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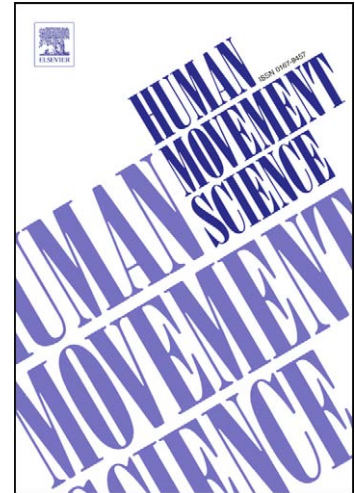
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MOTION PATTERN ANALYSIS OF GAIT IN HORSEBACK RIDING BY MEANS OF PRINCIPAL
COMPONENT ANALYSIS

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Abstract

As a consequence of the three interacting systems of horse, saddle, and rider, horseback riding is a very complex movement that is difficult to characterize by a limited number of biomechanical parameters or characteristic curves. Principal Component Analysis (PCA) is a technique for reducing multidimensional datasets to a minimal (i.e., optimally economic) set of dimensions. To apply PCA to horseback riding data, a “pattern vector” composed of the horizontal velocities of a set of body markers was determined. PCA was used to identify the major dynamic constituents of the three natural gaits of the horse: walk, trot, and canter. It was found that the trot is characterized by only one major component accounting for about 90% of the data’s variance. Based on a study involving 13 horses with the same rider, additional phase plane analyses of the order parameter dynamics revealed a potential influence of the saddle type on movement coordination for the majority of horses.

Keywords

Kinematic analysis, horseback riding, Principal Component Analysis

1. Introduction

Biological organisms that move, fly, jump, swim, and generally interact with their environments produce complex behavioral patterns, whose high dimensionality appears to be almost overwhelming. This is especially the case when two such biological systems move together in a more or a less coordinated manner, as in horseback riding. Besides the interaction between rider and horse, the system is complicated further by the existence of a third interfacing component, the saddle. All these three components of the combined rider-horse system have their own geometry, inertia, elasticity, degrees of freedom, etc. Rider and horse are actively driven by their own intrinsic musculature, while the third component moves passively, coupling the two active parts together. Rider and horse can learn to successfully coordinate their combined motion, which is intuitively perceived by equestrians and referred to as “harmony” (Peham, Licka, Schobesberger, & Meschan, 2001).

A better understanding of the interactions of the rider-horse system is of critical importance, since many orthopaedic symptoms become transparent exclusively in the ridden horse. Unfortunately, at times it can be almost impossible for a veterinarian to decide ad hoc whether a disturbed motion pattern stems from intrinsic processes in the horse or from external influences such as bad saddling or from poor riders riding their horses out of synchrony. Profound knowledge of the influences and effects of rider or saddle upon the consistency of the motion pattern are essential for any diagnosis and ensuing therapy in clinical veterinary routine (Licka, Kapaun, & Peham, 2004).

To mathematically describe the complexity of the motions of this three-body system in an encompassing manner appears impossible. It seems almost a mystery how the central nervous system controls the body’s motor systems with so many degrees of freedom with such an impressive level of fluency and efficacy.

Fortunately, the concepts of two related fields of science, control theory and synergetics, may provide some insight into the strategies that might be applied by Mother Nature to deal with this high dimensionality. One branch of control theory, known as “model order reduction”, is concerned with attempts to formally reduce system’s complexity, while preserving its input-output behavior. Likewise, synergetics, an interdisciplinary theory developed by Haken (1983), is concerned with the study of complex systems that involve the cooperative, nonlinear behavior of numerous subsystems and exhibit ordered structures far from thermodynamic equilibrium. In synergetics, an essential role is played by the concept of order parameter. Complex high dimensional systems tend to reveal an increase in “order” in their dynamical behavior (pattern formation), governed by the amplitudes of only a few “order parameters” characterizing the macroscopic outcome or pattern. This implies an enormous reduction in complexity, since this process of pattern formation is independent of the details of the microscopic interactions of the subsystems.

Evidence exists that biological systems indeed apply such dimension reduction strategies in motor control. For example, d’Avella et al. measured the electromyographic (EMG) activity of 19 muscles in frogs (d’Avella, Portone, Fernandez, & Lacquaniti, 2006). Theoretically, the activity of n muscles would constitute n independent signals. However, EMG signals have been observed to co-vary (Tresch, Saltiel, & Bizzi, 1999). Interestingly, such activation patterns can often be reconstructed to a high degree of precision with as few as 4 or 5 ratios of activity, which have been defined as muscle synergies (d’Avella et al., 2006). In two studies EMG data from 13 muscles could be fitted to 3 time varying synergies (d’Avella & Tresch, 2002; d’Avella, Saltiel, & Bizzi, 2003).

There are many methods for linear (time invariant) model order reduction. An important class of techniques known as projection methods attempts to find the best approximating subspace in terms of data variance upon which to project the system dynamics.

Among those, principal component analysis (PCA) is a popular, theoretically generic method, in part because it is numerically feasible for large dimensional systems (Braido & Zhang, 2004; Sadeghi, Allard, & Duhaime, 1997; Wu & Jue Wang, 2007). PCA is data-driven, implying that its results are inherently a function of the data set to which it is applied.

