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Editorial

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Dear readers:

Welcome to the winter 2007 issue of the **International Journal of Computer Science in Sport** (**IJCSS**).

Two original papers and three reports have been included within this issue.

Britta Weber, Josef Wiemeyer, Ingo Hermanns and **Rolf P. Ellegast** present a measuring device for recording and identifying everyday activity behaviour. A high classification accuracy was observed..

In the paper by **Thomas Mauthner, Christina Koch, Markus Tilp** and **Horst Bischof** a novel method is introduced for tracking beachvolleyball athletes in competition using one camera only. The authors presented their method during the 6th International Symposium on Computer Science in Sport in Calgary (June 2007) and were invited to submit a full paper version to IJCSS.

The report by **Florian Walter**, **Martin Lames** and **Tim McGarry** as well as that by **Tim McGarry** and **Florian Walter** have also been presented during that conference.

In the first of these reports, the potential and the challenges of a dynamical system's analysis with relative phase measurement of interaction phenomena in dyadic game sports are discussed. In the second, dynamical analysis techniques are successfully used to identify real squash dyads from distractors.

Francisco A. Iturriaga, **Pablo G. Marin**, **Jose I. A. Roque** and **Encarnacion R. Lara** investigate the relation of certain performance parameters to the outcome of water polo games.

If you have any questions, comments, suggestions and points of criticism, please send them to me.

Best wishes for 2008!

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Assessment of everyday physical activity: Development and evaluation of an accelerometry-based measuring system

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Abstract

By modifying an ergonomic motion analysis system, an accelerometry-based measuring system has been developed in the course of a feasibility study for quantitative and qualitative activity acquisition. To permit almost non-reactive long-term measurements in everyday situations, the scale of the original sensor equipment has been reduced by employing eight triaxial accelerometers. The existing evaluation software has been supplemented with appropriate functions. Movement intensity is determined and expressed in activity levels (*none, low, medium* and *high*), and a recognition algorithm has been implemented, which in its current version is capable of automatically identifying *walking* as well as different variants of *standing, sitting, lying, kneeling* and *crouching*. Activities were simultaneously videotaped to test classification accuracy. Tests yielded an agreement rate of 97.5% for measurements under controlled conditions. For measurements under everyday conditions, agreement rose to 99.0%. Preliminary testing by heart rate records confirmed the implemented intensity determination. In conclusion, the developed prototype is suitable for the objective recording and automatic identification of everyday activity behaviour. Using reliable hardware and enhanced, user-friendly software, the system has great potential for further development.

KEY WORDS: MEASURING PHYSICAL ACTIVITY, ACCELEROMETRY, ACTIVITY INTENSITY, ACTIVITY RECOGNITION

Introduction

Lack of physical exercise as risk factor for numerous chronic diseases as well as physical activity (PA) as multi-faceted health resource are well documented in the scientific literature (e.g., Pate, Pratt, Blair, Haskell, Macera, Bouchard, Buchner, Ettinger, Heath, & King, 1995). In the international public health discussion, a comprehensive conception of health-enhancing physical activity (HEPA) has been established over the last decade. In addition to leisure PA – usually including sport –, occupational and household PA and PA for the purpose of covering distances (such as cycling or climbing stairs) are now attributed the same importance.

However, until now there has not been sufficient knowledge of the dose-response relationship between PA in everyday life and the preservation or improvement of the functional state of health. In order to analyze the complex relationship between PA and its health outcome more precisely, the type and extent of daily PA has to be surveyed objectively and reliably in the population. However, the key problem with the quantification of PA is the lack of a generally accepted valid method for measuring PA (Woll, 2004, p. 58).

Research in PA often applies questionnaires and diary-based monitoring methods, which are distinguished by their economy and practicability even with large samples. Nevertheless, statements on one's own PA depend on the individual's capacity of remembering and his or her subjective estimations. Therefore, an electronic measuring system for the objective assessment of everyday PA is required. By means of such an instrument, interview- and questionnaire-based methods can be tested and developed further.

Electronic measuring systems for the monitoring of PA have already been designed and tested for applicability. In particular, there have been numerous efforts to develop accelerometer-based measuring systems. However, in health research the large-scale use of a valid and commonly accepted instrument which provides differentiated information on everyday PA has not been documented by now.

In ergonomics, an objective measuring system is regularly used to analyze movement and loading at the workplace. By means of various sensors, the CUELA measuring system (German abbreviation for "computer-assisted recording and long-term analysis of musculoskeletal loads") records trunk and leg positions and foot pressure distributions and evaluates these data automatically using ergonomic and biomechanical methods (see Ellegast, 1998; Ellegast, Hermanns, Hamburger, Post, Glitsch, Ditchen, & Hoehne-Hückstädt, 2006; Ellegast & Kupfer, 2000). The CUELA system is considered a viable starting point for further development towards an activity measuring instrument which can also be employed in everyday situations. By using miniaturized accelerometers, a scaled-down variant of the original system is conceivable.

The purpose of this paper is to discuss the existing measuring systems for assessing PA and to introduce a new system based on the CUELA system.

Literature review

Accelerometry-based assessment of PA

Accelerometry currently ranks as the most accepted and most useful method for the mobile recording of human movement (see Mathie, Coster, Lovell, & Celler, 2004, p. R2). Firstly, because of their size accelerometers are suitable for low-reactive movement recording. Being able to measure static and dynamic states, they secondly supply significant information for subsequent data analysis. In addition, accelerometers applied in existing studies (Bouten, Koekkoekk, Verduin, Kodde, & Janssen, 1997; Meijer, Westerterp, Verhoeven, Koper, & ten Hoor, 1991; Moe-Nilssen, 1998) have shown a high degree of measurement reliability with low variability over time. This has enabled the development of mobile systems with low weight and size which can be worn unsupervised for long time periods in everyday situations without having a major impact on the subject's movement behaviour. A broad range of applications – including movement classification, determination of physical activity intensity (PAI), estimation of energy expenditure, and movement analysis – can be realized with the aid of accelerometry-based measurement systems. Accelerometry can also be employed in combination with other techniques, for example heart rate (HR) measurement.

The systems developed to date can be subdivided into systems for the measurement of the *intensity of PA* and systems designed for *automatic activity recognition*.

Physical activity intensity (PAI)

As far back as almost 30 years ago, it was discovered that the integrated sums of the accelerations measured on the body are proportional to activity-induced energy expenditure

(EE_{act}) (Reswick, Perry, & Antonelli, 1978; Bhattacharya, McCutcheon, Shvartz, & Greenleaf, 1980). Today's systems designed for recording PAI are also based on this assumption. Activity is usually recorded using a single uni- or triaxial accelerometer placed on the hip or lower back (as rough representation of the body's centre of mass). Examples of the uniaxial variant are *Caltrac*® (Muscle Dynamics Fitness Network, Torrance, USA) and *ActiGraph*® (MTI Health Service, Inc., Fort Walton Beach, USA). The 3D measuring devices include the *RT3*® *Activity Recorder* (Stayhealthy, Inc., Monrovia, USA) and the not commercially available *Tracmor* (Philips Research, Eindhoven, Netherlands). The output supplied by these devices contains either so-called "activity counts", or EE_{act} calculated on the basis of linear regression models.

Studies have shown that both the uniaxial and triaxial instruments can be employed to distinguish between different degrees of PAI (see Bouten et al., 1997; Nichols, Patterson, & Early, 1992; Trost, McIver, & Pate, 2005; Westerterp, 1999). However, there is some uncertainty about EE_{act} determined on this basis (see Hagemann, Norman, Pfefferkorn, Reiss, & Riesberg, 2004; Montoye, Kemper, Saris, & Washburn, 1996).

A more precise estimate of the EE_{act} is achieved with the *Actiheart*® device (Cambridge Neurotechnology Ltd., Papworth, UK) by means of the combined use of accelerometry and HR measurement. To determine EE_{act}, a model is employed which differentially weights the acceleration and HR data (branched equation modelling). Compared to indirect calorimetry as reference method, the device calculates good estimates of the energy consumption for rest, walking and running (see Brage, Brage, Franks, Ekelund, & Wareham, 2005; Corder, Brage, Wareham, & Ekelund, 2005) and for activities of low to moderate intensity (Thompson, Batterham, Bock, Robson, & Stokes, 2006).

Automatic activity recognition

To obtain information on the *type* of activity performed, accelerometry-based measurement systems have also been developed which automatically recognize postures and activities. A representative sample of past work on activity recognition using acceleration is given in Table 1. For each system the measurement setup, the classes of identifiable activities, the evaluation strategy and the classification accuracy is quoted.

The spectrum of physical activity identified by these systems covers

- the distinction between *standing*, *sitting*, *lying* and *movement* (Aminian, Robert, Buchser, Rutschmann, Hayoz, & Depairon, 1999; Busser, Ott, van Lummel, Uiterwaal, & Blank, 1997; Kiani, Snijders, & Gelsema, 1997, 1998; Lyons, Culhane, Hilton, Grace, & Lyons, 2005; Uiterwaal, Glerum, Busser, & van Lummel, 1998)
- the recognition of specific classes of PA, such as household tasks, different strenuous forms of locomotion, falls etc. (Bao & Intille, 2004; Bussmann, Martens, Tulen, Schaasfoort, van den Berg-Emons, & Stam, 2001; Foerster, Smeja, & Fahrenberg, 1999; Kern, Schiele, & Schmidt, 2003; Mäntyjärvi, Himberg, & Seppänen, 2001; Mathie, Celler, Lovell, & Coster, 2004; Sherill, Moy, Reilly, & Bonato, 2005).

Table 1. Summary of existing activity recognition systems using accelerometry.

Investigation	**Channels**[a]	**Sensor placement**[b]	**Activity classes**	**Extracted features**[c]	**Classification technique**	**Accuracy**[d]
Aminian et al. (1999) "Physiolog"	2	Thigh (*s*), back (*v*)	Lying, sitting, standing, moving, "other"	Median, MAD	Comparison with preset ranges	89.3%
Bao & Intille (2004)	10	Right ankle/ wrist and left thigh/arm/hip (*v*, *s*)	Walking, sitting, standing, watching TV, running, stretching, scrubbing, folding laundry, brushing teeth, riding elevator, walking while	Time series, spectral and correlation features	Decision table (1) Nearest neighbour (2) C4.5 decision	46.8% (1), 82.7% (2), 84.3% (3), 52.4% (4)

			carrying items, eating or drinking, working on PC, reading, bicycling, strength-training, vacuuming, lying, climbing stairs, riding escalator		tree (3) Bayes classifier (4)	
Busser et al. (1997) (1), Uiterwaal et al. (1998) (2), "DynaPort ADL-Monitor"	3	Left thigh (*s*), waist (*v*, *s*)	Lying, sitting, standing, locomotion, playing	Not specified	Not specified	73-91% (1); 86-93% (2)
Bussmann et al. (2001), "Activity Monitor"	4	Both thighs (*s*), sternum (*v*, *s*)	Lying, sitting, standing, walking, walking upstairs/downstairs, bicycling, noncyclic movement	Angles, mean, frequency features	Determining distances to preset ranges	81-93%
Foerster et al. (1999)	4	Lower leg/ thigh (preferred leg) wrist (preferred arm), sternum (*v*)	Lying, sitting, sitting and talking, working on PC, standing, walking, walking upstairs/downstairs, bicycling	Mean	Determining distances to individual reference values	66.7-95.8%
Kern et al. (2003)	36	Left and right shoulder, elbow, wrist, hip, knee, ankle (*v*, *s*, *h*)	Sitting, standing, walking, walking upstairs/downstairs, shaking hands, writing on a whiteboard, working on PC	Running mean, SD	Bayes classifier	68-95%
Kiani et al. (1997) "AMMA-System"	4	Both thighs (*s*), sternum (*v*, *h*)	Lying, sitting, standing, walking, transitions	Mean, SD, vector magnitude	Hierarchical decision tree	98%
Kiani et al. (1998) , "AMMA-System"	4	Both thighs (*s*), sternum (*v*, *h*)	Lying, sitting, standing, walking, transitions	-	Probabilistic neural network	95%
Lyons et al. (2005)	4	Right thigh (*v*, *s*), sternum (*v*, *s*)	Lying, sitting, standing, moving	Mean, SD, angles	Comparison with preset ranges	84-93%
Mäntyjärvi et al. (2001)	6	Left and right hip (*v*, *s*, h)	Walking, upstairs, downstairs	PC/IC (wavelet transformed)	Multilayer perceptron	83-85%
Mathie, Celler et al. (2004)	3	Hip (v, s, h)	Lying, sitting, standing, falls, walking, transitions, "other"	Not precisely specified	Hierarchical decision tree	97%
Sherill et al. (2005)	10	Left and right forearm/thigh (*v*, *s*), sternum (*v*, h)	Treadmill, stationary bicycle, arm ergometer, walking (level/incline/stair), folding laundry, sweeping floor	Time series, spectral and correlation features; PC	Linear discriminant analysis	-

[a] Number of recording channels.
[b] Measurement direction according to the body fixed coordinate frame: vertical, sagittal, horizontal.
[c] MAD = mean absolute deviation, SD = standard deviation, PC/IC = principal/independent components.
[d] Correct classification compared with observation or fixed activity sequences.

For data acquisition, the measuring systems use up to twelve acceleration sensors, attached to different parts of the body. The critical factor for the identification of the activity performed is a suitable procedure for data analysis. By now, different strategies have been used for automatic activity recognition. The range extends from simple, rule-based approaches, which, for example, perform simple threshold value comparisons, and various statistical methods (e.g., Bayes classifier or discriminant analysis) to the use of artificial neural networks for the classification of acceleration patterns.
Looking at the classification results, no statement can be made on which type of data evaluation should be generally preferred. Due to considerable differences in the respective study goals (number and specificity of the activity classes being identified) and in the evaluated data (circumstances and duration of activity measurements, number and position of the accelerometers employed, number of test subjects, etc.), it is not possible to directly compare the performance of the systems presented.
The mentioned systems originate from a very wide range of research fields, for example preventive and rehabilitation medicine, psychophysiology, biomedical technology and the wearable computing/context awareness field. In the following, we are presenting a motion analysis system which is used in ergonomics. Unlike the systems described above, the use of which has so far been reported in only a small number of studies, this measuring system has been regularly used for almost ten years in ergonomic studies (e.g., Ditchen, Ellegast, Herda, & Hoehne-Hückstädt, 2005; Ellegast, Herda, Hoehne-Hückstädt, Lesser, Kraus, & Schwan, 2004; Glitsch, Ottersbach, Ellegast, Schaub, & Jäger, 2004; Hoehne-Hückstädt, Ellegast, & Ditchen, 2006).
Among the systems presented, only two are commercially available ("Activity Monitor" and "DynaPort ADL-Monitor"). Operating with 3 to 4 recording channels, they offer limited discriminatory power. In addition, it is difficult to modify or further develop a "finished product". The CUELA system provides the chance to connect different sensors and record up to 168 channels. The system is designed modularly, therefore hardware and software interfaces are open for application-specific adaptations. In its basic version, the CUELA system does not operate with acceleration sensors, but offers a variety of functions and opportunities in the field of data acquisition and data evaluation – including the automatic recognition of postures and activities – which are also of great benefit for activity analysis in everyday situations.

The CUELA measuring system

The CUELA system (Figure 1) is a mobile measuring system for the objective long-term measurement of loads on the musculoskeletal system. Using this measuring system, it is possible to effectively support the statutory accident insurance institutions in the identification of job-related health hazards and to supply specific information on the load situation, even at non-stationary workplaces. The basic version of the CUELA measuring system (Ellegast, 1998), under development at the BGIA since 1994, consists of the following components:

- Potentiometers to measure knee and hip joint flexions
- Gyroscopes and inclinometers and a digital rotary transducer to measure flexion/extension, lateral flexion and torsion of the trunk
- Piezo-resistive pressure-sensitive insoles to measure foot pressure distribution (Paromed GmbH, Neubeuren, Germany).

The movement data are stored in a portable storage unit and can be subsequently read out at a PC and processed further. Among others, the associated CUELA software provides the following evaluation functions:

- Display of body posture by means of a 3D computer-animated figure
- Graphic representation of angle/time curves
- Synchronous embedding of video, HR records, etc.
- Automatic classification of walking and body postures in accordance with the OWAS method (Karhu, Kansi, & Kuorinka, 1977)
- Recognition of load handling activities and determination of load weights
- Calculation of statistics over the measurement period.

Figure 1. Application of the CUELA measuring system on a carpenter's and an electrician's workplace.

With its convenient graphical user interface the CUELA software offers movement analysis and animation which, in that way, have not been reported in any of the systems described above. Another advantage of the system arises from its modularity: Besides the basic version there are extensions and modifications of the CUELA system for special applications, for example 3D motion analysis of the upper limb, motion analysis for sedentary workplaces or an interface for a 3D hand force measurement device.

Measurement instrumentation and evaluation software are in-house developed so that the interfaces are direct available. Thus, specific adaptations as well as enhancements are enabled. Due to continuous use, further development and inspection, the CUELA system provides hardware and software components proven in practice. By scaling down the sensor equipment by the use of accelerometers, we intended to develop a modified variant of the original system which is suitable for long-term everyday PA measurements. The "CUELA activity measuring system" shall integrate quantitative (PAI) as well as qualitative (activity recognition) PA examination.

Development of the CUELA activity measuring system

Requirements

The original measuring instrumentation is to be modified by introducing accelerometers to meet the following requirements:

- Reducing the equipment to a minimum (production of miniaturized sensors, using as few sensors as possible)
- Using triaxial accelerometers to still take the 3D character of human movements into account

- Realization of adequate sensor attachment suitable for the new field of application (under the clothes, non-slip, no limitation of freedom of movement, simple to affix).

The existing CUELA evaluation software has to be modified in order to adopt most of the original analysis functions for the accelerometer-based system. In addition, the implementation of a new function determining movement intensity is intended. Also, the automatic recognition shall be extended by further postures and activities, such *as lying on the side* or *walking upstairs/downstairs*.

