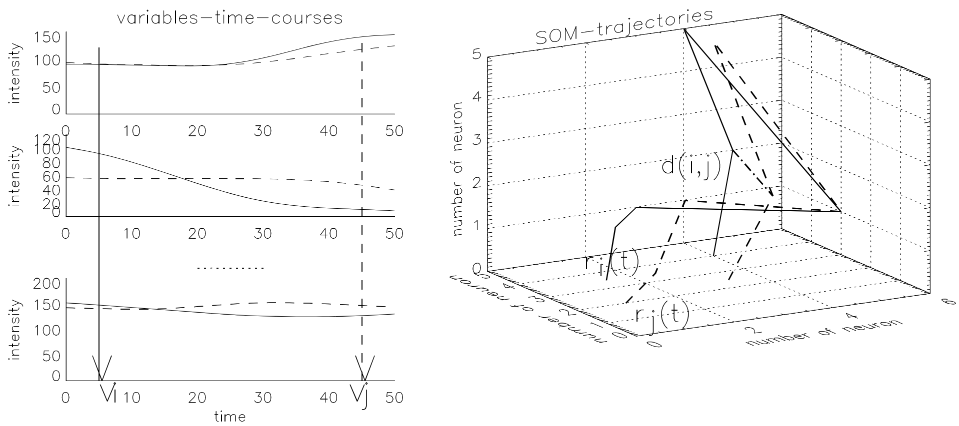
INTRODUCTION: Although single case studies are common in more generally oriented behavioral sciences (Yin 1988), they are still very rare in sports science. The lasting preference for group studies in sports science finds practical support in the opinion that by acquiring a system of reference values one will be provided with an 'optimal kinematic movement pattern' for every athlete at all levels of performance. Problems occur if the reference values are either considered as single independent variables or very often if the reference patterns are based on the performance of a best subject (Schmidt & Young 1991). A practical problem with such an approach arises by transferring the results to the training of an individual athlete in the form of instructions (feedback), particularly when we consider the disadvantageous effects of average feedback (Wulf/Schmidt 1996). Even if we have 'optimal training conditions' with individual feedback, common optimal movements as reference systems seem to be speculative, considering the problem of causality not in a classical linear way but rather from a nonlinear point of view. In nonlinear systems, as most biological systems can be assumed to be, small causes can have large effects and large causes can result in small effects. Whether the assumption of common achievable movement patterns is kinematically justifiable is the subject of this study, which uses a pattern recognition approach.

METHODS: The final throwing phase (app. 200ms) of 8 male and 19 female javelin throwers was filmed three-dimensionally using two high-speed cameras. The male throwers were finalists of the 1987 world championship in Rome, whereas the female group consisted of 10 world class heptathletes and 19 javelin specialists at the national and international level. For 2 female specialists 10 and 6 throwing trials were filmed respectively in different competitions. The throwers' movements were described by means of the time courses of the main joint angles and angular velocities. The joints at the ankle, knee, elbow, and head were assumed as planar, and the hip and shoulder joints were assumed to be three-dimensional. In addition, the orientation angle of the trunk axis and its velocity were considered for a physically complete description. This results in a sequence of 51 (time-normalized) 34-dimensional feature vectors $v_i(t)$ per trial i. The data were further processed by normalizing the individual dimensions to a mean of 0 and variance of 1.

We then trained the self-organizing Kohonen maps (SOM) to project the individual feature vectors to an N=7x6x6 neuron output space. Learning parameters were σ_{init} = 4.0, reduced to σ_{final}=0.2 during training, ε=0.9 $\rightarrow$ 0.01, $2x10^5$ learning steps (Bauer/Schöllhorn 1997).

The sequence of feature vectors $v_i(t)$ which constitute the original movement pattern is transformed by the SOM into a sequence of excited neurons $r_i(t)$. Instead of considering a distance between two feature vectors in the 34-dimensional input space (Fig. 1 left), we can now operate in the only 3-dimensional output space



(Fig. 1 right), with all redundant, noisy extra dimensions suppressed.

Figure 1*: Projection of movement patterns from a 34-dimensional input space (left side) to a 3 dimensional neuron output space (right side).*

$$d(i,j)=\sqrt{\sum_{t=1}^{51}(r_i(t)-r_j(t))^2}$$

This leads to a distance matrix

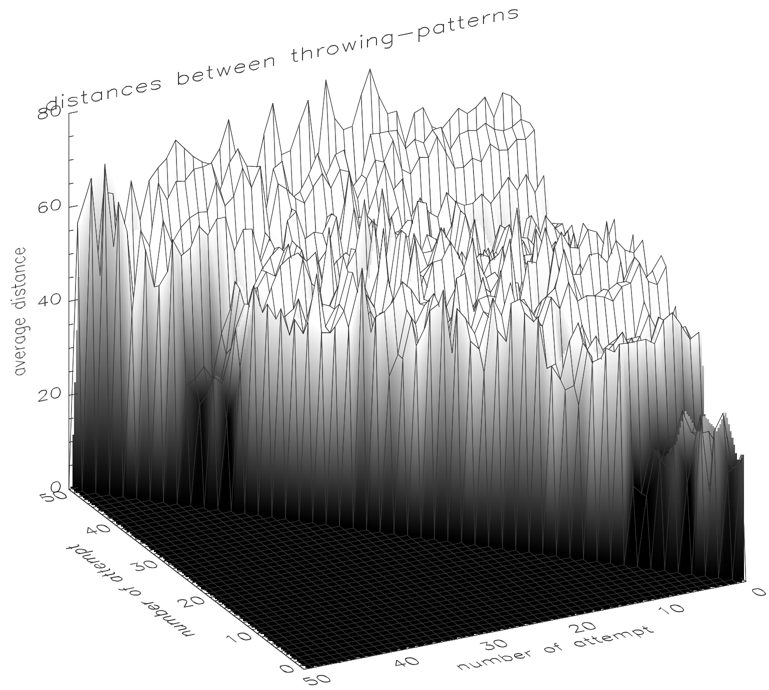
Then we applied a clustering algorithm to the distance matrix d(i,,j). The clustering algorithm (‚Average Linkage‘ included in the SPSS-Package) yields a clustering hierarchy of similarities between trials.