Mah, Hulliger, and Lee (1994) used PCA for a constructive analysis of gait patterns. By applying PCA to 15 segmental angles, they could successfully reduce the corresponding parameter set to only three components. The shapes of the phase portraits of these variables allowed gait discrimination under different neurophysiological conditions (Mah et al., 1994).

Many papers have singled out important kinematical parameters to characterize the gait of horses. Holistic approaches, however, remain scarce (Peham et al., 2001; Peham, Licka, Schobesberger, & Meschan, 2004). The aim of this study was therefore to show that the horse-rider system can be mathematically described in a comprehensive way, that is, by a minimal number of (order) parameters. To this end, PCA was used. By means of PCA, it is possible to determine whether the three gait patterns of the horse – walk, trot, and canter – are characterized by one or a few “order parameters”. If so, the next step will be to identify the parameter(s) of the system and represent its (or their) dynamics in a phase plane plot. On the basis of the qualitative description of the geometrical shape of the phase plane plot, possible differences in horseback riding due to using different saddles (e.g., Side Saddle vs. English Saddle) may be detected. This could give a hint of the influence of the saddle type on the dynamics of the horse-rider system.

2.0 Method

Data collection

Thirteen sound horses were ridden with Side Saddle and English Saddle in walk, trot, and canter in an indoor riding hall by the same rider. The rider provoked the horses by increasing the velocity of the different gaits. Motion was recorded with the Expert Vision System of the Motion Analysis Corporation (Santa Rosa, California) consisting of six video cameras (sample frequency 120 Hz). Fourteen marker positions on the left-hand side of the horse were used for kinematical analysis: eleven markers on the horse itself and three markers on the rider. Fig. 1a shows a typical configuration of the marker set. The explanation of the markers can be found in Table 1. In addition, Fig. 1 illustrates the difference between riding with a Side Saddle (SS, Fig. 1b) and with an English Saddle (ES, Fig. 1a). The time-series of each marker were smoothed using a lowpass Butterworth filter with a cut-off frequency of 15 Hz (for horse extremities) and 5 Hz (for horse trunk and rider). Assuming that the horizontal velocity is important for the forward motion of the horse, it was used to delimit the strikes and to apply the Principal Component Analysis. As in other studies of movement patterns (e.g., Haas, 1995; Haken, 1996), body angles were used as input for the Karhunen-Loève-method or PCA. Importantly, in a study on human walking and running, Witte (2002) found no significant differences between results obtained by using marker velocities or body angles. Considering the minimal absolute values of trunk angles and their variations during a movement cycle, it can be assumed that their use in PCA does not affect the values obtained with different gaits and saddles. Acceleration parameters were not chosen in order to keep the error as low as possible. The beginning and the end of each motion cycle was determined by the horizontal velocity-time-course of the right fore hoof. Horizontal velocity time-courses of other markers would be possible too, but use of the fore hoof marker provided relatively definite time points (cf. Fig. 2). Table 2 shows the subsequent number of motion cycles for each horse.

Principal Component Analysis (PCA)

PCA is a technique for simplifying a dataset by reducing multidimensional datasets to a lower number of dimensions than the original representation. By means of PCA it is examined how the variance of a data vector is composed of the variances of the single components. PCA linearly transforms the data to a new coordinate system in such a way that the greatest variance by any projection of the data comes to lie on the first coordinate (called the first mode), the second greatest variance on the second coordinate (called the second mode), and so on. For the definition of the data vector or “pattern” vector it is assumed that the horizontal velocity is important for locomotion. For this reason the pattern vector is generated of the horizontal velocity of each marker.

So the instantaneous horizontal velocities of the 14 markers at each time step, denoted as $v_j, j = 1, \dots, 14$, were combined to form the time-dependent pattern vector $\vec{v}(t)$:

$$\vec{v}(t) = (\vec{v}_1(t), \vec{v}_2(t), \dots, \vec{v}_{14}(t)) . \quad (1)$$

PCA then portrays the variance of $\vec{v}(t)$. For this decomposition this pattern vector $\vec{v}(t)$ is projected onto an arbitrary, time independent vector $\alpha = (\alpha_1, \alpha_2, \dots, \alpha_N)$ of unit length.

This time dependent projection can be written as

$$\vec{v}(t) = \alpha_1 v_1(t) \vec{e}_1 + \dots + \alpha_n v_n(t) \vec{e}_{14} , \quad (2)$$

where $\vec{e}_1, \dots, \vec{e}_{14}$ denote the unit vectors. The components of the vector α are estimated in such a manner that the variance of the projection reaches a maximum:

$$\sum_t |v(t) - \vec{v}|^2 = \text{Max}. \quad (3)$$

$$\text{With } \bar{v}_j = \frac{1}{T} \int_0^T v_j(t) dt, \quad j = 1, \dots, 14 \quad (4)$$

That means in other words that the variance of the difference between the pattern vector and the projection is a minimum.