Measurement setup

The hardware prototype of the CUELA activity system consists of a new configuration of eight triaxial acceleration sensors (Figure 2a), a sensor box for multiplexing the sensor signals and a data logger from the original CUELA system (Figure 2c). The system is set to a default sampling rate of 50 Hz and performs A/D conversion with a resolution of 10 bits. For acceleration measurement, the sensors ADXL103 (uniaxial) and ADXL203 (biaxial) from Analog Devices (Cambridge, USA) are employed. Both models operate on the principle of capacitive acceleration measurement. They are designed for an acceleration range of ±1.7 *G* and can measure both static and dynamic accelerations (e.g., inclination and vibration). To cover all three dimensions, the sensors are placed perpendicular to each other. In static cases, orientation is thus known in relation to the axis of gravitation.

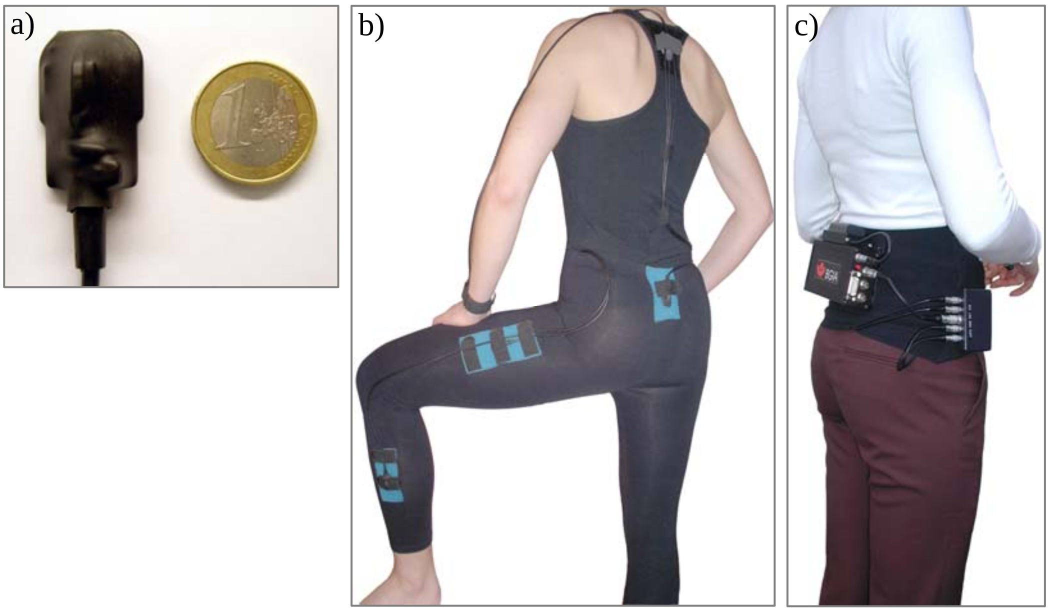

Figure 2. Sensor size (a), sensor attachment (b) and visible hardware components (data logger and sensor box) of the system worn under the clothes (c).

The sensors are attached to upper and lower back, both wrists and upper and lower leg of both legs. The leg and wrist sensors are placed in the sagittal plane, whereas the back sensors are positioned in the frontal plane (Figure 2b). Using elasticated, tight-fitting functional sports underwear, a measuring suit has been produced, to which the leg and back sensors are fixed with Velcro-type elements. The arm sensors are fixed with elastic Velcro-type tapes around the wrists. Figure 2c demonstrates how the measuring system worn under the clothing finally looks. Data logger and sensor box are attached to an elastic hip belt. Alternatively, the logger can also be carried in a waist bag. The sensor box has metal clip on its back for attaching it to a belt or trouser waist band.

Data analysis

The dimensionless digital values are imported into the analysis program and converted into acceleration data. The processing of the acceleration signals then branches. In one branch, calculations are performed to determine PAI. In the other branch, the body angles are calculated. These are required for automatic activity recognition and for animation of the 3D computer figure.

Determining PAI

Current PAI is calculated according to the approaches of above cited studies (e.g. Bouten et al., 1997; Sherill et al., 2005). For each body segment fitted by a sensor, PAI determination is performed into three steps:

1. To encompass all three directions of movement, the vector magnitude *VM* of the 3D acceleration vector (a_x, a_y, a_z) at time t is determined:

$$VM_{Segment_t} = \sqrt{a_x^{\;2} + a_y^{\;2} + a_z^{\;2}}\ . \qquad (1)$$

2. Subsequent high-pass filtering with a cut-off frequency of 0.1 Hz removes the constant signal portions, so that only the alternating portion – i.e., the signal representing actually movement – remains.
3. To obtain the current movement intensity $PAI_{Segment}$ a moving root mean square (RMS) is calculated for the high-pass filtered vector magnitudes (*VMfilt*):

$$PAI_{Segment_t} = \sqrt{\frac{1}{T}\int_{t-\frac{T}{2}}^{t+\frac{T}{2}} VMfilt_{Segment_t}^{\;2}(t)dt}\ . \qquad (2)$$

   The RMS is calculated across $T = 150$ readings, which equals 3 s at a sampling rate of 50 Hz.

The segment activities determined in this way are combined to calculate PAI of different body parts as well as whole body PAI. According to the distribution of segment masses assumed in biomechanical models (e.g. Winter, 1990) the PAI values are merged using the factors presented in Figure 3:

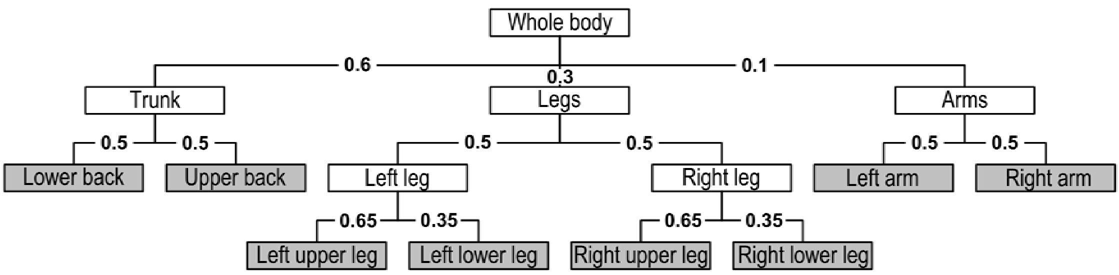

Figure 3. Weighting factors for merging the single segment PAIs (grey) to body part PAIs and whole body PAI.

To present the PAI curves in a more informative way for measurement evaluation, PAI is graded into four levels: *none*, *low*, *medium* and *high*. The corresponding threshold values are presented in Table 2. Due to the fact that a comparable categorization has not been implemented elsewhere, following existing thresholds was not possible. Considering the development of a prototype system, the levels were graded intuitively. The threshold values were generated experimentally based on available measurement data.

Table 2. Threshold values of the PAI levels.

	Activity level			
	None	**Low**	**Medium**	**High**
PAI	< 0.05 *G*	≥ 0.05 *G* and < 0.3 *G*	≥ 0.3 *G* and < 0.5 *G*	≥ 0.5 *G*

Figure 4 shows the colour-coded representation of the classified PAI levels displayed at the graphical user interface of the evaluation program. Both, video and computer figure demonstrate, that the person is lying currently and thus *not active*, which is represented by the grey areas of the intensity bars.

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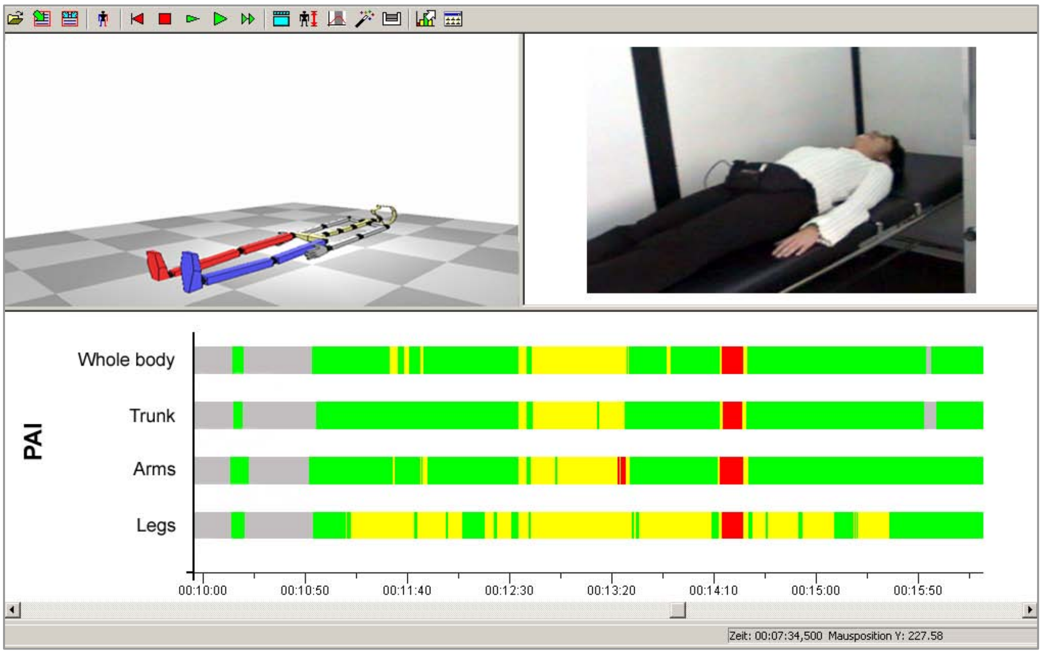

Figure 4. Data representation with the CUELA software by video (right), animated figure (left) and selected data stream (below), in this case the colour code of activity intensity for whole body, trunk, arms and legs (none, low, medium, high). Note: The displayed figure and video always refers to the left margin of the data stream.

Automatic activity recognition

For automatic activity recognition with the developed *BGIA activity/posture code*, the body angles and coordinates of the 3D figure are adopted as features for classification. The recorded acceleration/time curves can also be used for feature generation.

Feature generation: Computation of angles

The body angles are determined by using the quaternion notation for representing orientations and rotations:

1. First a quaternion is composed which describes the rotation of the gravitational vector (0, -1, 0) to the acceleration vector (a_x, a_y, a_z). This quaternion contains a rotation around an *arbitrary* axis.

2. To determine angles of flexion or lateral flexion, a quaternion, which describes the rotation around a *certain* axis (e.g. z-axis for flexion) is calculated out of the arbitrary quaternion. The interested angle can be read out from this quaternion.

The 3D movement animation is based on the calculated angles. Together with the segment lengths determined on the basis of subject size and gender, these yield the coordinates of the figure in space.

Feature generation: Acceleration features

The following acceleration features are considered:

- The acceleration signals (usually in the sagittal or horizontal plane)
- The vector magnitude of the 3D acceleration vector
- The frequency features of the acceleration curves.

However, none of the cited features is employed in the current version (January 2007) of the recognition algorithm. At present, only body postures are identifiable, whose classification is based on the calculated body angles and the coordinates of the 3D figure.

Classification: The BGIA activity/posture code

The recognition algorithm evaluates all postures concurrently. The following postures and subpostures are available as options within the code:

- Standing: with straight legs / with bent legs
- Sitting: on a chair or similar / on the ground
- Kneeling: on heels / upright on both legs / on one leg left/right
- Lying: supine / prone / on right side / on left side
- Crouching

For each posture, a membership value is calculated ranging from 0 (not true) to 1 (true) using a fuzzy logic approach. The degree of membership (DOM) with one of the postures is determined based on the calculated coordinates and angles. Every posture has a set of crucial features, which are examined in the classification procedure. In the course of this, the DOM is determined for each feature. The respective basic variables are linearly mapped to the interval between 0 and 1. Within this interval the DOM is defined by the following nonlinear function:

$$c(a) = (1 - a^{\omega})^{\frac{1}{\omega}}, \qquad a \in [0,1]; \ \omega \in \{3,6\} \tag{3}$$

The graph of the membership function differs in shape due to the characteristic of the predefined scope. For s*itting on the ground*, for example, the conditions below have to be met:

- Maximum distance between ground and pelvis at 35 cm
- Minimum distance between ground and thoracic spine at 35 cm
- Maximum backward inclination of lumbar spine at 75°
- Maximum lateral inclination of lumbar at 60° on either side.

Depending on the nature of the respective scope, the membership function looks like one of the examples presented in Figure 5:

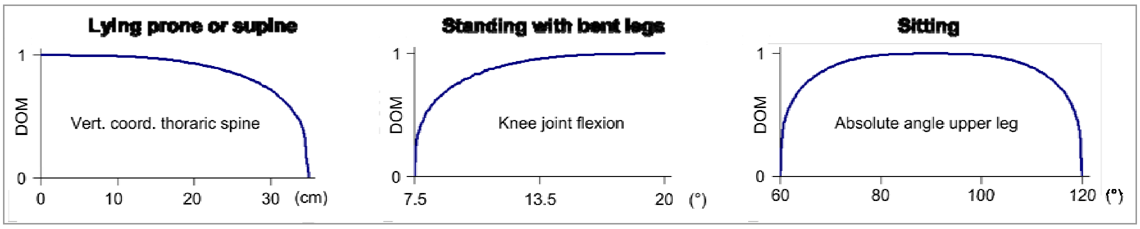

Figure 5. Exemplary membership functions for determining a feature's degree of membership (DOM) with a posture.

Either the scopes are characterized by having an upper or lower limit or they are limited both-way. In addition, the membership function is determined by ω, which denotes the level of selectivity between 0 and 1. As in most cases, in the sample graphs of Figure 5 ω = 3 was selected. To attain stricter discrimination between two postures, in certain cases ω = 6 was set. For example, harder transition boundaries were necessary for the vertical knee position to separate *crouching* from *kneeling*, because the membership with *crouching* terminates just when one knee touches the ground.
For every feature set the lowest of the determined values is considered as DOM with this posture. Of any postures the one with the highest DOM is classified finally as current activity.
The definition of features and determination of the threshold values for the validity ranges of body postures is based on theoretical assumptions, existing knowledge (from existing automatic recognition), and data from test measurements. By now, only the above-mentioned postures are tested in this way. To recognize walking, an algorithm already available in the original code is used. The planned identification of other activities has not been implemented yet. However, some generated acceleration features seem to be promising recognition criteria. For example, the frequency content of the lower leg accelerations could discriminate between walking upstairs and downstairs.
Just like PAI, the activity recognition is also illustrated by a colour code in the evaluation software. Both, the activity levels and the automatic recognition can be statistically evaluated (in absolute or relative terms) over the entire measurement period.

Testing the system

After development, the classification performance of the prototype measuring system was tested by performing a number of measurements with simultaneous video monitoring. To cover a broad range of activities, a standardized activity protocol was first carried out under controlled conditions, followed by longer measurements without specific instructions in the everyday environment. In order to get an estimation about PAI determination, HR records were consulted. Despite the known difficulties regarding the relationship between HR and PAI, HR measurement offered an easily realizable method for preliminary testings.

Methods

Classification testing (controlled conditions)
Procedure: Four test subjects (3 females and 1 male, age: $M = 29.9$ years; $SD = 4.6$) performed a 10-minute posture and activity protocol which is listed in Table 3. Activities were recorded by the CUELA activity system and videotaped simultaneously.
Evaluation: Classification of the video material (one of the recognizable activities was assigned by the video evaluator to each 1-s interval) and subsequent comparison for agreement with the automatic recognition of the BGIA activity/posture code.

Table 3: Activity protocol for testing the automatic recognition under controlled conditions.

Station	Activity	Duration
1	Standing	~60 s
2	Sitting	~120 s
3	Kneeling	~30 s
4	Crouching	~30 s
5	Sitting on ground	~30 s
6	Walking	~100 s

Station	Activity	Duration
7	Lying supine	~30 s
8	Lying on right side	~30 s
9	Lying prone	~30 s
10	Lying on left side	~30 s
11	Walking	~60 s

Classification testing (free-living conditions)

Procedure: Everyday activities without specific instructions were performed for 1 hour in natural surroundings (subjects: 2 females, 33.3 and 36.5 years) and measured and videotaped, respectively. The measurements included various household activities, shopping, looking after children, coffee break, etc.

Evaluation: With one exception the evaluation procedure was the same as in the first test. With regard to the total duration we adopted 15-s intervals for analysis. If multiple activities occurred in one interval, the activity which appeared dominantly was chosen.

PAI testing

Procedure: One subject (female, 25 years) performed a measurement of about 30 minutes, including several minutes of walking, cycling, standing and sitting as well as 30 s of running. In addition to activity measurement, HR was recorded (Polar® Vantage NV, Polar Electro Oy, Kempele, Finland).

Evaluation: Graphical comparison of whole body PAI and HR curves.

Results

Classification testing (controlled conditions)

The results of the comparison between video-aided classification and automatic activity recognition are listed in Table 4. Overall, 2341 of 2400 inspected intervals were correctly classified. The misclassification rate ranged from 2 to 3% for all test subjects.

Table 4. Results of the comparison between automatic and video-aided classification.

	Number of intervals	**Correctly classified**		**Misclassified**	
		Absolute	Relative [%]	Absolute	Relative [%]
Subject 1	600	586	97.67%	14	2.33%
Subject 2	600	586	97.67%	14	2.33%
Subject 3	600	586	97.67%	14	2.33%
Subject 4	600	583	97.17%	17	2.83%
Total	**2400**	**2341**	**97.54%**	**59**	**2.46%**

Classification testing (free-living conditions)

The results of the classification test under free-living conditions are illustrated in Table 5. Concerning the total of 480 analyzed 15-s intervals, there was agreement in the classification of BGIA code and video evaluator in 475 cases. Divergent classifications occurred for about 1% of the intervals.

Table 5. Results of the comparison between automatic and video-aided classification.

	Number of intervals	Correctly classified		Misclassified	
		Absolute	Relative [%]	Absolute	Relative [%]
Subject 1	240	237	98.75%	3	1.25%
Subject 2	240	238	99.17%	2	0.83%
Total	**480**	**475**	**98.96%**	**5**	**1.04%**

PAI testing

The comparison between HR and whole body PAI is represented in Figure 6. The subject's HR in rest (about 60 beats/min) was chosen as origin of the HR scale. For the most parts both graphs have a similar shape. During *cycling* and the following *standing* sequence both curves demonstrate a deviation, which is explained in the discussion.

