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Editorial

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Dear readers:

Welcome to the summer 2006 issue of the **International Journal of Computer Science in Sport** (**IJCSS**).

Four original papers have been included within this issue.

Mark Pfeiffer and **Jürgen Perl** use a neural network to identify types of tactical structures in team handball. They present a process-oriented observation model of the offensive play on the basis of offensive attempts. It is shown that the neural network method can be usefully applied to analyse complex tactical structures in the field of sports games.

In the paper by **Thorsten Stein**, **Andreas Fischer, Klaus Bös, Veit Wank, Ingo Boesnach** and **Jörg Moldenhauer** trajectories of limbs are analyzed and guidelines for motion planning are developed in order to construct universal models for the characteristics of human movements. These models shall be used to control the movements of humanoid robots.

Mario Heller and **Kerstin Witte** present a dynamic approach for modelling and simulation of motor unit discharge behaviour using recurrent fuzzy-techniques. Their model is able to generate a nominal force-time curve by means of the discharge behaviour of a single motor unit pool.

The report presented by **Jacek Dembiński**, **Ilona Kopocińska** and **Bolesław Kopociński** deals with two tests for synergy when considering the strength or efficiency of a triplet of players in a game.

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

Enjoy the summer!

Arnold Baca, Editor in Chief
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Analysis of tactical Structures in team handball by means of artificial neural networks

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Abstract

In the field of sports games, the analysis of the game structure as well as the analysis of the opponent team is of major interest for the training process in order to optimise tactical skills. Based on methodological problems of present game analysis, some recent approaches apply artificial neural networks to examine the game structure. With the intention to analyse types of tactical structures in team handball, we use a neural network to identify a number of such types which represent play processes with similar tactical structures. Therefore, a process-oriented observation model of the offensive play was developed on the basis of offensive attempts. 15 matches (12 teams) of the Women's Junior World Championship 2001 were observed. Afterwards, a prepared neural network (DyCoN) was trained with 2900 offensive attempts (processes) from all teams to coin offensive attempt patterns. The contribution shows that a neural network can be used in order to identify typical tactics of different teams.

KEY WORDS: NEURAL NETWORK, GAME ANALYSIS, MODELING

Introduction

Over many decades, research in sports games has concentrated on systematic observation of playing performance. Based on that data, recommendations have been developed in order to analyse and improve tactical behaviour and training processes. Apart from talent scouting and player selection, training science is mainly interested in aspects of sports structure and opponent analysis (condition selection) as well as of training and match control (person's modification) (Hohmann, 1997, p. 147). The area of condition selection and modification of personal characteristics is of major interest for the training process in order to optimise tactical skills. Therefore, conditional and technical elements of individual tactics, group tactics and team tactics are important, which aim at the optimum result and need to be analysed.

Problems in the analysis of sports games

Analysis of literature shows that – based on fast technological development in the area of computers, video etc. – a large number of methods have been developed to analyse the tactical structure of sports games (Winkler & Freibichler, 1991; Loy, 1994, 1995, 1996a, 1996b; Bernwick & Müller, 1995; Müller & Lorenz, 1996; Remmert & Steinhöfer, 1998). Most of these game analysis methods use structure-oriented observation models. They enable the researcher to register isolated elementary actions of a match, but do not allow for obtaining data about the match process – i.e. about tactical behaviour or concepts (Perl, 2002,

p. 92). The elementary actions of a sports game only form the static information basis for the actual play dynamics, which can be monitored and described only by the tactical context and interactions (Hein, 1993, p. 136).

In order to achieve deeper insight into the tactical match structure or the tactics of a team, it is necessary to record the substantial tactical actions in a chronological, sequential order. By means of a process-oriented model concept, the sequence of the structural components (here tactical actions) – and therefore the stream of tactical behaviour – can be analysed (Perl & Uthmann, 1997, p. 54). In a process-oriented model the match is characterised by a sequence of events and event-based temporal changes of the system’s state. Play phases or temporal tactical behaviour can define states while events are defined by the player's actions or the team's activities, i.e. by tactical actions. In the literature two kinds of process-oriented models are described, namely the state-transition models and the state-event models. If the analysis focuses on the change of states, a state-transition model can be used without the indication of event data. In sports game research, state-transition models are applied to analyse transition probabilities in the course of the match (Lames, 1991, Remmert, 2002, Zhang, 2003, Pfeiffer, 2005).