The pattern vector is then decomposed into two time dependent series, one time series lying in the direction of the projection of the greatest variance, and the other time series lying orthogonal to it. This procedure is repeated with this second orthogonal time series. This new direction of maximum variance logically is orthogonal to that of that first maximum variance. Consequently iterating the entire algorithm yields further directions of relative maximum variance and leads to a series of monotonically decreasing values for the remaining variance of the pattern vector $\vec{v}(t)$ at the intersection of the orthogonal complements. The directions of maximal variance paired orthogonal to each other are called modes. Each mode contains a part of the total variance, which is defined by the eigenvalue. For the purpose of clarity the sum of the eigenvalues is normalized to 100%. So, each eigenvalue indicates the percentage in the total variance of the related mode. In general, modes with an eigenvalue of less than 5% are disregarded.

Moreover, PCA is a procedure to estimate the number of parameters that are necessary to describe the system. If the second and the third mode are represented by small eigenvalues, which may be neglected, it is assumed that the gait pattern can be characterized by only one order or system's parameter. In a further step, this order parameter ξ is calculated. In our specific case we define this parameter as a projection of the pattern vector to the first mode and obtain a complex number. The dynamical behavior of ξ was displayed in a phase plane plot of ξ . Because of the complex number the real part and the imaginary part have to be analyzed separately. Fig. 3 shows a typical phase plane plot of the real and the imaginary part of the order parameter ξ . As will become apparent in the Results section, the order parameter could be calculated for the trot.

The closed curves are typical for cyclic movements. In comparison to the plot for the real part, the phase plot in relation to the imaginary part of ξ shows more individual anomalies. The basic geometrical figure is similar in many cases to an “overturned eight” (∞). But we can expect that the geometrical form varies as a function of the gait pattern and the individual horses. For this reason we look for common and different properties of the plots. Because the plots can be very irregular, objective mathematical algorithms cannot be applied. Therefore we used a subjective analysis of impression in the following way. The shape of the graphs in the phase portraits were categorized by their visual appearance (for instance cusps, convexities, spikes, dents, and loops) according to Table 3. Fig. 3 shows the results of the categorization of the phase portraits for the real parts (categories A-E), Fig. 4 for the imaginary parts (F-K), respectively. Since property “F” (round and symmetrical form without anomalies) was nonexistent in our diagrams, it was neglected in the subsequent analyses.

Following this subjective analysis, numerical analyses of these phase portraits (comparison of Side Saddle and English Saddle in different gaits) were performed.

In a first step, matrices of similarity were calculated. Table 4 shows an example for the horse Stu. The table can be interpreted in the following manner. Six categories were found for both saddles, three categories occurred only for the Side Saddle, and one category appeared neither for the Side Saddle nor for the English Saddle. In conclusion, no category was found only for the English Saddle.

By means of a fourfold table (Table 5), two similarity measures were computed (Bortz, 1999):

a) Similarity coefficient S (Jaccard, 1908; Rogers & Tanimoto, 1960):

$$S = \frac{a}{a + b + c} \quad (5)$$

b) the squared multiple correlation coefficient SMC, which permits the absence of a specific property (Sokal & Michener, 1958)

$$SMC = \frac{a + d}{a + b + c + d} \quad (6)$$

For our example (horse Stu) the following results were obtained: $S = .67$ and $SMC = .70$.

2. Results

By means of PCA the eigenvalues of the single modes of all motion cycles were calculated. Table 6 shows the mean values of the eigenvalues for each horse according to saddle type. Only the first two modes are shown, because the eigenvalues of the third and higher modes all fell below 5%. In the trot, the first mode dominated in all 13 horses, while all other modes remained small. It may therefore be assumed that the trot can be described sufficiently accurately with only a single order parameter.

As regards the eigenvalues of the first mode, no significant differences between the Side Saddle (SS) and English Saddle (ES) were found for the walk and canter using Wilcoxon tests. For the trot, however, a potential influence of saddle type on the eigenvalue of the first mode became apparent. For the English Saddle, the first mode was more pronounced.

In the next step, the system's parameter ξ was determined only for the trot and corresponding phase portraits were constructed. Fig. 4 shows the results for horse Xen. To quantify the geometrical shapes the properties A-E were marked. Figs. 5 and 6 represent the number of the phase portraits (real part) that were attributed to the properties A-E for the Side Saddle (SS) and English Saddle (ES), respectively. The similarity analysis produced the results depicted in Fig. 7.

3. Discussion and conclusion

The purpose of the present study was to describe the movement of the horse-rider system in a compact manner using concepts and methods from theories of low-dimensional motor control. Obtaining low-dimensional approximations of high-dimensional dynamical systems is known as model reduction, or model order reduction.

Application of PCA revealed that the dynamics of the horse-rider system at walk and at canter can indeed be described by not more than two order parameters, and at trot the system can even be described by only a single order parameter. This agrees accordingly with other studies from other species that have also reported a successful reduction in dimensionality in their motion data sets. For example, in their studies of the learning process of driving a pedalo, Haas (1995) and Haken (1996) assumed that cyclic, learned and automatic movements are governed by only one order parameter, and they could confirm this by using the PCA according to Haken-Friedrich-Uhl order parameter analysis (Haken, 1996). Looking for regularities in muscle activity, d'Avella et al. (2006) found that the EMG recorded from 19 individual muscles in the hind limb of bullfrogs could be reconstructed by no more than 4 to 5 ratios of muscle activity, such ratios having also been defined as 'muscle synergies' (d'Avella et al., 2006). In another study, Tresch et al. could successfully reduce the EMG recordings from 9 muscles excited by cutaneous stimulation of spinalized frogs to 4 synergies (Tresch et al., 1999). If the concept of synergies is extended from fixed ratios to time varying muscle activation patterns, EMG data from 13 muscles could be reduced to only three time varying synergies (d'Avella et al., 2003). Such synergies could very well be utilized by the central nervous system to simplify motor control and form the very bases of muscle activation in the motion of animals. "Modules" are functional units in the spinal cord circuitry that generate specific motor commands by imposing a specific pattern of muscle activation. D'Avella and Bizzi reported when recording