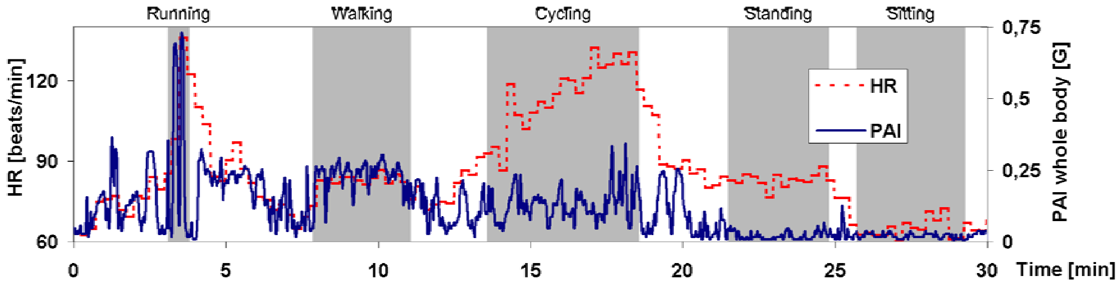

Figure 6. Whole body PAI compared with HR during different activities.

Discussion

By adapting the CUELA system an accelerometry based measuring system has been developed within a short period of time. Besides the quantification of movement intensity, the system is capable of classifying performed activity automatically. Due to the existing evaluation software and knowledge from many years of experience, a reliable recognition algorithm could easily be implemented.

The investigation of classification performance based on video observation showed that the recognizable activities can be identified with excellent accuracy. In most cases misclassifications occurred when different activities appeared in one interval. Since the dominant activity had to be determined in this case, divergent outcomes resulted between video and code evaluation. These discrepancies appeared frequently during transitions, especially within the evaluation of 1s-intervals if changing from one posture to another lasted several intervals. Some misclassifications were caused by the subjectivity of the observational evaluation. Extremely back-leaned s*itting on the ground*, for example, was detected as *lying supine*, and during very slow *walking* extended support phases were deemed to be *standing*.

There was no remarkable difference in the classification behaviour between the activity protocol and the field measurements. Compared to the laboratory setting Foerster et al. (1999) and Mathie, Celler et al. (2004) reported deterioration in classification performance using their measuring systems in the field. This discrepancy was not confirmed by our investigations. Measuring with 24 recording channels – unlike 3 or 4 in the two mentioned systems – might have been a benefit in the more complex free-living context. In addition, the possibility of disagreement in the field testings was reduced by analyzing 15s-intervals. By means of prolonged intervals, the problem of transitions lasting more than one interval was eliminated.

Considering the results listed in Table 1, the BGIA code yielded great classification accuracy. This may be attributed to the fact that the current algorithm detects predominantly static body postures. However *walking* is the only dynamic category by now. Therefore, the possible classification error is smaller than of those identifying more complicated, similar dynamic activities like *walking upstairs* and *walking downstairs*.
The PAI quantification was preliminary checked by means of HR records. The comparison between HR and whole body PAI indicates that the determined PAI offers a rough estimation for physiological strain at least for certain activities. Both graphs show analogy during walking, running and sitting. The biggest difference occurres during cycling. While HR increases, the PAI remains relatively low. This probably originates from the missing contact between feet and ground during cycling. The high acceleration peaks during walking and running are mainly caused by these foot strikes. In addition, PAI of trunk and arms tends towards zero during cycling. Considering the weighting factors given in Figure 3, whole body PAI is thus lowered significantly.
The following deviation between both curves during standing demonstrates the difficulty of using HR as reference for PAI. As consequence of the previous more intensive cycling phase, HR is still at a higher level, which does not correspond to the fact that during standing none or little activity was actually performed.

Conclusions and future prospects

The basic aim was to develop a sensor based measuring system which is suitable for quantitative and qualitative PA examination. This has been achieved by the modification of the existing system CUELA. Employing miniaturized accelerometers reduced the scale of the original sensor equipment to enable almost non-reactive measurements in everyday situations. It was considerable advantageous to modify available, field-tested hardware and software instead of developing a complete new system. For sensor attachment a measuring suit has been produced. By means of the modified sensor configuration, the existing analysis software can still be used. Further functions were implemented: Determining PAI in terms of activity levels as well as automatic activity recognition is performed. Preliminary testing of the classification accuracy revealed promising results (> 97 %).
Making use of reliable hardware as well as comprehensive and user-friendly software, the present prototype offers a good deal of scope for further development. Additional instrumentation (e.g., measuring insoles or EMG module) or newly developed sensors can be connected. Optionally, external recordings like video or HR can be embedded in the analysis program. Existing software tools can be enhanced as well as new functions added. By now, eight triaxial accelerometers are employed for activity assessment. Differentiated information on the activity performed is thus available. For both intensity determination and automatic activity recognition, this represents a huge potential for application-related adaptation of the system.
Primarily the identification of further dynamic activities like *walking* or *running at different speeds, climbing stairs* and *cycling* is planned. For this purpose we are currently developing a new type of sensor combining accelerometers and gyroscopes. By means of the additional information on the angular velocity, the determination of angles in dynamic states will become more precise. With the assistance of these sensors the discrimination between different types of dynamic activity may be facilitated.
Supplementation of PAI determination by gyroscope data is also intended. Thereby, the accelerometry-induced dependency on the type of locomotion (with or without foot strike), for example, can be excluded. Due to the inability of movement sensors to directly reflect

static muscle work, they can not measure the increased physical strain during activities like lifting and carrying loads or static exercises. According to the approach of the *Actiheart®* device, integration of HR data into the computation of PAI is therefore conceivable. However, the PAI determination should first be validated by means of a suitable reference method (e.g. mobile spiroergometry).
In order to allow very dynamic activities as *running* and to lower the reactiveness of the system, the hardware instrumentation has to be minimized further. In view of this, scaling down the data logger is indicated. Furthermore, a reduction in the number of sensors should be considered.

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Visual Tracking of Athletes in Beach Volleyball Using a Single Camera

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Abstract

This paper aims at successful tracking of beach volleyball athletes during competition using only a single camera. Due to the wide range of possible motions and non-rigid shape changes, the tracking task becomes quite complex. We propose a novel method based on integral histograms, to use a high dimensional model for a particle filter without drastic increase in runtime. We extend integral histograms to handle rotated objects. Additionally to the tracking process, a segmentation of the lower body parts enables generating real world player positions from a single camera view. Comparisons to hand annotated position data revealed sufficient accuracy for classical sport scientific purposes. The paper focuses on beach volleyball but the proposed methods can be utilized in other sports and non sports applications.

KEY WORDS: VISUAL TRACKING, BEACH VOLLEYBALL, TIME-MOTION ANALYSIS

Introduction

When analyzing sports games the main aspects of interest are the used techniques, the played tactics and the physiological demands of athletes. All three characteristics are important to quantify skills and shortcomings of athletes or teams and define requirements for training and competition.

For the analysis of technique and tactics, video technology has become very common and is utilized in several ways to analyze these aspects. The simplest way is to use video recordings to provide feedback for athletes (Liebermann & Franks, 2004) or to study opponent teams during crucial game situations in replay. Beyond these attempts interactive video systems (Dartfish®, Fribourg, Switzerland or Statshot®, Graz, Austria) are used to gather further information e.g. by counting frequencies of special techniques and by evaluating the effectiveness of actions. Such an attempt was successfully used by Tilp, Koch, Stifter & Ruppert (2006) to generate video based statistics for the analysis and comparison of world class junior beach volleyball teams.

The positions of actions in sports are often crucial for success or defeat and therefore an essential information to rate the quality of an action. In order to determine the playing position it became quite common to define relevant zones of the court and to estimate in which zone an action occurred (Hughes & Franks, 2004). Getting accurate information about positions is complicated due to several factors. A distortion caused by the perspective view, missing marks and the transitions from one zone to another often causes wrong rating decisions and errors.

Exact position information is furthermore required to calculate covered distances, velocities and accelerations of athletes with which the physiological demands can be estimated. The main advantage compared to classical methods like heart rate monitoring or lactate testing is that interaction with the athletes can be avoided. Different methods for such time-motion analyses have been used since the early 1970's. Before adequate technology was available such analyses were made manually via observation (Reilly & Thomas, 1976) or via audio recording (Yamanaka, Haga, Shindo, Narita, Koseki, Matsuura & Eda, 1988).
Due to accuracy reasons, methods based on video data followed by a manual computer supported analysis have become the preferred method in the last years (for review see Spencer, Bishop, Dawson & Goodman, 2005 or Bangsbo, Mohr & Krustrup, 2006). Determining positions during interesting game situations, ratio of action and recovery time or the amount of physically exhausting actions like sprints or jumps would require an annotation of nearly each frame of a video sequence. In order to obtain this information with a feasible amount of user interaction, an automatic system for position computation is needed.

Figure 1. The proposed method can handle characteristic player motions like jumps and digs, which occur frequently during tracking.

Commercial applications

Existing commercial applications for more or less automated tracking and position estimation demonstrate the interest of teams and coaches in gathering such information. They can be roughly divided into two groups: systems using markers (active or passive) and markerless systems. Two representatives for the first group are Cairos® (Munich, Germany) and LPM® (Abatec AG, Regau, Austria). Both systems use a radio based method, where every tracked object is equipped with a transponder which position is measured by several base stations. This technique has the advantages that the 3D position is computed up to 1000 times per second with a high spatial accuracy and that the number of tracked objects can be high. A disadvantage of such systems is the possible influence of markers on the athlete's behavior though this problem has improved remarkably by minimizing marker size. However, as most of the sport rules prohibit the wearing of markers during competition the use of these techniques is very limited in sport practice.

Markerless systems are mainly based on video input. Their main advantages are that the influence on players during competition is zero and that also opponents can be observed. Furthermore, the obtained video data can also be used for feedback or tactical observations. One of the leading systems is Amisco Pro® (Nice, France). It is a commercial multi camera match analysis system (8 stable, synchronized and fixed camera orientations) approved by several European soccer clubs. Recently, the system has also been used scientifically to estimate covered distances and running velocities in international soccer as reported by Salvo, Baron, Tschan, Calderon Montero, Bachl & Pigozzi (2007). Although this system may provide interesting data the required technical and financial effort (especially for hardware) is an excluding factor for most type of sports. Therefore, it would be necessary to improve vision based tracking software to get accurate results without an enormous amount of technical effort.

Computer vision related work

On the one hand one can see that computer vision and in particular tracking are increasingly important for digital game analysis. On the other hand many different games like soccer, hockey, tennis and other type of sports have been used as test data for new computer vision approaches.

To handle the unpredictable behaviour of objects of interest during tracking sport games, e.g. athletes and ball, particle filter based methods have become common in that area. Since its introduction into the computer vision by Isard & Blake (1998), the particle filter has been used for various tasks and is a common method for player tracking in sports. The simplicity of the method, the ability to recover from uncertainties during tracking, and the possibility of fusing different information cues in one tracker are major advantages of this tracking method (see Perez, Vermaak & Ganget, 2002; Perez, Vermaak & Blake, 2004).

For the analysis of handball and basketball games Kristan, Perš, Perše & Kovačič (2006) have developed an indoor tracking system. Due to ceiling mounted cameras, the mutual occlusions between players are minimized. The tracking method uses a color based particle filter, considering the player as an elliptical region. The position of an object is then estimated by the center of tracking ellipse. Okuma, Taleghani, De Freitas, Little & Lowe (2003) combined a particle filter tracker with the detection results of an offline trained classifier to track hockey players. The tracking region of a player was defined to be an upright rectangle. Although the tracking results were quite impressive, results on estimated ground positions were not published. A comprehensive framework for automatic annotation of tennis matches was made by the group of Joseph Kittler (Yan, Christmas & Kittler, 2005). The tracking of players was done by subtracting the current frame from a pre-computed background image and using a blob tracker on the results. In addition, a support vector machine is trained to detect tennis ball candidates and a particle filter is used to track the ball.

Our approach

This work presents our approach in beach volleyball for a vision based tracking system which can be used in practice by trainers and athletes without extensive technical effort.

To achieve these goals, the tracking algorithm should be able to track athletes during competitions only by the use of a single camera and without complex calibrations. This has the positive side effect that already existing beach volleyball videos can be analyzed as well. Tracking information should then be used to compute real world coordinates which provide exact position and enable time-motion analysis. We assume an offline annotation and tracking scenario, where the whole game video is available. The tracking and position estimation process must not be fully autonomous. Therefore a small amount of user interaction for correction and re-initialization is acceptable.

Due to the playing characteristics of beach volleyball (and most other game sports) and the constraints due to a single camera the tracking algorithms used have to handle rotations and scale changes of bodies, e.g. squatting during a receive action. Specifically for beach volleyball the tracking methods should provide position information to improve the rating of techniques as well as motion analysis to estimate physical load (e.g. by detecting jumping movements as seen in Fig. 1).

Our approach consists of in three main parts: configuration, tracking and position estimation. In the configuration step, the transformation between video image and court coordinates is calibrated. Furthermore color and scale references are predefined for each player, by marking them in a single image. A background model is created automatically from input video. A color based tracker which is computational efficient by using integral structures forms the second part. It allows rotations to follow players during all possible motions and estimates the size of a player using the data from the configuration step. The tracker is only applied on the upper part of a player, which stays more compact during motions. If player positions are needed an additional segmentation step, using a skin color classification which was trained beforehand, is applied. This segmentation is only performed within an area defined by the tracker, where the lower part of the body is assumed, and therefore the additional runtime is negligible. Real world coordinates are finally estimated using the calibration from the configuration step. Figure 2 visualizes the main parts and the work flow.

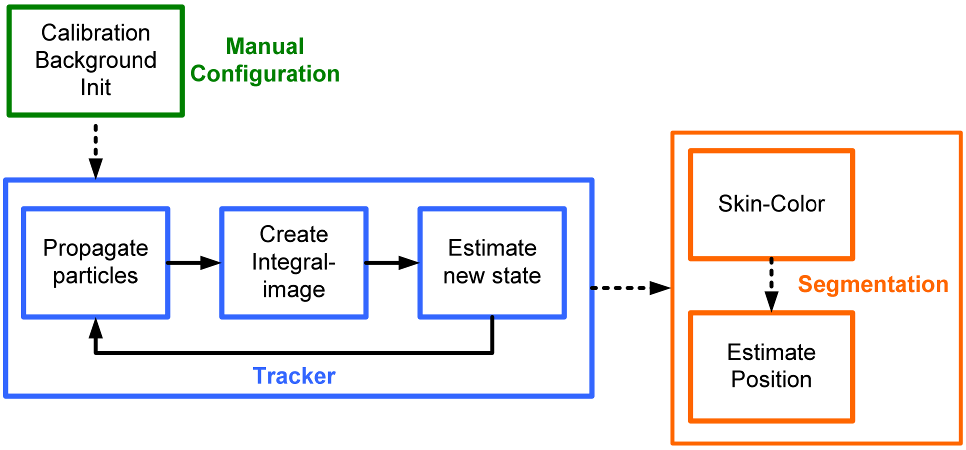

Figure 2.Vizualization of the main processing steps.

The remainder of the paper is organized as follows. First, the particle filter approach is summarized and the transition model used for tracking is explained. Furthermore, the computation of the color properties and the likelihood function of the particles for the single object tracker are described. Based on the tracking results, players are segmented from the background to allow the computation of real world coordinates. Experiments show an evaluation of tracking and position estimation results on manual annotated ground truth data. Finally, conclusion and summary are given at the end.

Methods

This section describes the tracking method used in this work. The particle filter concept is briefly explained in addition with the motion and appearance model used for player tracking. Object scale estimation and problems with position estimation from single view cameras are illustrated. In order to obtain real world coordinates, an additional segmentation step is performed.

Tracking with particle filter

The idea of the particle filter is to estimate the state $\mathbf{x}_t$ of a tracked object by using a set of weighted particles (Isard & Blake 1998). Each particle simulates the behavior of the object using Monte-Carlo simulations, a motion model and a measurement. Given a state space model $\mathbf{x}_{t-1}$ at time t-1 and all measurements up to t-1 known as $\mathbf{z}_{1:t-1}$ the posterior $p(\mathbf{x}_t \mid \mathbf{z}_{1:t})$ can be estimated by the recursion of Equations 1 and 2 using the new measurement $\mathbf{z}_t$.

Predict: $$p(\mathbf{x}_t \mid \mathbf{z}_{1:t-1}) = \int p(\mathbf{x}_t \mid \mathbf{x}_{t-1})\, p(\mathbf{x}_{t-1} \mid \mathbf{z}_{1:t-1})\, dx_{t-1} \quad (1)$$

Update $$p(\mathbf{x}_t \mid \mathbf{z}_{1:t}) = \frac{p(\mathbf{z}_t \mid \mathbf{x}_t)\, p(\mathbf{x}_t \mid \mathbf{z}_{1:t-1})}{p(\mathbf{z}_t \mid \mathbf{z}_{1:t-1})} \quad (2)$$

The required posterior density function p($\mathbf{x}_t$ | $\mathbf{z}_{1:t}$) of the new state can be approximated using sequential Monte Carlo simulations of a finite set of particles $\{x_t^i\}_{i=1\ldots Np}$. From an initial state, the weights $\{w_t^i\}_{i=1\ldots Np}$ associated with the particles are computed by sampling from a proposal distribution q($\mathbf{x}_t$ | $\mathbf{x}_{t-1}$,$\mathbf{z}_t$) (see Equation 3).

$$w_t^i \propto \frac{p(z_t^i \mid x_t^i)\, p(x_t^i \mid x_{t-1}^i)}{q(x_t^i \mid x_{t-1}^i, z_{1:t}^i)} \qquad \text{where} \qquad \sum_{i=1}^{N_P} w_t^i = 1 \quad (3)$$

Using the state transition model p($\mathbf{x}_t$ | $\mathbf{x}_{t-1}$) as proposal distribution leads to the bootstrap filter, where the weights are directly proportional to the observation model p($\mathbf{z}_t$ | $\mathbf{x}_t$). Finally, the posterior density can be approximated by $p(\mathbf{x}_t \mid \mathbf{z}_{1:t}) \approx \sum_{i=1}^{N_P} w_t^i x_t^i$. To avoid the degeneracy of the particle set, resampling of the weights is done if necessary (see Arulampalam, Maskell, Gordon & Clapp, 2002, for more details).