Regarding the previous sport games research, it turns out that on the basis of the detailed structural resolutions existing in the literature, the process of the play should be analysed by transition probabilities (Perl & Uthmann, 1997, p. 59). This is due to two reasons: Firstly the complexity of the processes leads to the fact that even with a small number of play states (conditions), the number of combinations can quickly become very large (Perl, 1997, p. 82). Secondly the structuring of different abstraction levels is also a problem. Conventional methods, usually statistics, are not able to solve these problems. The reason is that – because of the high number of dimensions on the one hand and the comparatively small number of example instances obtained from tests on the other hand – the instances do not form a representative distribution.

For this reason, some recent approaches apply artificial neural networks to game analysis (Perl, 1997, p. 87). With the help of neural networks, even extreme data complexity can be reduced to a manageable size, so that the substantial information from a multiplicity of processes can be compressed into a small number of process types (Perl, 2002, p. 67). In order to analyse tactical structures in handball it would be interesting to identify a number of such types which represent play processes with similar tactical structures. From the point of view of training theory, such an approach is interesting for the following reasons:

- For sports game analysis, process types with similar tactical structures can be very meaningful information.
- The findings of quantitative match observation could meet the requests of sport practice much better if they are based on information about individual process types instead of concerning general interrelations only.
- Depending on the frequency of their occurrence in typical game situations, technical-tactical behaviour could represent a priority training goal and thus get into the focus of training practice

(Perl & Lames, 2000, p. 211).

First studies with the Dynamically Controlled Network (DyCoN) developed by Perl (2001) show that in sport games such as squash or volleyball this method is able to identify types of rallies which represent a special tactical behaviour. Based on these studies, the DyCoN-approach has been used in order to examine the tactical structure in team handball to identify behavioural patterns in the offensive play.

The Model

The starting point of our model was the control of the ball. Therefore, the offensive play was modeled on the basis of offensive attempts. An attempt starts when the ball control changes from one team to the other (1), the match is continuing after a referee decision (2), or the attacking team forms up for a new trail (3). In the last case a new offensive attempt is organised. Accordingly, an offensive attempt ends if

- the ball is lost to the opposing team without a referee decision (loss of the ball) or
- the referee interrupts the match (e.g. after a technical or rule fault) or
- the attack attempt is broken, i.e. the team has to re-organise their offensive play.

Consequently, the offensive play of one team is made up of at least one offensive attempt and can also include many subsequent attempts. The offensive play always starts by winning the ball and ends with the loss of the ball or with a goal.
In order to describe the tactical structure of a handball match the offensive attempts are used as chronologically structuring units. Each offensive attempt can be characterised by a sequence of states (Figure 1).