from such spinal modules that 94% of the total variation of the data is explained by the first five principal components, which could potentially indicate that the dimensionality of spinal and perhaps supraspinal motor control is low (d'Avella & Bizzi, 1998). This view has been shared by Sanger (2000), who hypothesized that the low-dimensionality and convergence are attributable to combined properties of an internal controller and the musculoskeletal system. For instance, in a postural hand grasping study, Santello, Flanders, and Soechting (1998) found that two principal components accounted for >80% of the variance in the data and that the variance contributed by other principal components was small. This result was interpreted by Santello et al. (1998) to imply that there are two fundamental synergies governing the manner in which the hand is shaped to grasp objects.

A potential explanation why the dynamics of horse and rider can be reduced to just a single order parameter could lie in the fact that the highly symmetrical trot, where all four legs act as inverted pendulums entirely in synchrony or anti-synchrony to each other, perhaps utilizes just one major spinal pattern generator whose oscillations produce the entire muscle activation synergies needed at trot. D'Avella and Bizzi hypothesized that supraspinal motor control might act through a linear combination of low dimensional spinal modules with encoded sets of force fields (d'Avella & Bizzi, 1998). Perhaps a linear combination of the activity of two spinal modules is mainly responsible for generating walk and canter, both having a more elaborate quadrupedal phase dependence than trot and therefore perhaps also need a higher degree of activation complexity that is reflected in the higher dimensionality (~ the additional high second mode).

A more macroscopic speculative explanation might be that at trot horse and rider move in a more coordinated manner - a fact however that would appear rather counterintuitive light of the often voiced equestrian opinion that at trot it is more difficult to maintain a proper and stable sit than at walk or canter.

While the magnitude of the modes (~the eigenvalues of the covariance matrix) alone potentially lead to interesting conjectures regarding underlying motor control, they have not been discriminative enough to distinguish between saddle types. However, the phase plane analysis of the complex order parameter added further discriminative power and eventually succeeded in discerning the proper saddle type. The phase portraits of the respective first order parameter displayed similar trajectories to those found by Haas (1995), who studied the learning process of riding a pedalo and Witte (2002), who investigated walking and running in humans.

None of our phase portraits exhibited property F, which means that the ideal round and symmetrical form does not appear. The phase portraits of our study revealed a potential influence of saddle type on movement coordination for the majority of horses. Interestingly, both saddle types showed specific properties that were differently pronounced. There were horses with clear differences in movement coordination at trot depending on saddle type, with horse Xen as a typical example. It had the smallest similarity coefficients ($S = 0.22$ and $SMC = 0.30$). Fig. 6 shows the phase portraits for horse Xen. On the other hand, there were horses, whose phase portraits of SS and ES were very similar. For instance, the similarity coefficients of the horse Ove were $S = .50$ and $SMC = .80$. An example of both saddles is given in the phase portraits of Figs. 4 and 5. So, the phase portraits based on the real parts of the order parameter for ES were characterized by more round forms and characteristic convexities. They had fewer spikes than the corresponding SS plots. The phase portraits of the imaginary parts of the order parameter for ES showed also fewer dents. This could be interpreted perhaps as a phase plane reflection of the instability that Winkelmayr, Peham, Frühwirth, Licka, and Scheidl (2006) found when meas-

uring the excursion of the center of pressure under the Side Saddle and the English Saddle.

In sum, we have shown that even a very complex, high-dimensional system such as a horse and a rider, each consisting of a multitude of actively or passively moving musculoskeletal components can reveal a surprisingly low dimensionality in its kinematics, and can be described mathematically with a very small number of order parameters. This might have interesting implications for detecting and understanding the underlying muscle synergies and the corresponding neural control. The power of model order reduction can be improved further by analyzing the phase plane behavior of the order parameters, which could potentially yield further insights into the intricate mechanisms and subtle influences.

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Table 1. Markers of the horse and rider (cf. Fig. 1 a).

Horse markers		Rider markers	
Index j	Notation	Index j	Notation
1	nose	12	hip
2	3 rd cervical vertebra	13	Shoulder
3	withers	14	head
4	4th lumbar vertebra		
5	Os sacrum 2		
6	Fore hoof		
7	Fore fetlock joint		
8	Fore carpus		
9	Hind foot		
10	Hind fetlock joint		
11	Hind tarsus		

Table 2. Number of motion cycles analyzed for each individual horse.

Horse	Side Saddle (SS)	English Saddle (ES)
Ali	9	8
Bla	8	11
Faw	13	14
Fleur	18	17
Nom	16	14
Ove	11	15
Roc	15	15
Sav	15	15
Sca	15	15
Sch	12	14
Stu	14	15
Tri	15	15
Xen	15	15

Table 3: Properties of the graphical form of the phase portraits.