State model used for players

During the tracking process players are described with rectangles given by center coordinates, size and rotation angle. In image coordinates the state model of an player at time t is defined by $\mathbf{x}_t = [x_t, y_t, \upsilon x_t, \upsilon y_t, \varphi_t]$ where (x_t,y_t) are the center coordinates of the rectangular window, $(\upsilon x_t, \upsilon y_t)$ are the velocities and φ_t is the rotation angle of the player, see Figure 3. The size of a player (h,w) during tracking is computed directly, using the assumption of a fixed camera. The Homography **H** between image coordinates and real world court coordinates is determined with an initial manual calibration. If a player is annotated once as a reference, for example during initialization of the tracker, the scale parameters (h,w in Figure 3) for different court positions can be estimated using the Homography **H**.
The real state of a player $\mathbf{x}_t$ is estimated by a set of particles simulating possible states x^i_t. Applying an autoregressive model with an constant velocity assumption, the transition probability p($\mathbf{x}_t$ | $\mathbf{x}_{t-1}$) can be represented by:

$$\mathbf{x}_{t+1} = \mathbf{A}\mathbf{x}_t + \mathbf{v}_t \quad (4)$$

With this model the motion of particles is defined by a drift component defined in matrix **A**, equal for all particles of a player, and a random component in $\mathbf{v}_t$, which is assumed to be normally distributed for x, y and φ.

Using the homography

Assuming that image coordinates are given for each player, one would be interested in the real world coordinates. Reconstruction of full 3D coordinates of players or ball requires at least two cameras, which we do not have in our setup. However, under the assumption that the players are moving on a specified plane one can use a perspective mapping between two planes, defined by the Homography, to compute court positions of players (for details see Hartley & Zisserman, 2002).

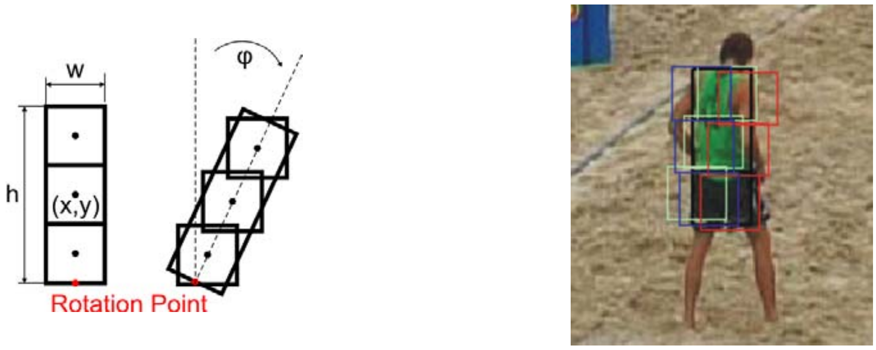

Figure 3. Left: Object description for players by a rectangular patch. For approximation of rotation the tracker is divided into three sub-parts. Right: Image shows 3 possible states of particles with different positions and orientations in blue, green, and red.

$$\begin{pmatrix} x' \\ y' \\ z' \end{pmatrix} = \begin{bmatrix} h_{11} & h_{12} & h_{13} \\ h_{21} & h_{22} & h_{23} \\ h_{31} & h_{32} & h_{33} \end{bmatrix} \cdot \begin{pmatrix} x \\ y \\ 1 \end{pmatrix} \qquad (5)$$

Estimating the unknown Homography matrix H in Equation 5, requires at least 4 points in the image and in the target view, respectively. The linear transformation uses the homogenous coordinates of image points $[x\ y\ 1]^T$ to compute the transformation to the given target coordinates $[x'\ y'\ z']^T$. In the resulting rectified view perpendicular angles are reconstructed and, with the metric world coordinates given, one can reconstruct real world court coordinates (e.g. 8x16m for beach volleyball, visualization in Figure 4).

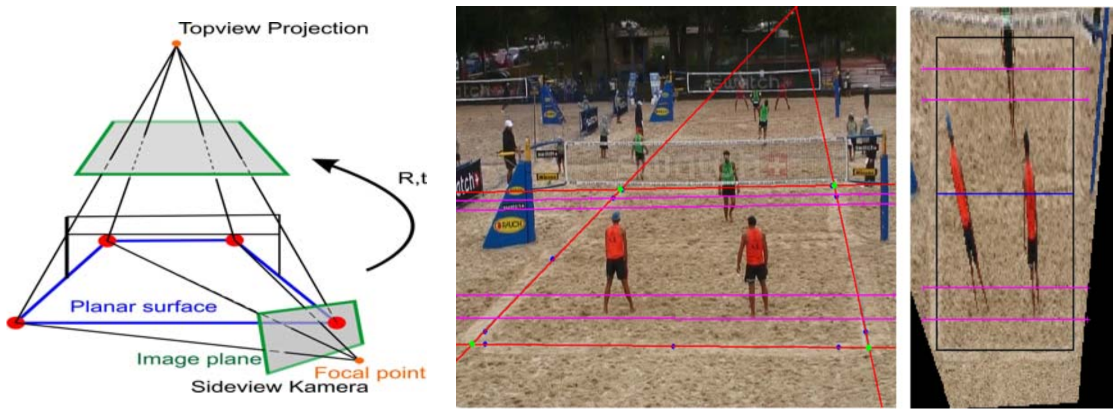

Figure 4. Left: Projection of real world points to the image plane of a camera and the transformation to a virtual top view projection. Right: The known coordinates of the playfield corners are used for calibration of the setup. Screenshot shows the perspective camera view and the undistorted top view image. The differences of the resolution in depth are shown by the parallel lines in both views.

With the world coordinates in meters and given the frame rate of the video stream, approximations of speed and acceleration can be calculated. The achievable accuracy of the field coordinates depends on the resolution of the camera as well as on the distance and orientation between player and camera. Players further away from the camera center have a lack of resolution, especially in the y-coordinates, and therefore less accurate positions can be calculated.

It has to be mentioned that the Homography transformation contains only the transformation between planes, as shown in Figure 4. Therefore, it only holds for points on the calibrated playfield. By tracking players who are not on the ground plane, the projected position would be wrong (see Figure 5).

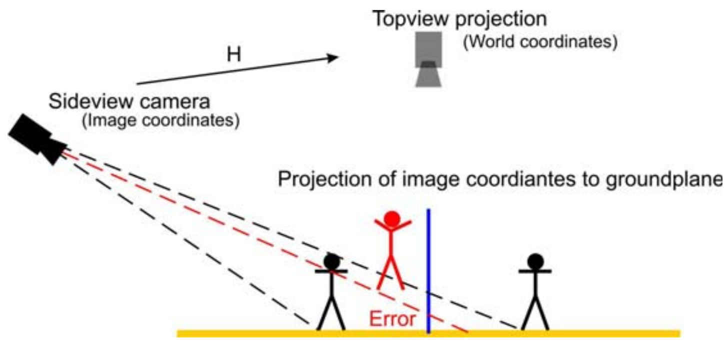

Figure 5. During jumps players are off the calibrated ground plane. The estimated positions contain an error especially in their y-coordinates, due to the assumed projection onto the ground plane.

Color tracking

To evaluate the set of particles, a measurement function has to be defined to see how good a particle fits to the real state of a player. Color information is a simple but powerful method to describe an object of interest. In contrast to shape description methods, which have also been used with particle filters, color information is less vulnerable to clutter. In particular, the intensive and distinct team colors in sports support the use of color histograms for our model description.

Using the HSV color space, an object is described with 3 independent N_B-bins histograms for the hue, saturation and value channel. An object, in our case a player, is initialized with three reference histograms [$\mathbf{h}^H_{ref}$, $\mathbf{h}^S_{ref}$, $\mathbf{h}^V_{ref}$] for the color channels. To compare candidate histograms [$\mathbf{h}^H_P$, $\mathbf{h}^S_P$, $\mathbf{h}^V_P$] sampled from a particle estimation with the reference histograms, the Bhattacharrya similarity coefficient $D(\mathbf{h}_P, \mathbf{h}_{ref})$ is used. Combining the color channels the likelihood model $p(z^C \mid x)$ is finally assumed as exponentially distributed with a weighting constant λ as shown in Perez et al. (2002).

Histogram creation for each particle is a very time consuming task. Moreover, the particles overlap most of the time, so that many image areas are described several times. Porikli (2005) computed the histogram information of an image using the integral image approach, which leads to a drastic speed up. Additionally, the integral structure is only needed for the image area covered by particles, which is usually much smaller than the whole image.

Once the integral histogram is computed for an image, the histogram information of particles can be obtained using only three operations independent from position and scale of the particle. The disadvantage of using the integral structure is that it cannot be rotated. Lienhart & Maydt (2002), proposed a method to compute 45° rotations in the integral image which is not sufficient for our aims. Barczak, Johnson & Messom (2006) extended the set of possible rotations to any angle by approximating from pre-computed rotated images. Applying such an approach to a huge set of particles with different rotations would diminish the speed up achieved by the integral approach.

We decided to use an approximation approach similar to Grabner et al. (2006). The original tracking rectangle is divided into N_S subparts to approximate the rotation in the integral image (see Figure 3). Assuming that the subparts are independent, the color likelihood for a particle with state x and consisting of N_S subparts is finally computed by:

$$p(z^C \mid x) = \exp(-\lambda \cdot \sum_{j=1}^{N_S} \sum_{C \in \{H,S,V\}} D^2(h_{j,P}^C, h_{j,ref}^C)) \qquad (6)$$

The improper approximation of the object due to the rotated subparts is compensated by the high number of available particles. In addition, a spatial relation is integrated into the likelihood computation of the particles, which was also shown by Perez et al. (2002). This leads to more stable tracking results. Furthermore, the number of subparts and their spatial relation can be changed.

Including information about background

Usually, kernel or mask functions are applied to take into account that some background pixels are always included in the tracking window. To measure the influence of background pixels in our integral approach, a background probability $p(z^B \mid x)$ is included in the formulation of the measurement likelihood of the particles. Because of the static camera, the background image can be computed in a preprocessing step. Using Equation 6 also for the background similarity, the final observation model for a particle is given by:

$$p(z \mid x) = \frac{p(z^C \mid x\ )}{p(z^C \mid x\ ) + p(z^B \mid x)} \qquad (7)$$

For every particle i with state x^i_t at time-step t, the background similarity $D(\mathbf{h}^i_{j,P}, \mathbf{h}^i_{j,B})$ is measured for each subpart j. The histogram $\mathbf{h}^i_{j,P}$ is sampled from the actual frame and $\mathbf{h}^i_{j,B}$ is computed for the same area in the background image. The integral structure for the background has to be computed only once beforehand (see Figure 6). Integrating the background probability prevents the tracker from drifting into background regions during mutual occlusions of the players.

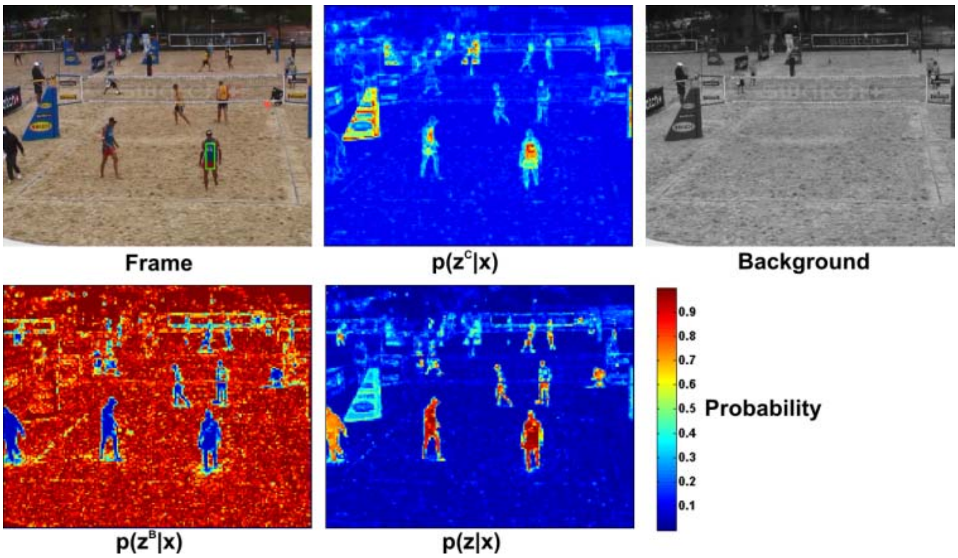

Figure 6. Top-row: Left: Actual input frame, where the green rectangle marks the patch used for the reference color histogram. Middle: Probabilities of pixels being the tracked object, using only color information. Similar colored objects in the background cause errors. Right: Pre-calculated background image. Bottom-row: Left: Probability of areas to be background. Right: Combined probabilities where background areas with colors similar to the tracked players, like advertisement spaces, are less likely now.

Segmentation and position estimation

Based on the obtained tracking results which are valid for the upper part of the athletes, the computation of the real field position is bounded on a smaller area. Knowing the position of the player, the rotation-angle of its body and an estimated scale, an area for segmentation is defined in the video frame.

The similarity between skin colored and sand colored pixels makes it hard to segment the patch in player and background. We chose to transform the RGB pixel into the YCbCr color space, which has shown good performance for face or skin segmentation tasks (Phung, Bouzerdoum & Chai, 2005). Using about 2 millions of skin, sand and background training pixels, a mixture of Gaussian models have been computed in an offline process to describe the different classes in the YCbCr color space (Figure 7 shows some segmentation results).

Figure 7. Left: Original input video frame. Middle: Segmented sand-colored pixel. Right: Skin segmentation can be used to create more accurate information about player positions.

Using the segmentation results of skin colored pixels and pixels containing to the player, known from tracking, the image can now be divided into player and background regions. Morphological operations are used to filter out small segmentation errors. The final segmentation result, which can be seen as an example in Figure 8, is a combination of the biggest segmented regions.

The estimated ground position in image coordinates (x,y) of a player is computed by the mean of all x-coordinates of the segmentation and the maximum y-coordinate. This is motivated by the fact that the mean represents the center of gravity of the region, respectively the player. The maximum y-coordinate is taken because of the used projection from image coordinates to real world coordinates.

One can see that the combination of tracking and segmentation results leads to more accurate results. Assuming a fixed size for the lower part of the player, or using only a rectangular window, would only be valid for players standing upright.

Evaluation experiments and first results

The following section contains an evaluation of the proposed tracker. The method is compared to manual annotations in terms of overlaps on players and estimated field positions. Therefore, a set of 12 test-sequences, each consisting of several hundred frames was used. All sequences, including male and female rallies, have been annotated manually at every third frame. Additional results for multi-object tracking in sport applications can be seen in Mauthner & Bischof (2007).

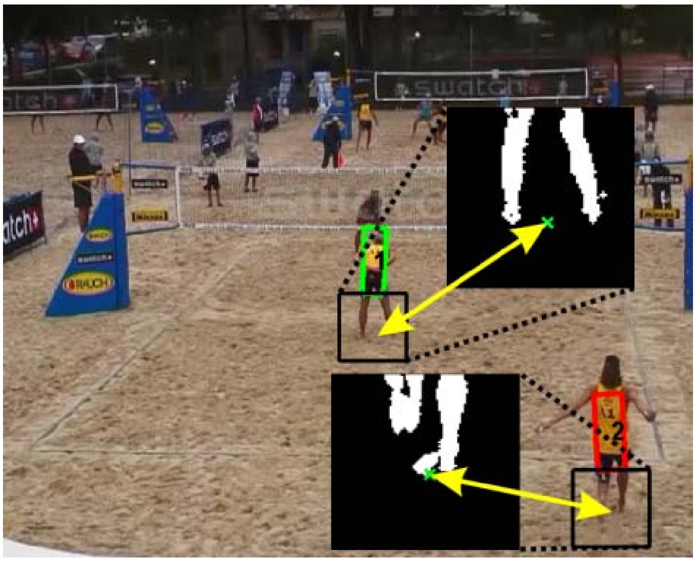

Figure 8. Segmentation of patches into player and background regions. Size and position of the segmented region are derived from the tracker result. Estimated positions are indicated by arrows.

Verification of tracker results

The reference ground-truth was manually annotated by experts familiar with beach volleyball. A rotated rectangle was placed over the upper part of the player by the annotators in every third frame of the test videos.

An overlap factor is computed from the shared area between the manual reference and the tracking result in relation to the total area of both rectangles (Figures 9 and 10). Total overlap of reference annotation and tracking result in an overlap factor of 1 and no overlap leads to a factor of 0.

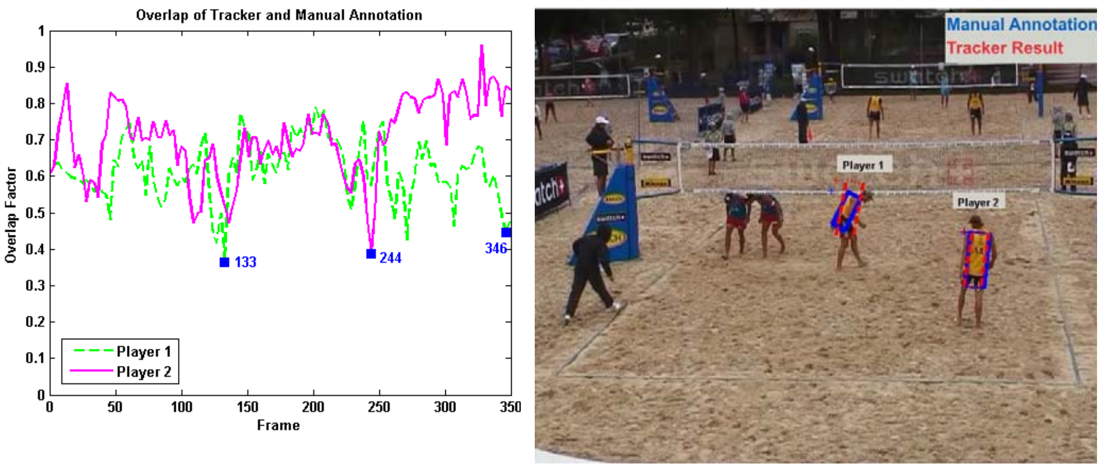

Figure 9. Left: Progression of the overlap factor during tracking of two players during sequence 1. Right: Manual annotation (blue rectangle) and tracking result (red dashed rectangle) for frame 346 in sequence 1. Both players are fully covered by their trackers, but according to the bending of player 1 the overlap factor is about 0.4, and lower than for player 2.