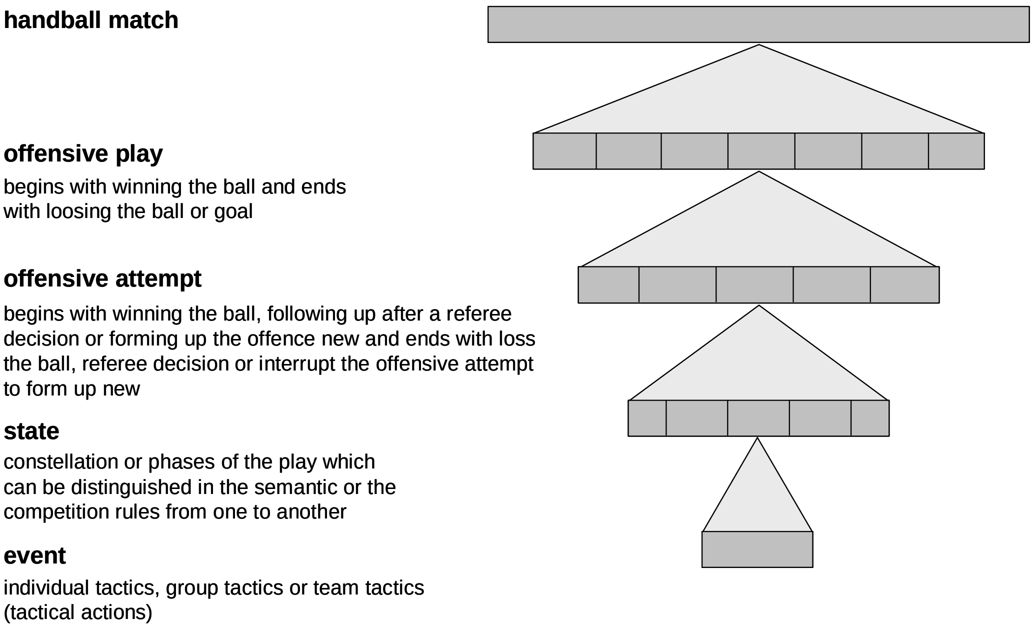


Figure 1. Process oriented structure (model) of a handball match

In the following second step of modeling it is necessary to define the states and events used to analyse the tactical behaviour. The content as well as the structure of the system of states are based on handball-specific concepts and therefore have a theoretical foundation in scientific findings on handball (Czerwinski & Taborsky, 1997; Pfeiffer, 2001, 2002; DHB, 1997). Therefore, the process of each offensive attempt is structured by the following states: "offence formation” (general formation of offensive play preceding the first tactical action), "initiating" (first tactical action), "1st continuing action" (second tactical action), "2nd continuing action "(third tactical action) and "goal throw" (Figure 2). With this model of an offensive attempt a handball match can be described as a process of chronological order with changing states. The state “offence formation” is compulsory for the start of a new offensive attempt, which can turn into one of the next states. Up to the general offence formation, an offensive attempt does not inevitably go through all remaining states. The state “1st

continuing action” for example is only attainable if a preceding tactical action (initiating) has taken place. In the same way, the state “2nd continuing action” requires the preceding state “1st continuing action”.
Figure 2 shows the matrix structure of states and respective selections of possible events that results from the structure model of Figure 1. It particularly contains virtual "doesn't happen"-events. The reason is that the way we use the neural network (see next chapter) requires a constant process length for each attempt. Therefore, if an attempt contains a state in which no tactical actions happens, such a "doesn't happen"-event has to be added for completion.

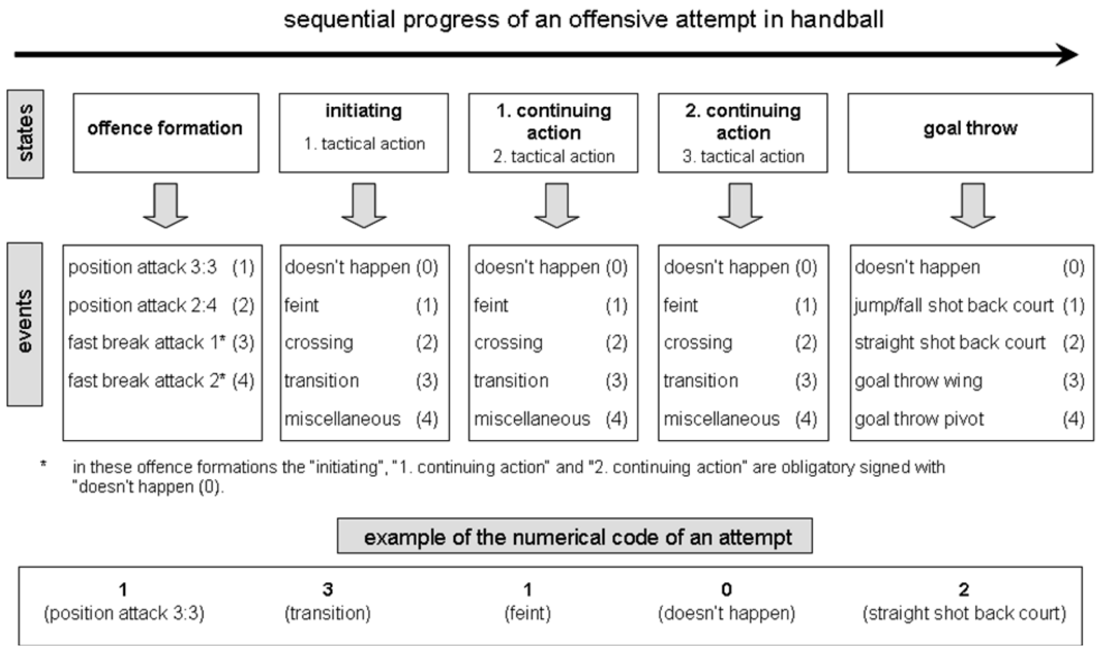


Figure 2. Model of an offensive attempt using a sequence of states[1]