Properties for plots which base on the real part of the order parameter	Properties for plots which base on the imaginary part of the order parameter
A Round, without cusps	F Round and symmetrical
B Round + characteristic convexities left and right	G ∞ -form + cusps/dents
C Spikes top and down	H ∞ + loops and also cusps
D Spikes + characteristic convexities left and right	I Heavy furrowed
E Distinctive convexitie(s) top or down or rather top and down	J One ore few loops + heavy furrowed
	K Relative round + small loops + small spikes/dents

Table 4. Matrix of similarity for the horse *Stu*, “1” means that the category is present, “0” means that the category is not present.

		SS	
		1	0
ES	1	6	0
	0	3	1

Table 5. Fourfold table for the calculation of similarity quantities (Eqs. (5) and (6)), Compare with Table 4.

		SS	
		1	0
ES	1	a = ...	c = ...
	0	b = ...	d = ...

Table 6. Averaged eigenvalues of the first and the second mode for walk, trot, and canter for the Side Saddle (SS) and the English Saddle (ES).

Horse	Walk				Trot				Canter			
	1 st mode		2 nd mode		1 st mode		2 nd mode		1 st mode		2 nd mode	
	SS	ES	SS	ES	SS	ES	SS	ES	SS	ES	SS	ES
Ali	62.2	50	31.9	45.6	90	92	5.1	4	57.1	60.7	39.4	36.3
Bla	53	64.4	43	31.2	91.4	84.9	4	7.8	50.3	52.8	47	44.5
Faw	54	53.8	39.8	40.3	82.6	87.6	11.1	6.8	50.9	52.4	45.4	44.4
Fleur	52.8	53	42	42.5	90.6	89.8	5.2	5.1	64.9	53.3	29.1	43.2
Nom	59	58.3	33.6	35.5	81.7	87.7	3.7	8.3	71.6	72.2	25.7	24.8
Ove	52.1	52	41.7	43.1	90.7	92	5.5	4.7	52.2	51.4	45.4	46.3
Roc	52.3	52.5	43.5	43	90.2	91	5	4.7	58.2	60.1	38.9	36.8
Sav	56.2	57.2	37.6	35.8	86.9	87.9	7.4	6.9	55.6	54.3	40.1	41.4
Sca	58.4	52.9	36.5	43	90.7	92.6	4.5	4	57.3	55.5	40.6	42.5
Sch	54.1	50.6	40.4	43.5	89.1	90.2	4.9	5.3	51	53.1	45.8	43.9
Stu	66.7	56.6	23.3	29.5	88.7	89.4	7.7	7.2	52.5	64.4	44.8	45.1
Tri	55.1	53.1	40.5	43.7	92.9	93.4	3.6	3.5	51.6	52.2	46.5	45.8
Xen	56.2	51.4	38.3	42.5	91	90.9	5	5.1	59.3	52.4	37.9	44