As described in the method section, the result of the tracker is computed over a weighted sum of the particles. The size of each particle is estimated from its position, and therefore, the size of the tracker result is always a combination of different scales. Additionally, the size of a torso is assumed to be fixed, which is not true, in image coordinates, if the players bend or crouch during the game. These mentioned difficulties do not exist if annotation is performed by a human, and therefore experts always scaled their reference rectangles to the visible part of the upper body. Low overlap values during such frames can be traced back on the differences between human perception and automatic computation (see Figure 9 and Figure 10).

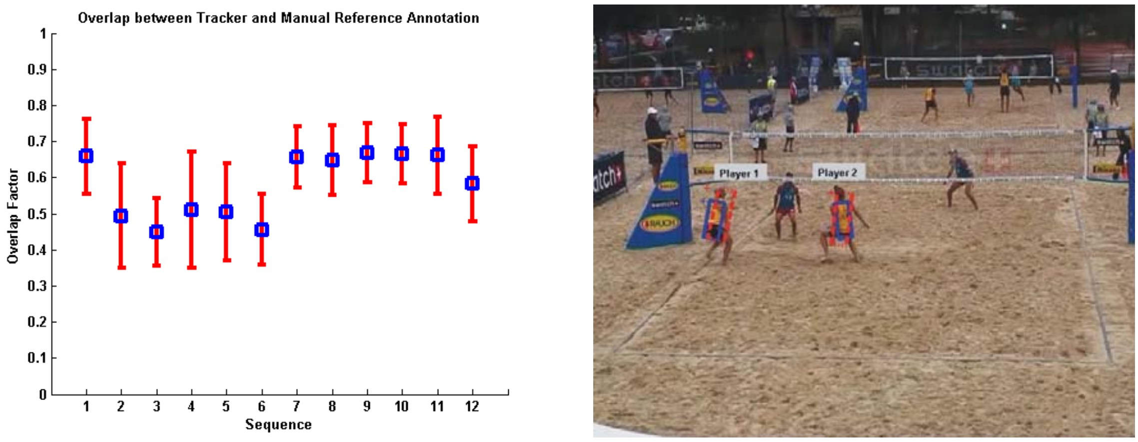

Figure 10. Left: Tracker overlaps on all test sequences, given by mean values and standard deviations. The sequences 2 - 6 belong to female games for which automatic tracking is less accurate due to the smaller amount of specific colors and the similarity between sand and skin color. Right: Manual annotation and tracking result for frame 133 of sequence 1.

A notable difference between sequences extracted from male and female games can be seen in Figure 10. Sequences from 2 to 6 are taken from female games, while sequence 1 and sequences 7 to 12 are from male competitions. This effect can be explained by the different appearances of the athletes. Male athletes wear shirts which, most of the time, are distinguishable from the background due to specific team colors. Because of the similarity between skin and sand color, the appearance of female athletes is not that precise during tracking which makes it harder to estimate the correct scale of a player. Nevertheless, the overall performance is balanced over the sequences. Considering the example frames given for sequence 1, an overlap factor of 0.45 still means an acceptable tracking result. Please note that no manual interaction was needed during the 12 test scenes.

Estimation of field positions

Similar to the tracker evaluation the reference position data consists of manual annotations. For every third frame of the test sequences, an image coordinate per player was defined as the reference position. The difference between manual reference and automatic position result is given as the Euclidian distance in image and real world coordinates.
Results of estimated positions are directly compared with the manual ground truth, without any additional filtering. The variance in the results could be reduced, if situations like jumps and occlusions between players would be excluded or corrected manually. Note that even varying human annotations can result in different position results. Figure 11 shows a visual comparison between estimated positions and reference annotations. Trajectories of one team during a rally are show individually in two separate top-view projections.

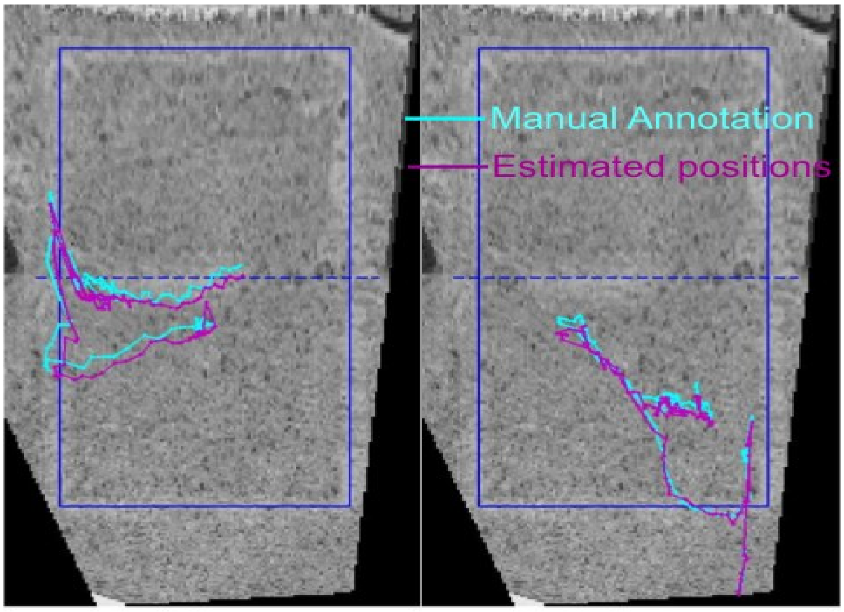

Figure 11. Comparision between manual annotation and results of our method. Positions are shown for every third frame only. Left and right images show the manually in comparison with automatically generated trajectories of two different players during a rally. Note left image: Projection causes a wrong position estimation into the opponent field during a jump movement (left side of the field). After the landing the player position was estimated correctly again.

As previously observed, several problems may occur when computing an exact athlete position from a single camera view. Depending on the point which is projected to real world field coordinates, the position can vary. Even the distance between both legs can be around half a meter. Additionally, the accuracy of the projection depends on the geometric resolution per pixel. In the used test sequences, the resolution varies between 3 cm/pixel and 10 cm/pixel, depending on the distance to the camera. Considering this fact, the results shown in Figure 12 are satisfying. Compared to the tracking results no difference between male and female games is observed. This effect can be led back to our special skin segmentation step.
Nevertheless, the results are accurate enough to answer several sport scientific questions and can be used for further analysis. Based on this position data, other parameters such as velocity and acceleration can be derived. Using the projected coordinates of the tracker, the resulting speed during jumps is not realistic due to projection errors (see Figure 11). Furthermore, a characteristic motion occurs, consisting of acceleration away from the camera followed by the inverse motion back towards the camera. The whole jump motion takes place in a maximum timeslot of about 30 frames. Such a shaped pattern can easily be found in the provided velocity data of each player and therefore could be exploited to detect jumps.

Conclusion and further work

A simple and yet effective method has been presented for tracking multiple objects within the scope of sport applications. The presented approach aims at obtaining position and motion information using the video input of a single camera, as this is the typical situation in sports practice. This aim could be achieved by combining several computer vision methods. By dividing the tracker window into subparts, the approximation of rotations in the integral histogram is possible. Therefore, sport specific motions can be followed with almost no additional runtime compared to using only an upright rectangle. Tracking results and segmentation of skin colored regions are combined to estimate real world court positions of athletes. Together with the possibilities of using the calibration for scale estimation during tracking and computation of real world coordinates, we are able to create useful tracking and position results for beach volleyball games.

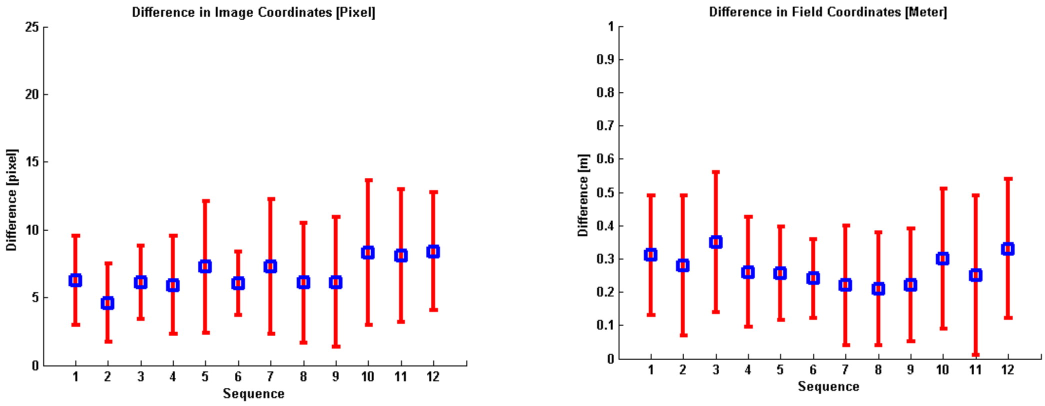

Figure 12. Comparison of manual annotated positions and the results of the automatic method in image and real-world coordinates.

The main advantages compared to existing methods are the rotation sensitivity, which delivers tracking results more similar to human annotation, and the combination of tracking and segmentation. As shown in the results, our methods deliver more information to analyze player positions than common rectangular or elliptical shaped trackers. We believe that the presented methods, together with a reasonable amount of manual interaction, are sufficient for motion analysis and the evaluation of physical demands in beach volleyball. Preliminary results indicate that it will be possible to detect frequency of jumping movements automatically in future. Furthermore, position data can be used to improve accuracy of action annotations and tactical analyses. The presented results are valid for beach volleyball but can be principally transferred to similar outdoor sports where fixed multiple camera systems are not available. A successful application of the presented method would be a great relief for the annotation process in several types of sports.
The integration of the proposed methods into existing game analysis software is the next step. Tracking and position data should be combined with expert annotations about player behaviour and used techniques.

Acknowledgement

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Analysis of Sports Performance as a Dynamical System by Means of the Relative Phase

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KEYWORDS: DYNAMICAL SYSTEMS, SPORTS-MODELLING, INTERACTION, RELATIVE PHASE

Introduction

The notion of relative phases plays an important role in synergetic approaches to movement science. Coordinative patterns between the movements of several limbs within a person (Kelso, 1995) for example, can be characterized by means of the relative phase. Additionally, there are various successful attempts to utilize the cognition of dynamical systems to analyse coordinated interpersonal behaviour (Schmidt, et al. 1990). It is a broadly accepted fact that the theory of dynamical systems helps to deal with the degrees of freedom (Bernstein) problem and that the notion of relative phase is fit to describe and explain the patterns that emerge from coordinated behaviour. But, as all the variables of a complex system are being reduced to one essential - collective – variable (i.e. *order parameter*), which constitutes its' behaviour, one has to be very precise with the choice of this variable. This paper wants to shed light on the potential - but also on the challenges - of a dynamical system's analysis with relative phase measurement of interaction phenomena in (dyadic) game sports.

Theoretical Background

Oscillations consist of multiple *phases* (one period of an oscillation from trough to crest to trough) (Figure 1). The position of an oscillating object within a phase can be measured in degrees from 0° phase angle (trough) to 360°, indicating the final turning point (trough) of a phase and the beginning of a new one. relative-phase measurement determines the objects` position within their cycles and sets them into relation: the relative-phase is the difference of the objects' position in their cycles. In other words, the relative-phase is able to quantify degree and order of interaction of two oscillating objects.
According to the theory of dynamical systems, coordinated behaviour is a result of the interaction between two or more microscopic components of any complex system; the components self-organize to form a stable macroscopic pattern. This theory of pattern formation in complex systems was found to be accurate for various phenomena, even if the components of a complex system are not physically coupled. Even light photons obey to the principle of self-organization (Haken, 1978) or pattern-formation: If confined, they begin to interact and organize to homogeneous laser light. In sports, the relative phase is applicable to numerous examples of – intra (see Kelso, 1995)- and interpersonal – pattern formation. While in an intra-personal coordination task the components of the complex system "human body" are coupled via the central nervous system, the components of a system in which interaction takes place inter-personally (for example in tennis) act in a coordinated manner on basis of common, shared information. This information could for example be acoustic, like a

rhythm that is commonly perceived and shared by the components (e.g. *paired canoe*) or a visual, for example, the commonly perceived position of a ball (tennis, squash, soccer …).

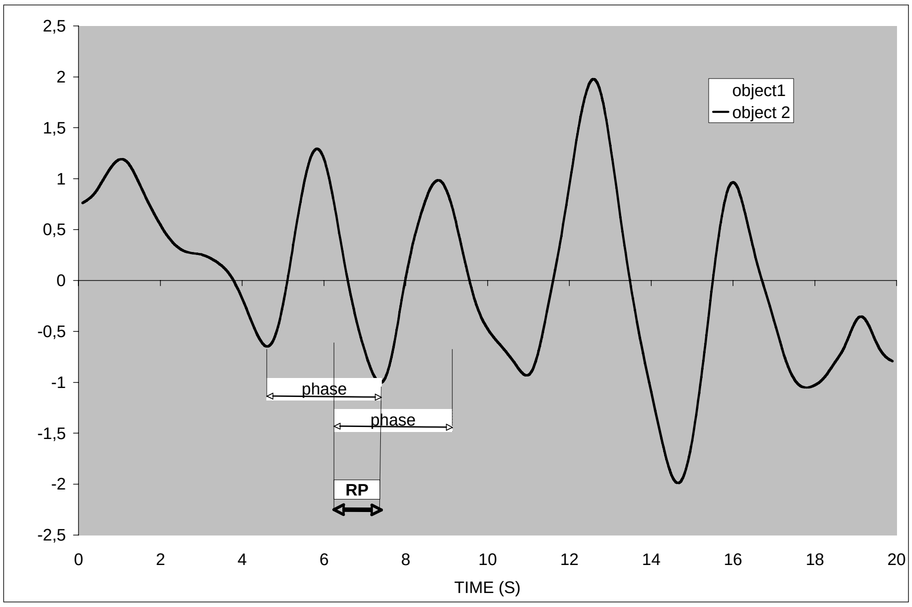


Figure 1. Oscillations and phases of Tennis players (Lateral Displacement)

The Relative Phase – an Example from Sports Behaviour

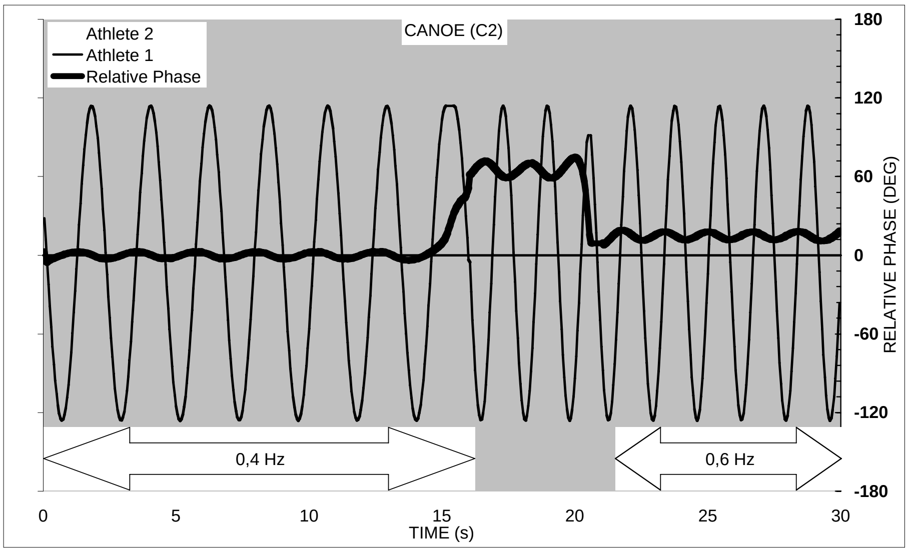


Figure 2. Paired canoe time-force curves (fictional data)

The actions of a sprint-canoe pair are a simple example for interpersonal coordination: The pattern of their behaviour (namely “pulling”) determines position and velocity of the canoe and can be seen as the collective-variable (i.e. *Order Parameter*). The optimum state for this variable would theoretically be perfect synchronicity. The calculation of relative phase for these canoeists on the basis of their time-force curves is a straightforward thing – the cyclical structure of their movements is apparent. The relative phase sets the two canoeists’ actions into relation and identifies periods of stable interaction (i.e. *Attractors*); it quantifies these attractors on a scale from 0 to 360 degrees. Also, fluctuations of synchronisation can be identified, quantified and attributed to one of the athletes. Figure 2 shows a force-time plot of two canoeists (the data is fictional). Pulling with a frequency of 0,4 Hz, the two athletes' force plots are congruent – they are in a state of perfect synchronisation. The corresponding value of the relative phase is 0º, *In-Phase*. When changing the rate of strokes, the formerly stable phase-relation becomes imbalanced. The relative phase displays value of about 90º. This fluctuation from a stable state cannot be a liveable condition of the system (i.e. *Perturbation*). From the direction the value changes, one can tell who of the two athletes caused the perturbation: a positive fluctuation identifies athlete 1; he leads distinctly for a moment in relation to athlete 2. After this short fluctuation, the two fictional athletes find back into a stable coordinated behaviour but still athlete 1 is slightly in arrears to athlete 2. And again, the positive value means that athlete 1 is now beating the time in this example (or "leading the rally"," putting pressure on his opponent", "being the actor instead of being the reactor", in other examples…). The system "paired canoe" showed two stable patterns, quantified with relative phase values of 0° and approx. 15° in this instance. A system can have various preferred states (*Attractor*). An Attractor is also a state of the system in which it could persist indefinitely. Apart from that, there are variations of the relative phase that do not indicate transitions between attractors, but report intolerable changes to the systems' stability. If the system does not manage to settle back into any Attractor-state immediately, these *perturbations* usually result in the breakdown of the interaction (or the rally).