As Figure 2 shows, our model only includes two continuing actions, i.e. a total of three tactics. The reason for this limitation are our findings in preliminary studies that show that more than 92 % of the offensive attempts are already finished after three tactical actions, i.e. the state “2nd continuing action”. In case of more than three tactical actions in an offensive attempt, our model does not differentiate between these attempts further more.
By using the model depicted in Figure 2, the process of each offensive attempt can be described with a five figure number (process length), which represents a certain tactical behaviour. In Figure 2 (bottom area) an example is given how to describe an offensive attempt with model symbols.

[1] With the sequence of numbers 1 3 1 0 2 in the example, an attempt is illustrated which started in the offence formation “position attack 3:3” (1). Subsequently, – as the first tactical action – a transition to the pivot position took place (3) which contained a change of the offence formation from position attack 3:3 to position attack 2:4. The 1st continuing action, i.e. second tactical action, was a feint (1), the offensive attempt finished without a second continuing action (0) by a goal throw from the back position (2).

DyCoN

DyCoN – i.e. Dynamically Controlled Network – is a neural network approach which particularly has been developed for the analysis of dynamical adaptation. A DyCoN-network is able to learn and recognise types, frequencies, and distributions as well as time-depending changes of patterns. The pattern itself can be either a static structure of item values (e.g. in case of medical diagnosis or fraud detection) or a dynamic time series of item values (e.g. in case of strategic behaviour in sport or in rehabilitation processes). Items primarily scalar numeric attributes, but also non-numeric attributes can be used as items.
Because of its ability to identify patterns and recognize suspicious features in complex data sets, DyCoN is used for supporting data-based decisions – e.g. in the fields of medicine or sports.

Scientific background

DyCoN is based on the concept of Kohonen Feature Maps (KFM), where neurons are trained with information, thereby building clusters of similar information.
The basic idea of KFMs is that of similarity and inherent correlation: As briefly mentioned above, the single information like a movement pattern is encoded in a vector of attribute values, standing for instance articulations' positions, angles or speeds. During the iterative training process, each neuron develops a correspondence to a specific pattern – i.e. it contains a vector of attribute values, where in any training step the respective input vector is compared to each neuron vector in order to find the most similar one and so identify the winner neuron. This winner neuron and – with decreasing intensity – the neighboured neurons "move" towards the new input – i.e. adapt their attribute vectors to the input vector according to a given learning rule.
One result of this information or pattern training is that similar input patterns build connected areas of neurons or "clusters". Moreover, neighboured clusters normally characterise similar types of patterns. Therefore, a high-dimensional space of patterns can be flattened onto a 2-dimensional map with a strong similarity structure. This improves the handling of complex patterns and in particular that of trajectories by far. Note that, contrary to statistical clustering tools, the cluster distribution has not to be given by the user but is generated by the network.
The second useful result comes from the inherent correlation of the attribute values of patterns, as can easily be seen from the example of movement patterns from above: Supposing the attribute values of articulations' positions, angles or speeds are independent results in a huge amount of different vectors of which most do not correspond to real movement patterns. Rules for characterising "correct" movements depend on a lot of context information and therefore are difficult to find. In turn, the network learns from real patterns and therefore implicitly learns the inherent correlation between the values without a need for explicit rules. This on the one hand helps for recognising "fuzzy" but characteristic types of movements. On the other hand, missing or incorrect attribute values are not a problem (if there number is not too large), because the characteristic information is imbedded in the inherent correlation structure – an effect that is similar to that of holograms, where each single part of it contains nearly the complete information.
A once trained network can easily be used for analyses of similarity or correspondence, where for instance movement patterns of different athletes can be compared inter-individually, or patterns of the same athlete but from different movements or movement types can be compared intra-individually.
A problem with conventional KFMs is the missing learning dynamics. The learning process is controlled by once, given external functions that run the network to a final and