Fig. 1

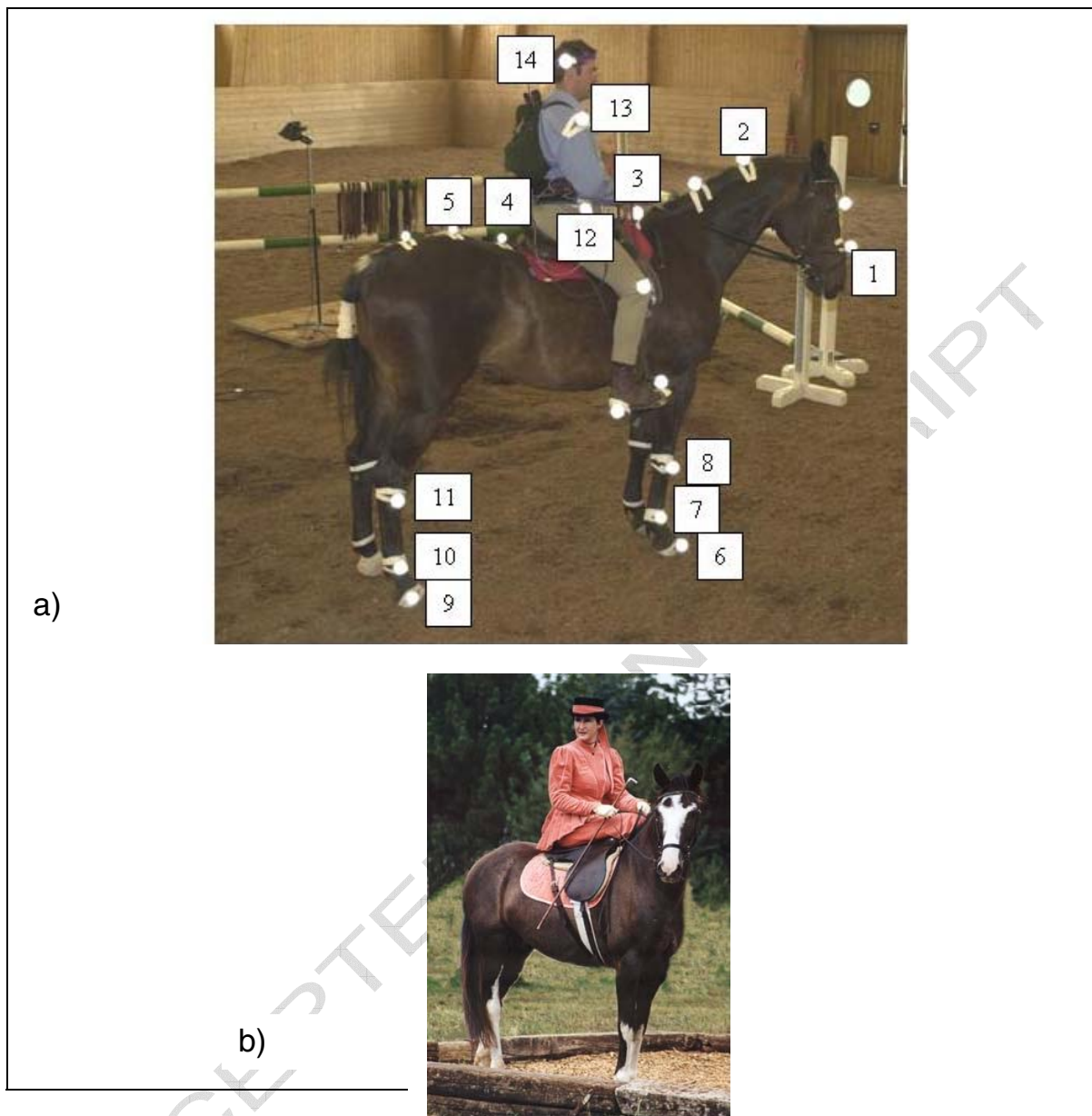


Fig. 1. Marker configuration and saddle types studied.

a) English Saddle (ES) with marker indices (cf. Table 1)

b) Side Saddle (SS).

Fig. 2

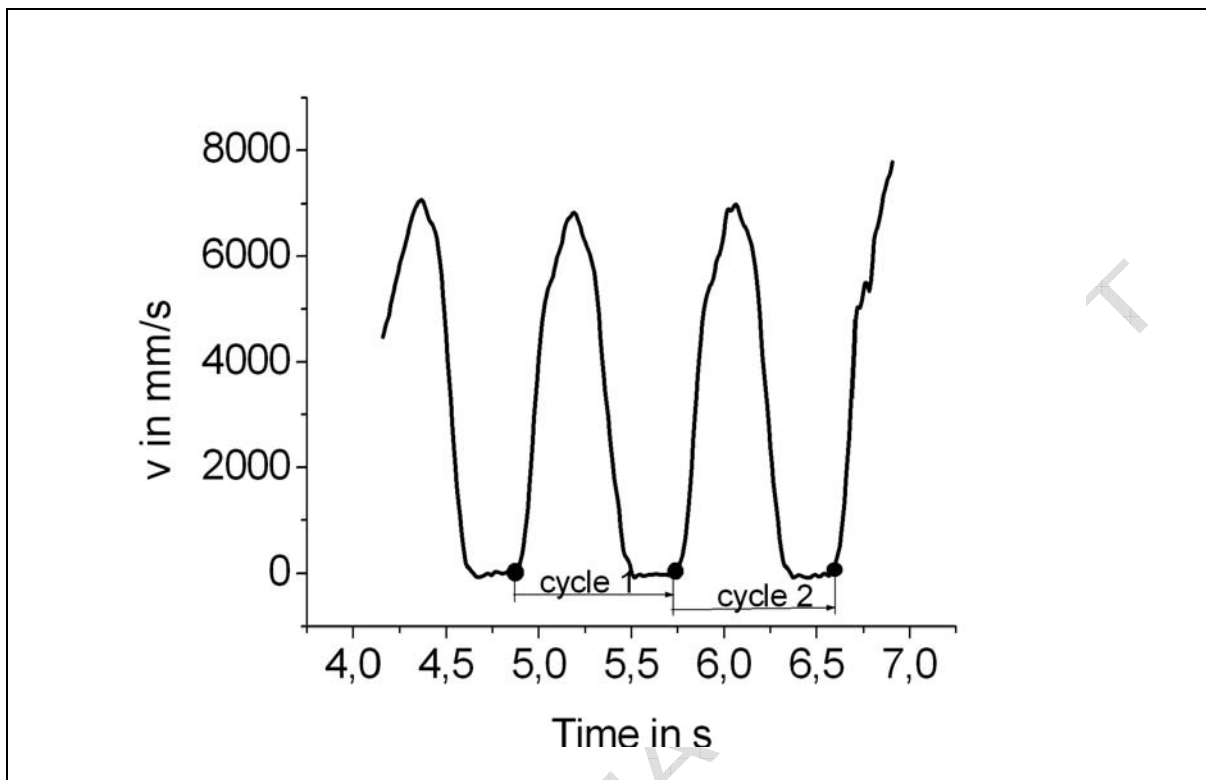


Fig. 2. Separation of the strikes on the foundation of the time-course of the horizontal velocity of the fore hoof.