The Relative Phase and Dyadic Game-Sports

The behaviour of players of dyadic game sports is also synchronised or, in other words, coupled: action and reaction are interdependent. If a reaction does not match the action prior, the formerly stable action-reaction pattern becomes imbalanced: one player is "ahead" of the other and controls the rally by imposing pressure on the other player. The major problems in the theoretical approach to game sports are:

- to find an appropriate description for the characteristic patterns of these sports
- to quantify their most essential property, namely the interaction process between the players

(a.) Many game sports – first and foremost the dyadic racket sports Squash (see Figure 3), Tennis (see Figure 5), Badminton, Table Tennis, etc. – show quite distinct patterns for the interaction of the players: they perform a "dance" around a central position on the court they aim to defend. On the other hand, they try to force their opponent to leave his centre-position and to make it impossible for him to return in time: the pattern can generally be described as oscillation to and from one central point on court.
(b.) From a dynamical systems view, these spatial interactions can be described by means of relative phase (Mc Garry, et al., 2005; Palut & Zanone, 2005; Lames & Walter, 2006).

The ability to quantify stable patterns, but also to detect critical situations by means of the relative phase (RP) was examined at the instances of squash and tennis.

Methods

For squash (see also McGarry et al, 2005), 47 rallies from the quarter finals of a world cup tournament – for tennis (see also Lames & Walter, 2006), 25 rallies of matches of the 2005 US Open tournament were selected for analysis. The two-dimensional positions of the two players were tracked at a frequency of 10 Hz for squash and at 25Hz for tennis.

Squash

The pattern of movement of the squash players is a regular, two-dimensional oscillation around the central T-position on the court – the centre of the pattern is static. Both longitudinal and lateral motion have the same amplitude. Therefore, radial displacement data was used for relative phase analysis.

Tennis

The tennis pattern is different from the squash pattern: tennis players do take and leave a certain position on court, but this position changes dynamically from stroke to stroke (see Discussion). To cope with this lack of a central reference point, velocity data (2D-speed: the sum of lateral and longitudinal movements per time unit) was chosen for analysis.
The relative phase was calculated on these signals using the Hilbert Transformation (see McGarry et al., 2005 for details of calculation)

Results

Squash

The radial displacement of the players from the T-position on the court is a good source for the essential tempo-spatial information required. It corresponds to the pattern the squash players adopt. Therefore the, pattern is clearly represented in the data: there is a significant tendency towards *Anti-Phase* in the oscillations of the players throughout all 47 rallies analysed (Figure 4). An overall distribution of all the data collected displays only one attractor state for radial displacement. Taking a look at the data of single rallies (Figure 3), a deviation from this stable state can be regarded as an indication of the existence of pressure or a role allocation (initiator/responder). These deviations can be identified, quantified and allocated to one of the players with the relative phase.

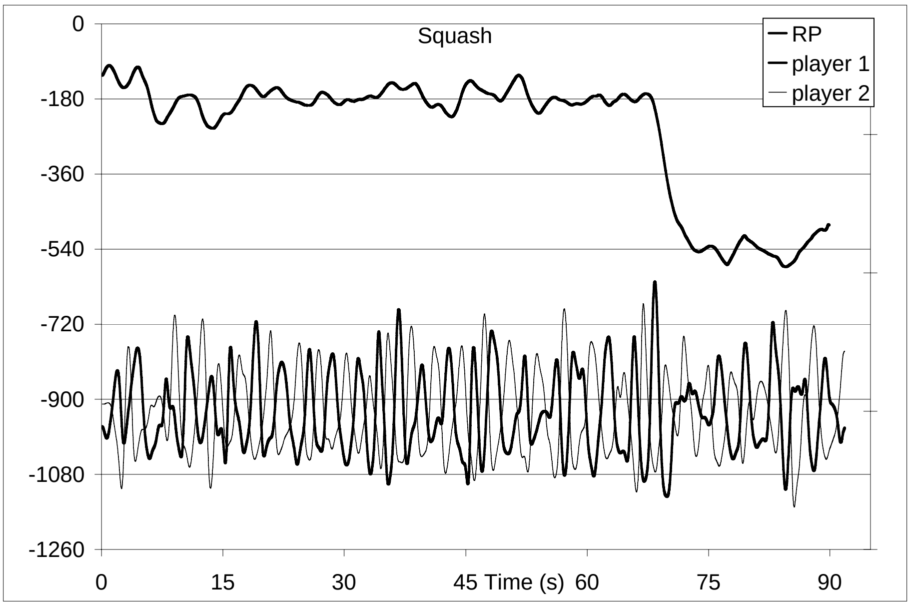


Figure 3. Squash: displacement-data of players and the respective relative phase

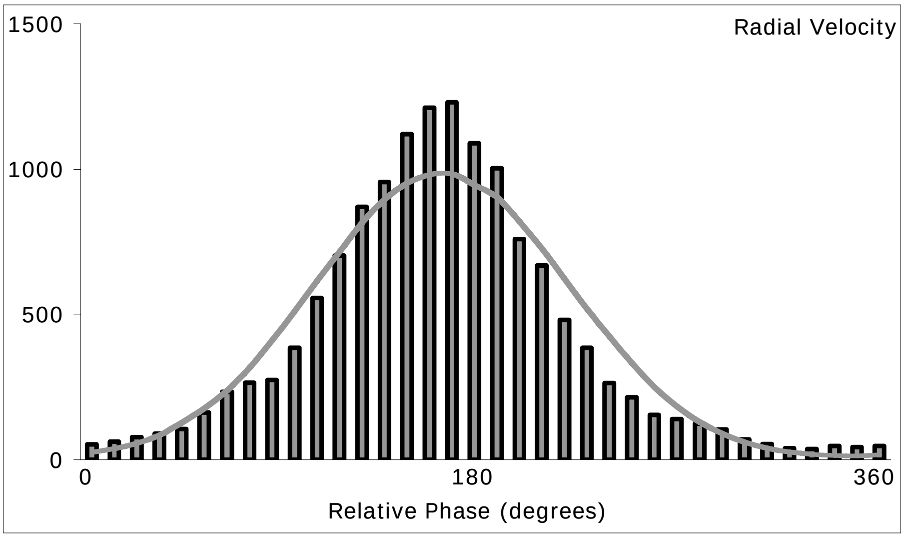


Figure 4. Squash: Histogram of the distribution of relative phase values

Tennis

Cross-play returns RP-values of approx. 180 degrees. For long-line-play, relative phase values of 0 degrees or 360 degrees are obtained. Those two values represent the two stable states/patterns of tennis: anti- and in-phase. Changes between the two stable patterns of tennis play can consequently be identified by the relative phase and are indicated by transitions between *In*- and *Anti*-Phase (Figure 5/Figure 6). Beyond that, the relative phase is capable to identify the initiator of a transition: the down-shift of the RP signal identifies the server as initiator and vice versa. Likewise, instable periods, deviations from one of the attractor states, which occur for example as a result of the creation of "pressure", can be identified, quantified and allocated to one of the players.

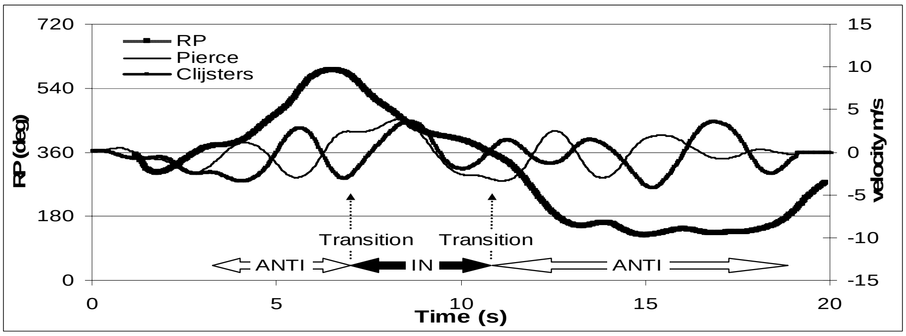


Figure 5. Tennis: Velocity-data of players and the respective relative phase

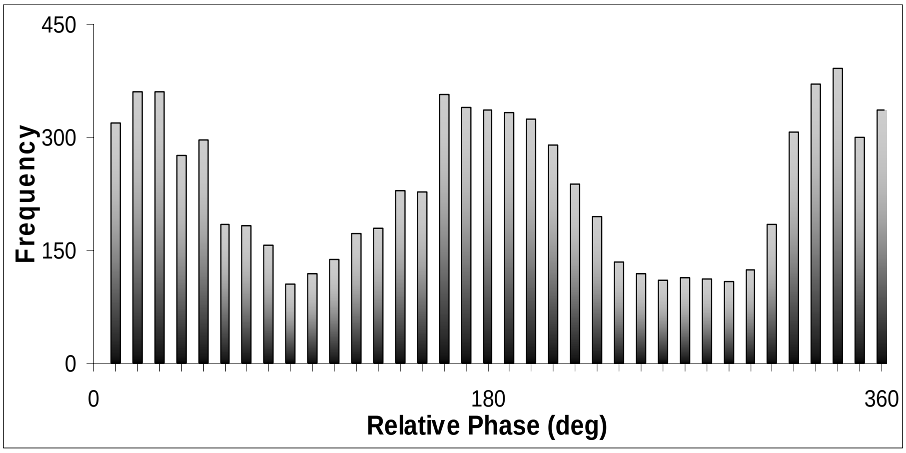


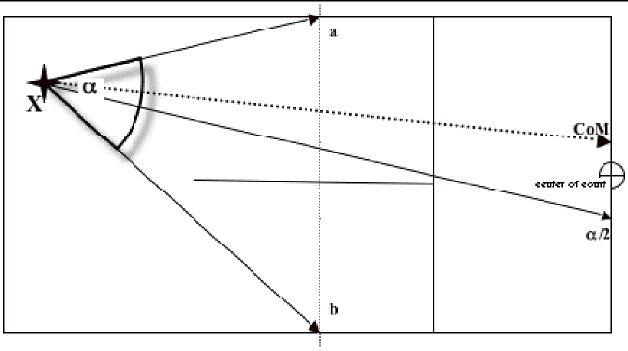
Figure 6. Tennis: Histogram of the distribution of relative phase values

Discussion

The relative phase has turned out to be a promising tool for the analysis of sports behaviour. Indeed it is one of the few, if not the only method that is able to quantify what is the essential basis for performance in all game sports, namely the interaction with a partner and/or an opponent. The most important prerequisite for a dynamical systems analysis of interaction phenomena with the relative phase, is to choose the right collective variable; if this choice is made carefully, an analysis with dynamical system's methods is possible: There is sports behaviour with clear and almost static patterns like rowing or canoeing, when interaction is simply a matter of synchronisation and the choice of the collective variable is straightforward (syncronication/rythm in rowing, etc.). But there is also more complexly patterned behaviour in sports that requires some effort to identify a order parameter For example : "What is the pattern of soccer?". Whoever is able to answer this question is a rich person. – Finding a precise definition of the pattern of soccer is likely to be a very challenging endeavour, but that does not mean that there is none to be found: Humans tend to have a very accurate intuition on patterns. Who does not know the feeling that one has from time to time, when you are watching a soccer game and for some reason you could literally *feel* that team X would be about to score – and a few seconds later they really do. Some information in the spatio-temporal movement of the teams or maybe just of a few players of one or the other team, conveyed to the watcher that the stability of attacking and defending has become out of balance, that the stable pattern is perturbated and something (a goal) is likely to happen, as a result. Tim McGarry (2005) did some very interesting research on the human capability to identify patterns. Human common sense could indeed do a great deal of help in the definition of control variables.

What makes things a bit easier also is that sports games do generally have oscillating characteristics. As mentioned before, there is always action and reaction – and these spatial interactions of the two players finally incorporate what is essential to the game.

For more complex sport game there will definitively no static pattern, no spatial oscillation around a fixed centre to be found. It is more likely that the search has to be for oscillations around a dynamical probabilistic centre: An example: In tennis, this centre of probability is located in dependence on a player's shot and on the opponent's possible reaction: "What situation am I possibly creating with my action? What is the possible reaction I have to expect? AND: Where is the place from which I am best prepared for this?" This scenario can be anticipated by a player and has to be updated for every phase of the rally. In other words, the centre of a pattern can be considered the dynamical centre of a (symmetrical) "room" of possible states of the system.



Excursus tennis: Centre of Movement (COM)
The moment a player places a shot, he estimates the position where the opponent reaches the balls and which range of possible answers he has to expect from this position. According to this knowledge, he positions himself in the centre of this spectrum – he anticipates the shot. For Tennis, this probability-centre is generally assumed to be the bisector(α) of the shooting players range of possible shots. (see Fig. 7) Furthermore, one has to take velocity into account: As a result, the centre is shifted from the bisector towards that side where the opponent could hit a faster ball.

Figure 7. Centre of Movement (Tennis)

In dyadic sports like tennis, squash, badminton, etc., this position is the location where a player is best able to react, and this centre is to be defended. If both players always managed to return to this point, the rally would go on indefinitely: The oscillation relative to this point can be regarded as the order parameter or collective variable of tennis and other game sports. Generally, a good understanding of the the very nature – the pattern – of the discipline that is to be analysed is indispensable. If this collective variable of a sports game is being chosen conscientiously and precisely, interaction phenomena can extensively and precisely be analysed by means of the relative phase. Coaches' or athletes' expertise is a good source to obtain or affirm a choice on this essential information; likewise is significant agreement of human common-sense on a pattern.
Studying dyadic game sports as a dynamic system using relative phases provides a methodological approach to previously hardly measurable, but essential aspects: creating and recovering from pressure, dominating a rally and preparing the winning stroke. It may be expected that this new approach will be of great practical impact.

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ON THE DETECTION OF SPACE-TIME PATTERNS IN SQUASH USING DYNAMICAL ANALYSIS

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Abstract

Previous research has interpreted the patterned relations produced from the space-time interactions of squash players as a dynamical system. Importantly, the theoretical basis for pattern formation within dynamical systems is predicated upon the shared information exchanges among the parts that comprise them. Thus, the patterned dynamics of a squash rally are the supposed product of shared information (meaningful interactions) of the squash dyad instead of the random interactions that might otherwise be expected to occur from the happenstance pairing of two independent squash players. To investigate the squash dyad for this essential feature of a dynamical system, four data sets of 47 trials were created. Each trial within a data set comprised the individual movements of a number of independent squash players, or distracters (N = 2, 2, 4 and 6 for the four data sets, respectively), as well as the individual movements of two squash players taken from the same squash rally. Thus, a trial within a given data set comprised of a number of distracters (two, four or six) as well as a squash dyad (two players). The question of interest was whether the squash dyad could be identified from the trial using dynamical analysis techniques. To this end, all pair-wise comparisons for all trials were subjected to dynamical analyses and the subsequent outputs were then used to identify the squash dyads using predetermined criteria. The results demonstrated that the outputs from the dynamical analyses were successful in identifying the squash dyad from the distracters well beyond chance expectations for all data sets. These findings were interpreted as compelling evidence that the dynamical features of the squash dyad, as reported in previous research, are indeed the result of shared information exchanges among the players as consistent with dynamical systems theory.

KEYWORDS: DYNAMICAL SYSTEM, PATTERN RECOGNITION, SQUASH

Introduction

From earlier investigations that searched for patterns of play in squash, we offered the possibility that squash – and the other racket sports too – be considered in terms of a dynamical system (McGarry, Anderson, Wallace, Hughes & Franks, 2002). The reader is referred to Kelso (1995) for a general introduction to the underlying principles of dynamical systems, and, as such, we present only a brief account of what the main features of a dynamical system are as they pertain to our interest in racket sports. To this end, the main ingredients of a dynamical system are as follows: First, a dynamical system is comprised of two, or more, parts with each part demonstrating rhythmic, oscillating, tendencies about some point, and; second, the system parts share information with each other – and it is these information exchanges among the system parts that produce the self-organizing, and sometimes selfreorganizing, patterns of behaviour that typify a dynamical system. Interestingly, each of the racket sports exhibits these two ingredients for a dynamical system, as identified, leading to the proposition that the racket sports might usefully be considered in terms of a dynamical system (see McGarry et al., 2002, for additional considerations).

Indeed, some of the trademark features of a dynamical system, for example the rapid transition between two different stable patterns following system reorganization, were subsequently reported for tennis when the lateral (side-to-side) velocities of a pair of players exchanging baseline shots were subjected to dynamical analysis (see Palut & Zanone, 2005, for additional details). The two different stable patterns of behaviour were reported as inphase (observed when the lateral movements of both players were in the same direction at the same instant) and antiphase (observed when the lateral movements of both players were in opposite directions at the same instant). Similar findings were likewise reported for the lateral (side-to-side) and longitudinal (forward-backward) velocities of squash players (McGarry, Walter & Franks, in review), suggesting a common dynamical description for these different racket sports as hypothesized. Using radial velocities instead of lateral and/or longitudinal velocities, however, resulted in a mono-stable pattern with the anti-phase relation providing the single attractor for the dynamical system (McGarry et al., in review). Once again, the anti-phase relation was observed when the radial movements of both players were in opposite directions at the same instant, meaning that the squash players moved from and to the T-position – approximately, centre court – in alternating sequence. This latter finding is of particular importance for this experiment as the strong tendencies of the squash dyad to anti-phase, evidenced when the radial velocities were subjected to dynamical analysis, constitute the basis for pattern detection reported herein.

Since shared information among the system parts provides the basis for pattern formation within a dynamical system, we posit that the information exchanges within the sports dyad produces the dynamical behaviours reported previously for baseline tennis (Palut & Zanone, 2005) as well as squash (McGarry et al., in review). This said, the nature of squash (and the other racket sports) is for both players to oscillate in alternating fashion as each makes shots in sequence within the rally, leading to the formal possibility that the dynamical tendencies identified in the data thus far are the simple product of chance (i.e., the combined outcome of what individual squash players do without particular regard for the opponent) rather than the self-organized behaviour of the squash dyad as a direct result of information exchange, as proposed. Following this line of thought, we demonstrated in recent work that unique information within the squash dyad indeed exists on which the space-time patterns are predicated (McGarry, 2006). Such demonstration was obtained from experimental trials that used point-lights to represent the space-time movements of the squash players (imagine looking down at a squash game from a position above the T with the x-y movements of each player on the squash court represented as a single point-light), the experimental task being to identify using human observation the squash dyad from two distracters that were likewise presented in the same visual display. In one experimental task, the distracters comprised the movements of squash players other than those that formed the squash dyad, and in the other experimental task, the distracters comprised the movements (from other rallies) of the same players as those of the squash dyad. The two distracters were not permitted to constitute a squash dyad themselves under any circumstance. That human observers identified successfully the squash dyad from the distracters well beyond chance expectations for both experimental conditions provided unequivocal evidence that the space-time dynamics of the squash dyad are unique and subject to detection using human perception. The information embedded within the space-time dynamics of the squash dyad that affords pattern detection, however, remains unknown at present and awaits further investigation. Therefore, the aim of this experiment is to examine whether such information contained within the squash dyad is dynamical in nature, as hypothesized, and whether a dynamical analysis of these data is thus sufficiently discriminatory for pattern detection as predicted.