unchangeable state, which not always is satisfying – in particular if the number of training vectors is too small.
The DyCoN approach basically is following the above described concepts of KFMs. The new idea of DyCoN is that each neuron learns and offers information individually and continuously without using external control functions (Perl, 2001, 2002). This way, the network can be trained in different phases, depending on the respective training success, and so can be optimised with regard to available data on the one hand and required precision on the other hand. In particular, besides the original data also synthetic data can be used for net training, if properly generated from the original ones (e.g. by means of Monte Carlo-methods). Using these artificially generated surrogate data the amount of original data necessary for training can be reduced drastically.
Moreover, continuous learning allows DyCoN for continuous completing already learned patterns and trends by new information that was not available during the initial learning phase. This enables the using of DyCoN as a tool for the analysis of learning processes. A current project deals with children's learning of creativity in sport games and promises a lot of qualitative information that could not be obtained from quantitative statistical analyses (publication in preparation).

Application
As has been mentioned above, DyCoN is a useful tool especially for recognition of behavioral and decision patterns. Two examples from practice presented in the following may give an impression of the broad spectrum of possible DyCoN applications.

DyCoN as a tool for process analysis in medicine
A systematic or even statistical analysis of medical processes often fails because of the complexity of the data. For example, in the field of rehabilitation one frequently faces the situation that a large number of status-attributes of the patient (e.g. 10 to 30 attributes per week) contrast to a small number of recorded time intervals (e.g. 5 to 10 weeks).
In such a situation, the DyCoN approach first of all provides the advantage of taking Monte-Carlo-generated data for net training, which allows for compensating the deficit of original data. On the basis of a pre-trained net, the DyCoN approach allows for evaluating a rehabilitation process in its time-depending development – thereby enabling recognition of critical situations in time. DyCoN has been applied in a number of interdisciplinary projects with medicine in the areas of "weaning" (i.e. conversion from artificial to natural breathing) and rehabilitation (in particular: post-operative treatment of knee injuries (Rebel, 2004)) as well as in psychological post-operative treatment of high-risk patients (not yet published).

DyCoN as a tool for process analysis in sports
The analysis of processes in sports, e.g. biomechanical motion processes (Perl, 2004) or strategic processes in sports games (Perl, 2002), contrasts to the situation in rehabilitation processes at least in one main point: While rehabilitation processes offer small numbers of imprecise data, processes in sport often provide a huge amount of data of high precision.
In such a situation, the net approach helps for filtering the relevant information out of the vast set of complex data and making them available for further evaluation and decision processes. This way, patterns of motion or behaviour can be recognised in order to evaluate their effectiveness. The obtained information can be fed back to the training process. During the last years, about 20 projects with national and international partners have been run in a broad spectrum of disciplines. A current project funded by the German Federal Institute of Sport Science deals with transferring some phenomena of creativity as well as of associative

thinking and operating to the DyCoN approach in order to compare net-behaviour with the behaviour of players in sport games.

Data

In the context of a performance diagnostic investigation, 15 matches (12 teams) of the Women's Junior World Championship 2001 were observed (Pfeiffer, in print). The instrumental consistency of the observation system (objectivity) was examined by the inter-rater consistency of two observers (inter observer agreement). The Cohen’s Kappa values of the observation categories were found to be between 0.75 and 0.92, which according to Robson (2002) represents an "excellent" classification (> 0.75). The data of the systematic game observation were reorganised according to our model of an offensive attempt. In the following a prepared neural network was trained with 2900 offensive attempts (processes) from all teams to coin offensive attempt patterns. Based on the specific form and position of these patterns of behaviour, conclusions can be drawn on the tactical structures of the offensive play (Perl, 2002, p. 257). For technical reasons, offensive attempts without tactical actions and without goal throws, i.e. attempts with the coding "10000" and "20000", were not included into our analysis.

Results

Some selected results are presented below to indicate the kind of conclusions about the tactical structure in team handball which can be provided by DyCoN. Figure 3 illustrates the trained network, where the marked surfaces represent those patterns of offensive attempts which exhibit a similar tactical structure.