Beside the complete set of variables we separated the movement into variables of the a) lower and upper body, b) left and right side, and c) angles and angular velocities.

RESULTS AND DISCUSSION: The distances between the whole (all variables) throwing movement patterns are shown in Figure 2. Due to the symmetry of the distance data, only one half of the matrix is displayed. The 'distance landscape' provides a first qualitative impression of the data structure. Thereby three characteristics attract attention: The trials with numbers higher than 44 (in the background) show higher distances in comparison to the others, and two groups (trial number 1 to 10 and 38 to 43) of throws display lower distances. Assigning the numbers to the persons reveals the identification of the group of men (higher distances) and the groups of the two female athletes with multiple trials.

A verification of this grouping is given by the cluster analysis (Figure 3). The 10 (suffix ‘p*‘) and 6 trials (suffix ‘t*‘) of the two female specialists are clustered into separate groups. Although both athletes' throws had the same range of thrown distances as well as others (55m to 68m), they were not in the same cluster, but were separated into extra clusters. This separation equals to the identification of individual throwing styles independently of the athletes' performance. The men's (4th letter 'm') cluster could only be identified according to tendency. Only 5 of 8 men's throws were grouped in a separate cluster. These clusters, even in the subgroups of variables, provide a clear indication for highly individual throwing styles not only as a whole, but also in upper and lower body movements, as well as in the left and right side movements, and in the angle and angular velocity, respectively. Clusters of male and female techniques are distinguishable only according to tendency in the complete variable group. No performance dependence could be diagnosed by the cluster analyses of any variable set, neither of men nor of women.

Figure 2*: The distance matrix of the movement patterns (all variables)*

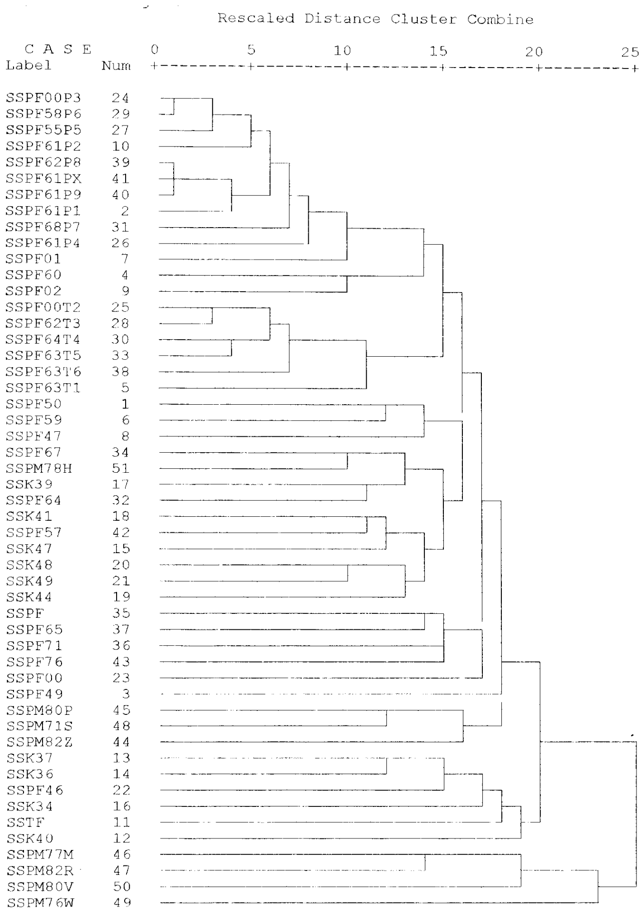


Although the men's main cluster is separated from the others, it has a larger variance within the cluster, which means that men's throwing techniques in world class athletes display greater variety than those of the female group. Whether this is caused by a gender specificity or by the variety of analyzed nations or ideologies can not be answered using these data. The idea of 'nation-specific techniques' or 'different ideal technical concepts' gets further support from a cluster which mainly includes the female finalists of an international championship, except for the two former West German female throwers with their multiple trials. Their clusters can be assigned in the next cluster level to a mainly West German group.

In analogy to recent investigations (Schöllhorn/Bauer 1997), the identification of individual movement styles and the higher variations within the clusters of international athletes provide further evidence against the assumption that a common optimal movement pattern exists for this type of movement (Brisson/Alain 1996).

CONCLUSION: The identification of individual throwing styles by analyzing just a duration of 200ms leads us to rethink the idea of ideal throwing techniques and its pure imitation in learning strategies. One should question whether an athlete learns a coach's conception of a movement technique or whether an athlete acquires a technique which is optimized to his or her boundary conditions. To solve such problems sport science needs more emphasis on single case studies.

Figure 3 Dendrogram of the movement patterns' cluster analysis (all variables).



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