Method

Eight squash players from various squash rallies were selected for analysis of movement patterns from video records of four quarter-final matches. These same video records were used in previous experiments from which a description of shot selection behaviours using probability measures yielded unsatisfactory results. The reader is referred to McGarry and Franks (1996) for further details.

Twelve squash rallies from each quarter final were selected at random from the data set, thus yielding 48 squash rallies for analysis. (In fact, 47 rallies instead of 48 rallies were available for analysis because of experimenter oversight in data collection.) Using a graphics tablet (12 inches by 8 inches), the movements of each squash player in each rally was transcribed from the video records by the experimenter as follows. First, the dimensions of a squash court were laid onto the surface of the graphics tablet. The image of the graphics tablet obtained from a video camera pointed at the graphics tablet was then superimposed onto the video data by mixing the signals from the video camera with those from the video recorder. In this way, a dual image was created and displayed on a television monitor. The superimposed image was arranged such that the squash court dimensions on the graphics tablet were matched with those squash court markings evidenced in the video records. The movements of each squash player were then tracked by the experimenter on a trial-by-trial basis using the stylus pen of the graphics tablet. Touchdown of the stylus marked the onset of data collection, as determined from the instant that the squash racket of the server first made contact with the ball. Thereafter, the experimenter tracked in real time the centre of gravity of the player as perceived, with visual feedback of the stylus and the player in the mixed video image being available at all times. Following data tracking of both players in a squash rally, the data were time-locked to each other using the start of each rally. The x-y data were sampled from the graphics tablet at 10 Hz.

Intra-rater reliability

The experimenter performed as many tracking tasks (trials) for a given squash player in a given squash rally as deemed necessary for that data to be considered as satisfactory. For reliability assessment, at least two satisfactory trials were recorded for each squash player from all squash rallies from the first and second quarter-final data. In the third and fourth quarter-finals, however, only the data from a single trial considered as satisfactory was collected except when the data from the squash rally was considered as being particularly difficult to record. In these instances, at least two satisfactory trials were collected as before. Intra-rater reliability was assessed from the repeat trial data using the Pearson product moment correlation coefficient. The results demonstrated a high level of reliability in data collection as evidenced in the mean correlation coefficients of 0.977, 0.956, and 0.939 for the lateral (x), longitudinal (y), and radial ($\sqrt{(x_2 + y_2)}$) data, respectively.

Data Preparation

The radial displacement data (i.e., the distance from the T) were used to obtain estimates of the radial velocities of the squash players. To standardize the information content within the data set, and thus within each trial (see experimental design), the radial velocity data were truncated to 10 seconds information (from the start of the third second of data collection through to the end of the twelfth second). The radial velocity data were then subjected to Hilbert transformation (see McGarry et al., in review, for further details on this procedure) for purposes of relative phase analysis and subsequent identification of the squash dyad.

Relative Phase

The relative phase is a measure of where a squash player is in his/her movement cycle with respect to the other player. For example, if a movement cycle is defined from the T (say, from when a player leaves the T to retrieve a shot to when the player returns to the T to await the next shot) then an anti-phase relation (180°) indicates that as one player is at the start of his/her cycle the other player is exactly half-way through his/her cycle. Thus, an antiphase relation would be evidenced if one player were at the T and the other player at the point of shot retrieval, and so furthest from the T in his/her movement cycle, as well as vice versa and likewise for any intermediate points.

Similarly, if both players in the squash rally were at the same point within their respective movement cycles then an in-phase relation (0° or 360°) would be evidenced. Other phase relations between the two players from 0-360° may likewise be evidenced depending on where each player is in his/her movement cycle with respect to the other at any instant. In this article, we are interested primarily in the anti-phase relation, as it is the principal measure that will be used to try to identify the space-time patterns that are known to be unique to the squash dyad (McGarry, 2006).

One more point. Since the phase relations are measured using circular statistics, the phase relations are always expressed within 0-360° values, or multiples of 360° thereof. Thus, just as -360°, 0° and 360° and so on represent a given pattern (in-phase), so too does -180°, 180° and 540° and the like represent a given pattern (anti-phase) also.

The same comment likewise applies to all the other phase relations (from 0-360°) and their 360° multiples.

Experimental design: Part 1

For ease of explanation, we report the experimental design in two parts. In the first part, two experimental conditions were used to investigate the usefulness of the anti-phase relation as a discriminator for pattern detection based on the space-time dynamics of the squash dyad. The Squash-Unrelated condition comprised of two squash players from the same squash rally (i.e., the squash dyad) and two distracters taken at random, with counterbalancing, from the remaining data. For example, if the data from the four quarter-finals are represented as A_{1-12} - B_{1-12}, C_{1-12} - D_{1-12}, E_{1-12} - F_{1-12} and G_{1-12} - H_{1-12}, respectively, and if A_j - B_j constitutes the squash dyad for a given trial, where j is any integer from 1 through 12, then the two distracters were drawn at random from the remaining data (i.e., C_{1-12} through H_{1-12}), making certain that the distracters did not happen to constitute a squash dyad themselves. Similarly, the Squash-Related condition likewise comprised of a squash dyad and two distracters, the difference being that the distracters in this condition were drawn at random, with counterbalancing, from the same data as those of the squash dyad. Thus, if A_j - B_j once more constitutes the squash dyad for a given trial, then the two distracters were drawn from the A_{1-12} - B_{1-12} data (one distracter was drawn from A_{1-12} and the other distracter from B_{1-12}, excluding A_j and B_j of course), once again making certain that the distracters themselves did not form a squash dyad by chance selection. Each experimental condition contained 47 trials with each trial consisting of a squash dyad and two distracters selected as described. For distinction, we will refer to the two experimental conditions as Squash-Unrelated-2 and Squash-Related-2, respectively, the suffix integer 2 denoting the number of distracters used per trial.

Experimental design: Part 2

In the second part of the experimental design, two additional experimental conditions were used to investigate further the usefulness of the anti-phase relation for discriminating the squash dyad. Using the Squash-Unrelated condition, the number of distracters per trial was increased from two (as used in the first part of the experimental design) to four and six distracters for the two experimental conditions, respectively. Once again, the distracters were drawn at random, with counterbalancing, from the remaining data sets. In keeping with our earlier nomenclature, we will refer to the two additional experimental conditions as Squash-Unrelated-4 and Squash-Unrelated-6, respectively.

Results and discussion

The experimental task in each condition is to identify the squash dyad from the distracters using relative phase analysis. In an experimental condition that contains two distracters, there are six combinations of pairs per experimental trial with only one of the six comprising the squash dyad. Unsurprisingly, the number of combinations in an experimental condition increases as the number of distracters increases. Thus, four distracters yield 15 combinations of pairs per experimental trial and six distracters produce 28 combinations.

Figure 1 presents relative phase data from a trial from the Squash-Unrelated-2 condition with the results from each of the six combinations presented in separate panels. The different combinations are identified by the number one through six located in the upper right corner of each panel. Since the combination order was randomized for each trial, the relative phase data presented for consideration with a view to identifying the squash dyad might be located in any place within the combination sequence with equal probability. Thus, only the relative phase data contain information that might be useful for detecting the squash dyad from the six combinations of data pairs.

In each panel (Figure 1), the relative phase data obtained from Hilbert transformation on the radial velocity data are presented as a solid black line. For ease of data interpretation, the dotted line in some of the panels represents the anti-phase relation. On the experimental hypothesis that the anti-phase relation might be a good discriminator for detecting the squash dyad, visual inspection of the data (Figure 1) suggest the second and fourth combinations as the most likely candidates for the squash dyad. To automate the process of selection, we used absolute (unsigned) error from the anti-phase relation as our measure for pattern detection, with the least error reported among the six combinations being selected as the most promising candidate for the squash dyad. Using this criterion for selection, the automated process identified the second combination in this example as the squash dyad. Subsequent examination of the data for this particular trial indicated that the automated process was correct in this particular instance.

The number of correct identifications of the squash dyad made by the automated detection process for each of the experimental conditions is documented in Table 1. The data demonstrate that the search process worked well beyond chance expectations regardless of the make-up of the distracter set, each distracter set seemingly being of equal difficulty for pattern detection (see Table 1, Part 1). This finding offers good evidence that the space-time interaction of the squash dyad on which pattern detection is founded is unique to the squash dyad, a finding that is consistent with the earlier result using human perception as the mechanism for pattern recognition. Thus, the squash dyad acts as a unified system whose patterned behaviours demonstrate strong tendencies to anti-phase, as reported previously (McGarry et al., in review). Importantly, these findings are predicated on the interactions of the squash dyad, as consistent with dynamical principles for reasons outlined below.

Table 1. Number of correct identifications of the squash dyad per experimental condition using the automated process for pattern detection.

Experimental Condition	Number Of Trials	Number Of Combinations	Number Of Correct Identifications	Chance Number Of Correct Identifications
Part 1:				
Squash-Unrelated-2	47	6	(76.6%) 36	(16.7%) 8
Squash-Related-2	47	6	(74.5%) 35	(16.7%) 8
Part 2:				
Squash-Unrelated-4	47	15	(42.6%) 20	(6.7%) 3
Squash-Unrelated-6	47	28	(38.3%) 18	(3.6%) 2

Increasing the number of distracters in the data set, and thus the number of squash pairs for comparison, reduced the number of correct identifications, as expected (see Table 1, Part 2). That said, the success rate of the anti-phase relation as a predictor of the squash dyad is impressive, particularly when one considers that we are reporting on its efficacy using the most stringent measure possible – that is, the squash dyad is identified as successful or unsuccessful without consideration in the latter instance of where the squash dyad placed in the prediction ranking. For example, while it would seem reasonable to consider the squash dyad when ranked second (of 28, for example) as a good assessment, as compared to a ranking of nineteen for instance, no such considerations were accounted for in our measure of efficacy. Nonetheless, the anti-phase relation presents itself as an excellent (and simple) predictor for detecting the squash dyad from its space-time patterns. The results from both parts of the experiment furthermore lend unequivocal evidence that the movement patterns of the squash dyad can be described usefully in terms of a dynamical system, since it must only be the shared information within the squash dyad (i.e., the shared information among the squash players) that is responsible for the self-organizing tendencies towards the anti-phase pattern that characterize it. Of course, there is no possibility of a meaningful sharing of information in any of the distracter pairs, and any appearance of such sharing (Figure 1, panel 4 for example) is the product of happenstance. That the squash dyad is well discriminated from the distracter pairs therefore excludes chance as a possible explanation for the strong anti-phase coupling of radial velocities that for the most part typifies the space-time relations of the squash dyad.

Conclusions

In this report, we extended previous considerations of the space-time patterns of squash players as a dynamical system by seeking to address whether the measure of relative phase, specifically anti-phase, might be used as a useful discriminator for pattern detection. The data demonstrated that the anti-phase relation indeed discriminates the squash dyad from other distracter pairs at a degree of efficacy that well exceeds chance expectations. These findings provide unequivocal support for the contention that the movement patterns of the squash dyad subscribe to dynamical principles, since it is the shared information between the two players that form the squash dyad that produces the patterned behaviours – the anti-phase relation – in keeping with dynamical systems theory.

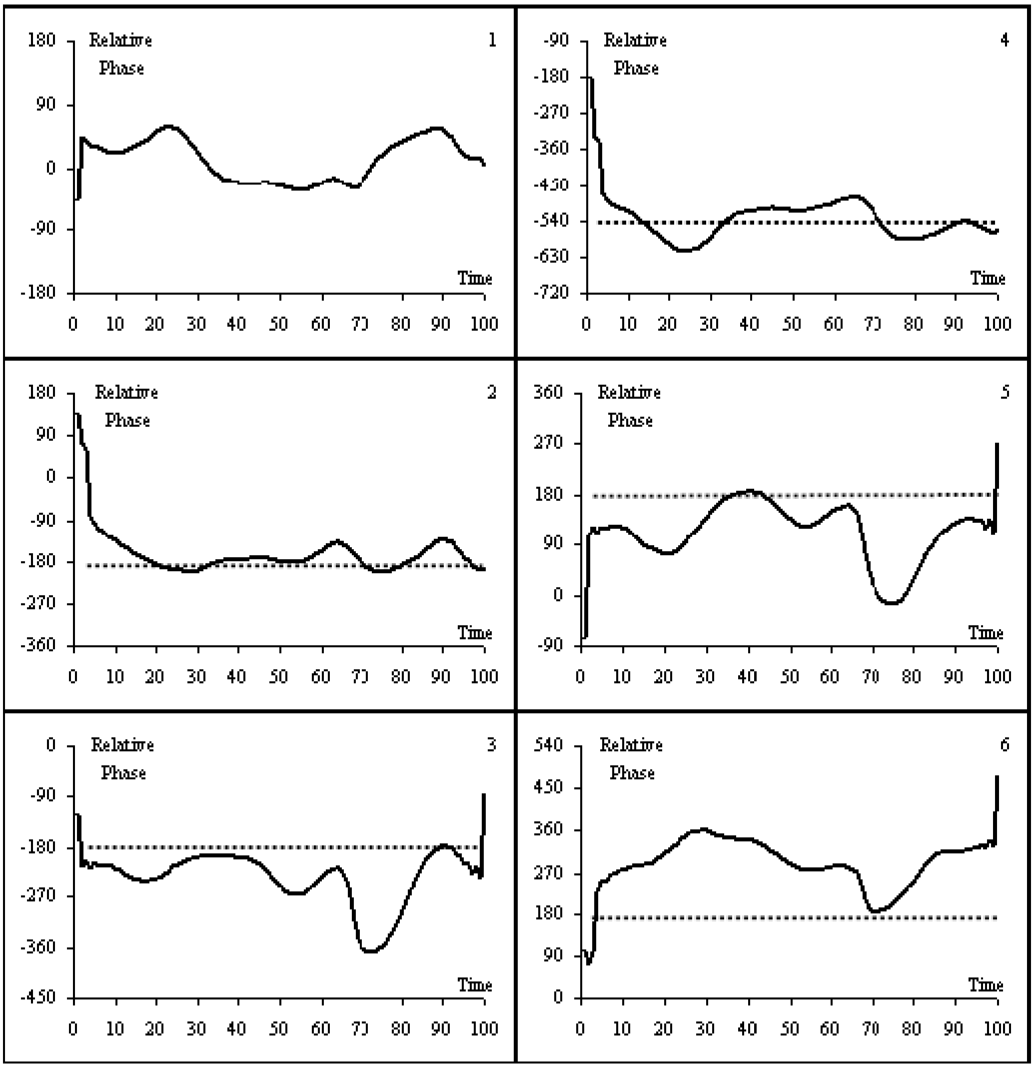

Figure 1. Relative phases obtained using Hilbert analysis of the radial velocities of each (6) combination pairs contained in an example trial. Panel 2 contains the squash dyad as evidenced in the least error from the anti- phase (180) relation. See text for further details.

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INFLUENCE OF EFFICACY VALUES ON THE CONDITION OF WINNER OR LOSER IN NUMERICAL EQUALITY IN MALE AND FEMALE WATER POLO

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Abstract

The purpose of this study was to find efficacy values in playing microsituations in numerical equality with or without ball possession and to analyze the relation between these and the condition of winner or loser. The matches of the X World Championship of Water polo which did not end in a draw were analysed. Playing microsituations in numerical equality were evaluated by means of coefficients in order to obtain efficacy values. Some differences were revealed, in male category, in the following coefficients with possession: concretion, definition, resolution, accuracy and blocked shots received ($p<.001$) and precision ($p=.001$). Without possession: concretion, definition, resolution, accuracy and blocked shots made ($p<.001$) and precision ($p=.001$). In female category with the following coefficients with possession: concretion, definition and precision ($p<.001$), resolution ($p=.001$), possibility ($p=.005$) and accuracy ($p=.017$). Without possession: concretion, definition and precision ($p<.001$), resolution ($p=.001$), possibility ($p=.005$) and accuracy ($p=.017$); taking as a reference a value of $p<.05$. To conclude, it can be said that in twelve out of the fourteen efficacy coefficients proposed for evaluating the playing microsituations in numerical equality with or without ball possession in male and female water polo there are significant differences between the condition of winner or loser.

KEY WORDS: WATER POLO, EFFICACY, WINNER, LOSER, NUMERICAL EQUALITY.

Introduction

This study is about water polo. Although nowadays this water sport is popular and played everywhere, it is a young sport. According to Majoni (1954) it appeared in the second half of the 19th century in Great Britain as a result of the Industrial Revolution. Water polo, which is played in a limited pool by two teams of seven field players (six players and the goalkeeper) who try to introduce the ball in the opponent´s goal post (Lloret, 1994), is an aquatic team sport, institutionalized and subject to some rules. This author proposed to define water polo as (1995): regulated sport of cooperation and opposition, which strategically communicates through the execution of some playing actions in the water environment.

The intrinsic goal of the sports practice channelled towards competition is the success in itself, that is, the attainment of the best possible results and the beating of the other contenders. Sports training has become a traditional practice to improve the preparation and, thus, to be able to obtain better results in the competition. An intense physical activity linked to the sports discipline at issue could make the sportsmen competitive. However, the sports success has become tremendously difficult, nowadays. The preparation, which a sportsman and/or a team needs to be competitive at a high-level, has been becoming tremendously complex and sophisticated. It is therefore evident that the evolution of the sports training has been one of the key factors, which has contributed to the mentioned increase in sports performance.