Fig. 3

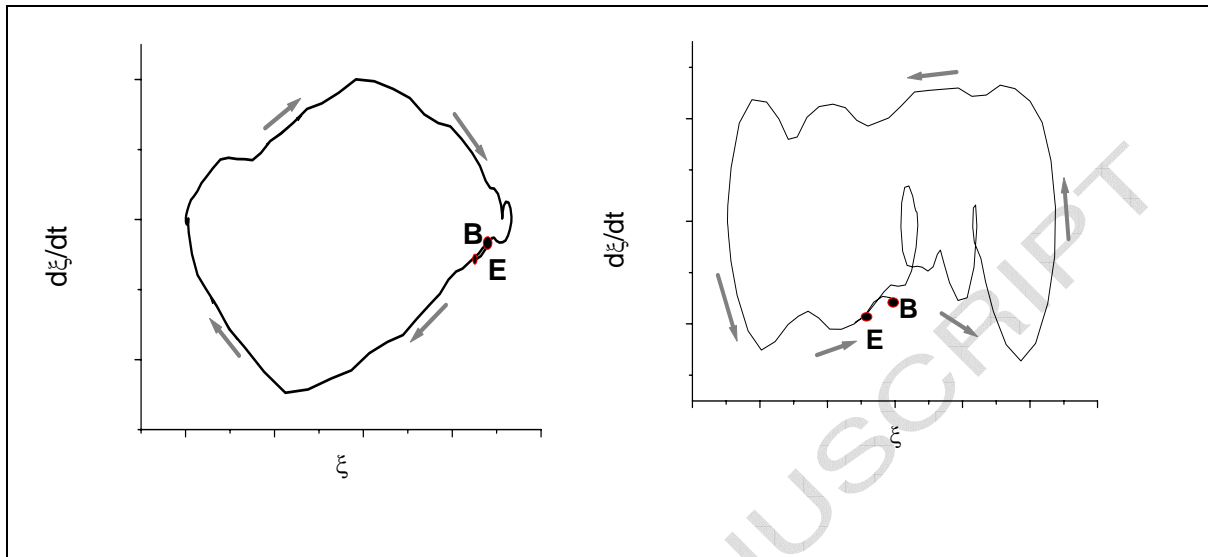


Fig. 3. Typical phase portraits of a trot cycle. Left side: real part; right side: the imaginary part of the order parameter ξ . Beginning (B), end (E), and the course of the phase portrait (with arrow) are marked.

Fig. 4



Fig. 4. Phase portraits of all analyzed cycles of the horse Xen for trot distinguish between SS and ES.

Fig. 5

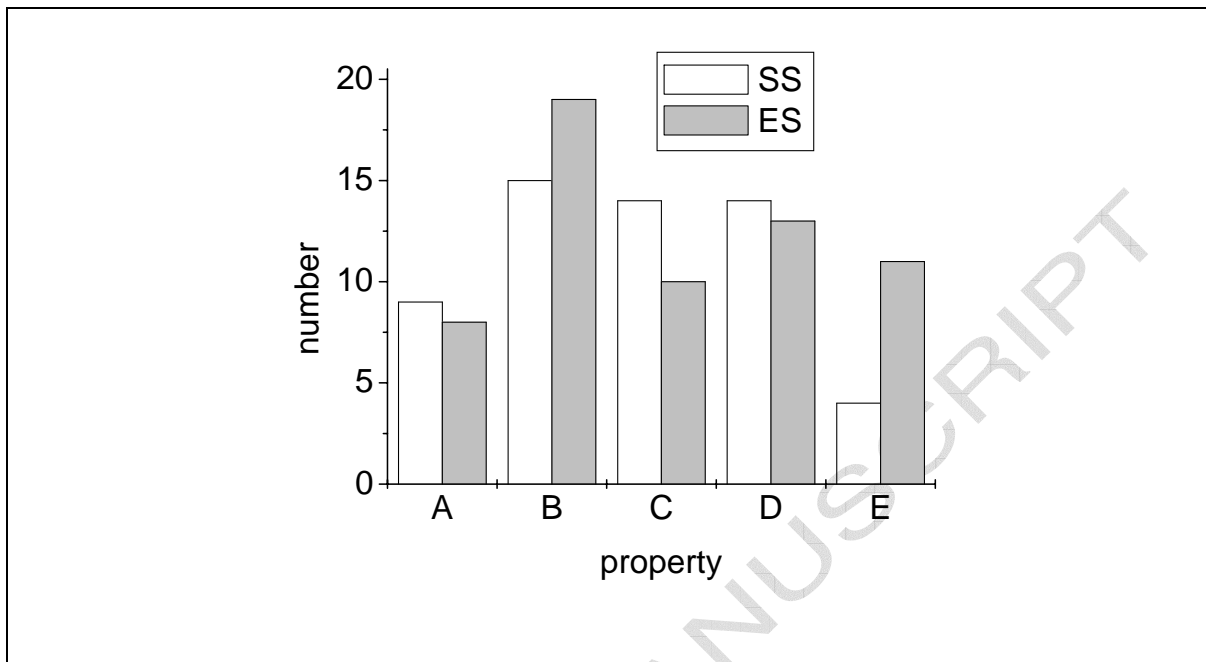


Fig. 5. Number of phase portraits (real part) that were attributed to the properties A-E for the Side Saddle (SS) and the English Saddle (ES).