If we want to assess the tactics of water polo teams in training or in a competition, it would be very complicated to face it as a whole. Therefore, it is necessary to divide the playing situation into microsituations, which maintain the structure of the sports modality. Thus, we may face several differentiated units, which make their quantification, valuation and action much easier. The context in which each microsituation develops is called situational framework, defined as the set of present motor behaviours in the playing dynamics in team sports, determined by the following factors: symmetry of the teams, organization of the tactical playing systems and ball possession. In the specific case of water polo we can distinguish four factors: a) numerical equality, b) transitional, c) numerical inequality and d) penalty.

The first one, that is, the numerical equality framework in water polo, object of this study, is a playing microsituation developed from the organization and structuring of the tactical playing system, with or without possession, to the loss or recovery of the ball possession, where all the components of both teams are present in the playing field and can coincide in the pool at the same time according to the regulation: six players and a goalkeeper per team. Besides, we can differentiate the fact of having or having not the ball. Then, the numerical equality with possession in water polo is a playing microsituation developed from the moment of the organization and structuring of the tactical playing system, with ball possession, to the loss of the same one, where all the components of both teams are present in the playing field and can coincide in the pool at the same time according to the regulation, six players per team, and whose main objective is to maintain the possession obtaining a goal. In turn, the numerical equality without possession in water polo is a playing microsituation developed from the moment of the organization and structuring of the tactical playing system, without ball possession, to the recovery of the same one, where all the components of both teams are present in the playing field and can coincide in the pool at the same time according to the regulation, six players per team, and whose main objective is to get back ball possession without taking a goal (Argudo, 2005).

When a water polo match ends, could we know the reasons for victory or defeat? If we take into account the results obtained by the quantification of the playing actions, we can value their efficacy from some coefficients (Argudo, 2002). According to Gayoso (1983) efficacy can be considered as a result of the correctly executed actions inside a number of attempts or trials. This same author thinks that the measurements and evaluations of the behaviours both *alive* and *in vitro* are very important.

Particularly in water polo, we can mention studies of conceptualization, elaboration of evaluation instruments, and first studies of efficacy values (Argudo, 2000; Argudo & Lloret, 2006; Argudo & Ruiz, 2006a, b; Canossa, Garganta & Lloret, 2001; Dopsaj & Matkovic, 1999; Enomoto, 2004; Lloret, 1994, 1999; Platanou, 2001, 2004; Sarmento, 1991; Sarmento & Magalhaes, 1991) that show some formulae to clarify and to justify the level of offensive and defensive work in the matches of this water sport. Thus, an efficacy coefficient is a mathematical formula that determines a numerical value, which results from the relation among the actions, the individual tactics, or the tactical procedures, the group tactics; or the tactical playing systems, the collective tactics, the executed and the amount of attempts carried out in the different playing microsituations. As a result of it, we would have a value of efficacy, which is a performance numerical indicator that reveals us the necessary information to continue or to modify the planning or programme of the tactical content in the training or in the competition (Argudo, 2005).

Currently, the need has been realised to do an analysis in which the most important performance indicators are registered, to know the sequences of play, own and adversaries, to collective and individual level.

The goals of this study were: a) to find out efficacy values in the playing microsituations in numerical equality with or without ball possession and b) to analyze the relation between these efficacy values and the winner or loser condition in water polo at the end of the match both in the male and female modality. The hypothesis of this study was that the winning teams obtain higher efficacy values than the losing ones.

Methods

Participants

The sample studied has been extracted from the X World Championship in Barcelona 2003. 32 national teams, which show a great level of homogeneity were studied, being disputed 96 matches; though only 46 male and 47 female matches whose final result was not a draw were selected.

Tools

All the matches selected have been analyzed with the Polo analysis v 1.0 direct software (Argudo, Alonso and Fuentes, 2005), a tool developed for the quantitative tactical evaluation in water polo in real time (see Figures 1 and 2).

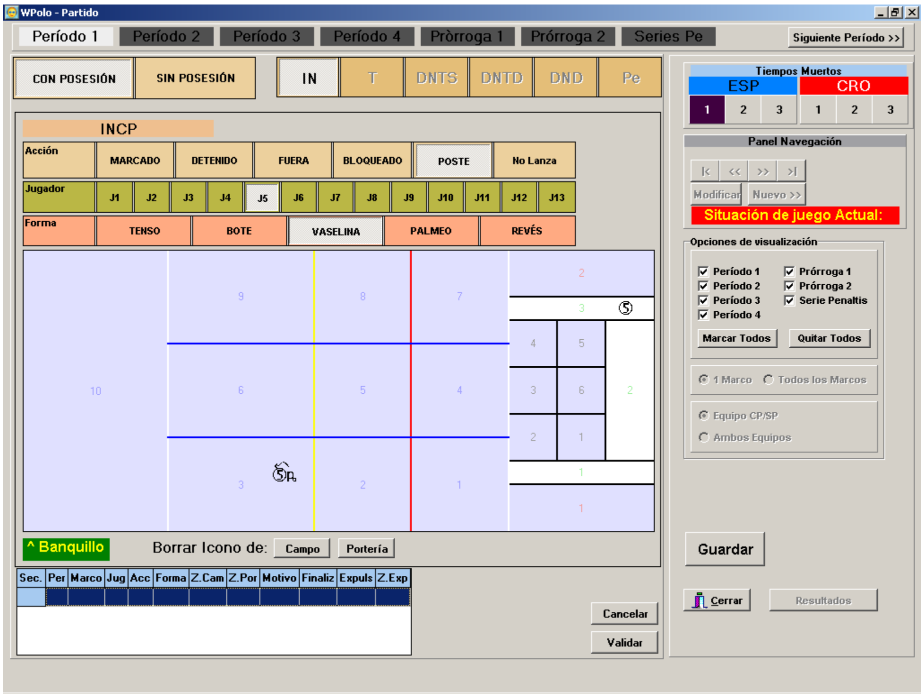

Figure 1. Screen to register the actions in the playing microsituations, in numerical equality with or without possession.

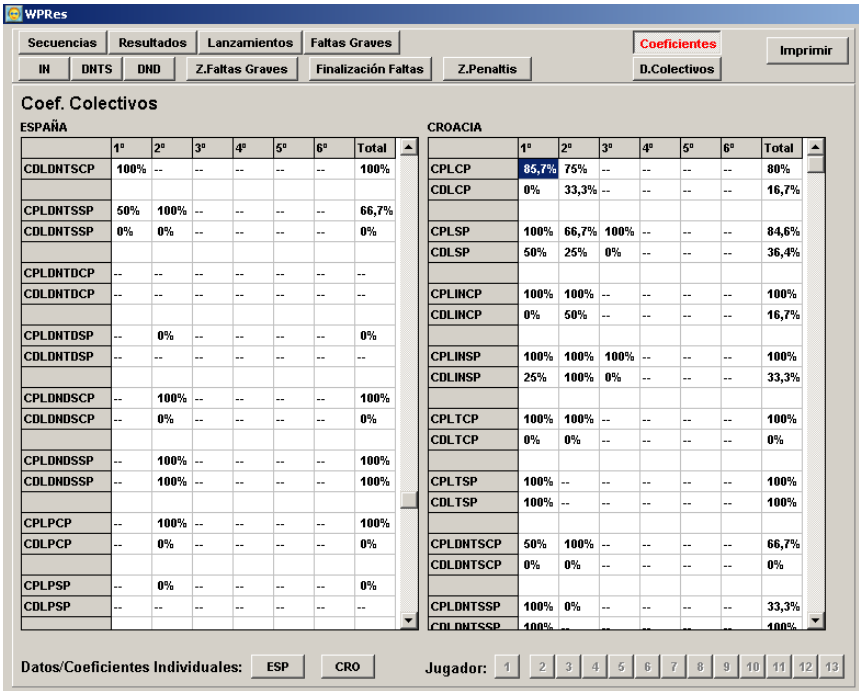

Figure 2. Screen of the different collective and individual efficacy values of both teams.

This was the first software created to capture microsituations during a match in real time. It incorporates the functionality to obtain in real time efficacy and significance values, besides graphic representations of the match. All this permits to receive direct information about players, teams and situations.

The variables studied have been the condition of winner or loser at the end of the match and the efficacy values obtained from the coefficients proposed to evaluate this playing microsituation, which is developed subsequently:

1. Coefficient of shots possibility in numerical equality with possession. Mathematical formula that determines a numerical value of the relation between the shots carried out and the playing microsituations with possession.
   CSPNEP = Σ shots carried out x 100 / Σ microsituations with possession.
2. Coefficient of shots concretion in numerical equality with possession. Mathematical formula that determines a numerical value of the relation between the shots scored and the playing microsituations with possession.
   CSCNEP = Σ shots scored x 100 / Σ microsituations with possession.
3. Coefficient of shots definition in numerical equality with possession. Mathematical formula that determines a numerical value of the relation between the shots scored and the shots carried out.
   CSDNEP = Σ shots scored x 100 / Σ shots carried out.
4. Coefficient of shots resolution in numerical equality with possession. Mathematical formula that determines a numerical value of the relation between the shots scored and the shots to goal posts.
   CSRNEP = Σ shots scored x 100 / Σ shots carried out – (Σ shots out + Σ shots blocked + Σ shots posts).
5. Coefficient of shots precision in numerical equality with possession. Mathematical formula that determines a numerical value of the relation between the shots to goal posts and the playing microsituations with possession.
   CSPRNEP = [Σ shots carried out – (Σ shots out + Σ shots blocked + Σ shots posts)] x 100 / Σ microsituations with possession.
6. Coefficient of shots accuracy in numerical equality with possession. Mathematical formula that determines a numerical value of the relation between the shots to goal posts and the shots carried out.
   CSANEP = [Σ shots carried out – (Σ shots out + Σ shots blocked + Σ shots posts)] x 100 / Σ shots carried out.

   The higher these coefficients' numerical value, the greater is the efficacy. Besides, a series of relations is established among them:

   1. CSDNEP should approach or be equal to CSANEP.
   2. CSCNEP should approach or be equal to CSPRNEP.
   3. CSCNEP should approach or be equal to CSPNEP.
   4. CSPRNEP should approach or be equal to CSPNEP.

7. Coefficient of shots possibility in numerical equality without possession. Mathematical formula that determines a numerical value of the relation between the shots received and the playing microsituations without possession. CSPNEWP = Σ shots received x 100 / Σ microsituations without possession.

8. Coefficient of shots concretion in numerical equality without possession. Mathematical formula that determines a numerical value of the relation between the shots inserted and the playing microsituations without possession.
   CSCNEWP = Σ shots inserted x 100 / Σ microsituations without possession.
9. Coefficient of shots definition in numerical equality without possession. Mathematical formula that determines a numerical value of the relation between the shots inserted and the shots received.
   CSDNEWP = Σ shots inserted x 100 / Σ shots received.
10. Coefficient of shots resolution in numerical equality without possession. Mathematical formula that determines a numerical value of the relation between the shots inserted and the shots to goal posts.
    CSRNEWP = Σ shots inserted x 100 / Σ shots received – (Σ shots out + Σ shots blocked + Σ shots posts).
11. Coefficient of shots precision in numerical equality without possession. Mathematical formula that determines a numerical value of the relation between the shots to goal posts and the playing microsituations without possession.
    CSPRNEWP = [Σ shots received – (Σ shots out + Σ shots blocked + Σ shots posts)] x 100 / Σ microsituations without possession.
12. Coefficient of shots accuracy in numerical equality without possession. Mathematical formula that determines a numerical value of the relation between the shots to goal posts and the shots received.
    CSANEWP = [Σ shots received – (Σ shots out + Σ shots blocked + Σ shots posts)] x 100 / Σ shots received.

The lower these coefficients' numerical value, the greater is the efficacy. Besides, a series of relations is established among them:

1. CSDNEWP should approach or be equal to CSANEWP.
2. CSCNEWP should approach or be equal to CSPRNEWP.
3. CSCNEWP should approach or be equal to CSPNEWP.
4. CSPRNEWP should approach or be equal to CSPNEWP.

13. Coefficient of shots blocked received in numerical equality. Mathematical formula that determines a numerical value of the relation between the shots blocked received and the shots carried out.
    CSBRNE = Σ shots blocked received x 100 / Σ shots carried out.
14. Coefficient of shots blocked made in numerical equality. Mathematical formula that determines a numerical value of the relation between the shots blocked made and the shots received.
    CSBMNE = Σ shots blocked made x 100 / Σ shots received.

While in the first small coefficients indicate greater efficacy, in the second it is contrary. Besides, a relation is established between them:

1. CSBMNE should surpass CSBRNE.

Procedure

The method of recording started from the initial approach to the midfield, so that once any of the two teams had the ball, it would carry out a sweeping technique centring the image in the midfield where the playing action is developed. The observation of the matches was carried out agreed by consensus between two trained specialists, Anguera et al. (2000) and Anguera (2003).

Statistical analysis

We calculated the variance homogeneity tests through Levene's statistical tool. Later on, an ANOVA of a single factor was carried out; then by the Tukey test, the analysis of the statistically significant differences among the efficacy values in the numerical equality and the condition of winner or loser at the end of the match was carried out. All the statistical analyses mentioned were carried out with the SPSS 12.0 statistical package with a level of confidence of 95% and an error probability of 5% (meaning level of .05).

Results

After applying the statistical analysis, the comparison among the efficacy values obtained in the playing microsituations in numerical equality with and without possession has provided the following results, which are shown in Tables 1 and 2.

Table 1. Values of significance of the efficacy values in numerical equality with or without possession between male teams winners and losers.

winners – losers	
CSPNEP	.200
CSCNEP	.000*
CSDEP	.000*
CSRNEP	.000*
CSPRNEP	.001*
CSANEP	.000*
CSBRNE	.000*
CSPNEWP	.201
CSCNEWP	.000*
CSDNEWP	.000*
CSRNEWP	.000*
CSPRNEWP	.001*
CSANEWP	.000*
CSBMNE	.000*

* Denote significant differences (p<.05) between winners and losers.

These results show that the winning male teams do not have significant differences p=.200 and p=.201 respectively in the CSPNEP and in the CSPNEWP as opposed to the losing teams. On the contrary the efficacy values obtained by the winning teams do show significant differences p<.001 in the CSCNEP, in the CSDEP, in the CSRNEP, in the CSANEP, in the CSBRNE, in the CSCNEWP, in the CSDNEWP, in the CSRNEWP, in the CSANEWP and in the CSBMNE. Also, the efficacy values obtained by the winning teams as opposed to the losing teams show significant differences p=.001 in the CSPRNEP and in the CSPRNEWP.

Table 2. Values of significance of the efficacy values in numerical equality with or without possession between female teams winners and losers.

winners – losers	
CSPNEP	.005*
CSCNEP	.000*
CSDEP	.000*
CSRNEP	.001*
CSPRNEP	.000*
CSANEP	.017*
CSBRNE	.564
CSPNEWP	.005*
CSCNEWP	.000*
CSDNEWP	.000*
CSRNEWP	.001*
CSPRNEWP	.000*
CSANEWP	.017*
CSBMNE	.564

* Denote significant differences (p<.05) between winners and losers.

On the hand, the winning female teams do not show significant differences p=.564 in the CSBRNE and in the CSBMNE as opposed to the losing teams. However, the efficacy values obtained by the winning teams as opposed to the losing teams do show significant differences p<.001 in the CSCNEP, in the CSDEP, in the CSPRNEP, in the CSCNEWP, in the CSDNEWP and in the CSPRNEWP. Also, the efficacy values obtained by the winning teams as opposed to the losing teams show significant differences p=.001 in the CSPNEP and in the CSPNEWP. At the same time the winning teams as opposed to the losing teams obtained efficacy values showing significant differences p=.005 in the CSRNEP. and p=.017 in the CSANEP and in the CSANEWP.

Discussion and Conclusions

If we compare the data obtained in this study with previous studies by Argudo (2000), we have the possibility to note that among the male teams with the condition of winner or loser, there are coincidences in the CSCNEP p=.129, in the CSDEP p=.742, in the CSCNEWP p=.129 and in the CSDNEWP p=.742. Likewise, among the female teams with the condition of winner or loser there are coincidences in the CSCNEP p=.022 and in the CSCNEWP p=.050. However, we noticed the opposite in the CSDEP p=.281 and in the CSDNEWP p=.551.

As the main conclusion of the quantitative tactical evaluation of the playing microsituations in numerical equality with and without ball possession in the X World Championship of Water polo of 2003, carried out in the male matches, we can infer that, in twelve out of fourteen efficacy coefficients there are significant differences between the condition of winner or loser, that is why the hypothesis raised comes true in the CSCNEP, in the CSRNEP, in the CSANEP, in the CSBRNE, in the CSCNEWP, in the CSDNEWP, in the CSRNEWP, in the CSANEWP, in the CSBMNE, in the CSPRNEP and in the CSPRNEWP.

In turn, we can infer from the female matches that in twelve out of fourteen efficacy coefficients there are significant differences between the condition of winner or loser, that is why the hypothesis raised comes true in the CSCNEP, in the CSDEP, in the CSPRNEP, in the CSPNEP, in the CSRNEP, in the CSANEP, in the CSCNEWP, in the CSDNEWP, in the CSPRNEWP, in the CSPNEWP, in the CSRNEWP and in the CSANEWP.

If we want to make a transfer from the conclusions we have reached, to the training of the playing microsituations in numerical equality in male water polo, we should keep in mind, on planning the sessions and the matches, that there are not going to be any differences between both teams as for the shot possibilities, that is why we will have to plan some tasks whose main objective is that a player can shot in the best conditions to obtain the greatest efficacy. Since it is very difficult to move around in water polo, the way to obtain that profitable situation should be through simple and coordinated actions among few players, which lead to a momentary numerical imbalance in a specific space, where the benefited player can shot from with the greatest possibilities of success. That is why the coaches must demand the maximum concentration and success in the decision-taking process when shooting. We must make each player aware of the great importance and significance that the simple fact of shooting to the goalpost has. And on the contrary, other tasks whose main objective is to stop any shot by means of individualized pressure and anticipation in order to avoid those strategically dangerous spaces that are created. In the case of female water polo, besides the importance of being accurate when shooting, the training of blocking these shots should be increased, since it can allow the players to improve the possibilities of victory.

In future studies we could tackle the analysis of the same variables with a greater number of matches, if we study different games from different championships and the time of ball possession permitted, especially with the regulation modifications proposed by the FINA for the 2005-09 period, and if we compare the data obtained with this study.

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