Fig. 6

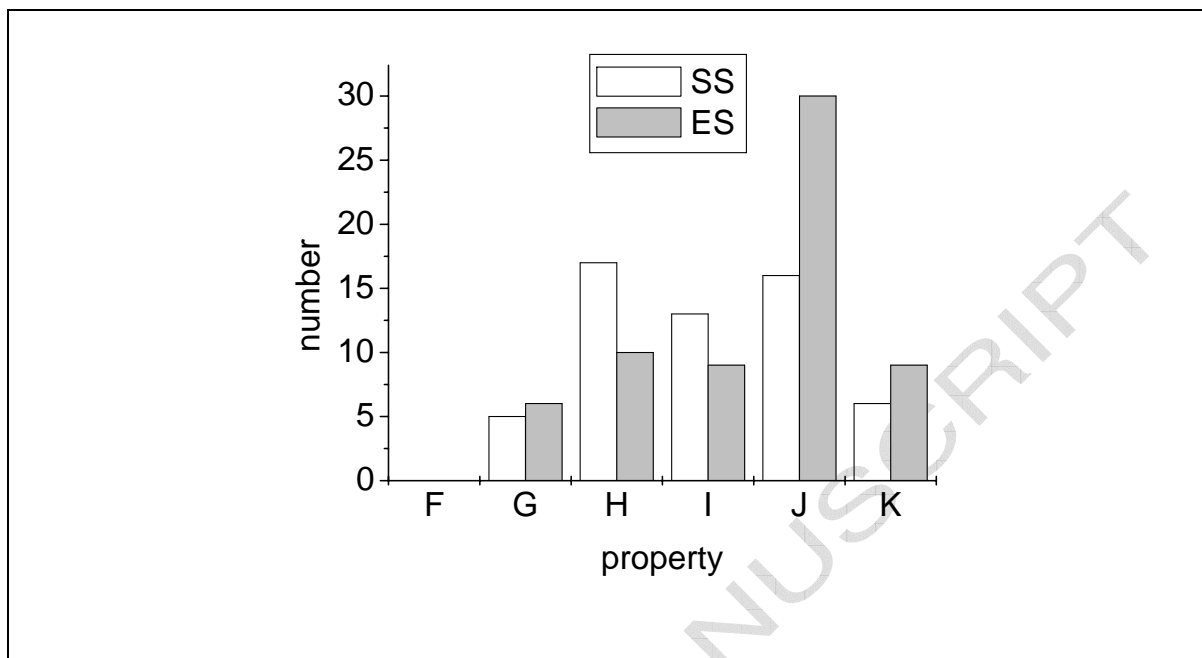


Fig. 6. Number of phase portraits (imaginary part) that were attributed to the properties F-K for the Side Saddle (SS) and the English Saddle (ES).

Fig. 7

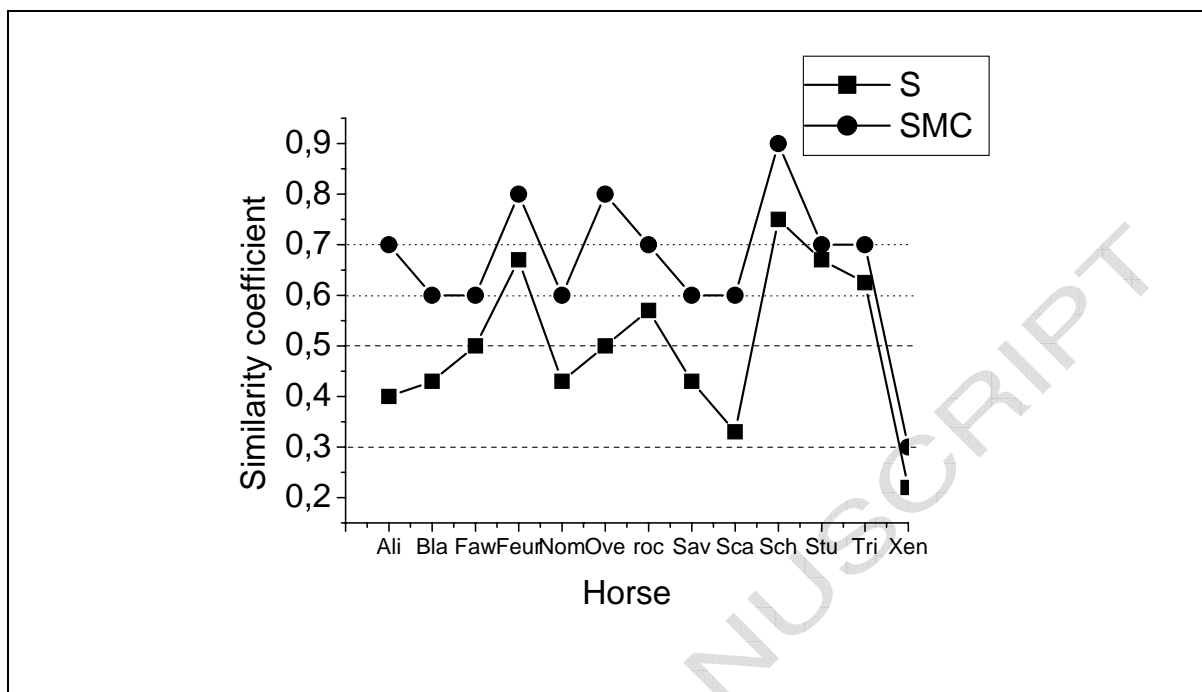


Fig. 7. Estimated similarity coefficients S and SMC for the phase portraits of the trot for each horse. The dotted lines show the limits for the high and small similarities.