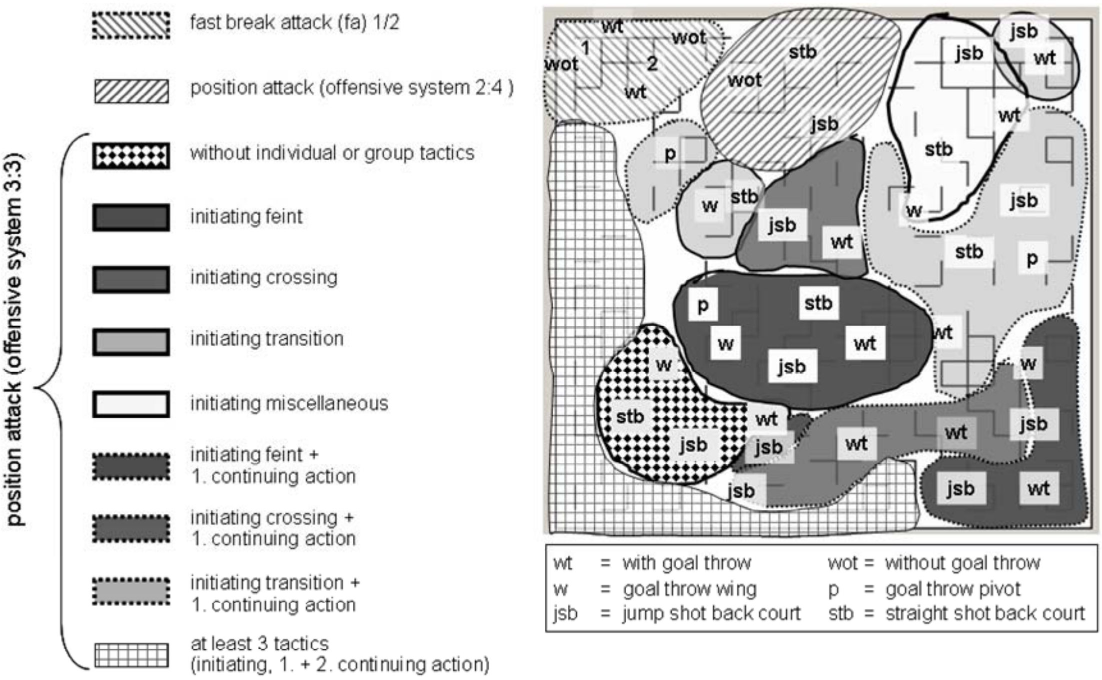


Figure 3. Pattern of the identified types of the offensive attempts (Women’s Junior World Championship 2001)

In the upper left corner of the network, offensive attempts are identified which are formed in fast break attacks (solid dashed line). Those attempts in the position attack with the system 4:2 are classified by the network on the top within the middle area (striped area). The remaining network represents attempts in the position attack 3:3. Within these, larger network area clusters of neighbouring neurons are identified, which are connected by lines (called edges) while an edge indicates that similarity exceeds a given minimum.

In a next step, the neurons and clusters identified by the network architecture can be specified and analysed with regard to the tactical behaviour (figure 3). In the diagonal from the top right to the bottom left attempts with none or only one individual or group tactic actions were located (bold line). Here, obviously simple tactical concepts were used or further tactical actions were prevented by the opposing team. Also note the large area in the lower middle range of the network area, where attempts with only one individual tactic (feint) are illustrated. Offensive attempts consisting of two tactical actions (initiating and 1st continuing action) were assigned (with one exception) to the right network area (bold dashed line). Finally, the left as well as the lower edge of the network represent attempts with more complex tactical structures. In these offensive attempts at least three individual or group tactics were accomplished (cross-hatched area).

By using neural networks, which classify attempts according to the similarity of their tactical structure, different teams can be examined in view of their tactical behaviour. As an example, the offensive attempts of the three best teams were isolated from the training data and tested afterwards with the network. A network pattern for each team in which the quantity of an offensive attempt type is represented by the circle diameter is shown in Figure 4. For a better illustration, the frequently occupied areas, i.e. dominant types of attempts, are marked grey in Figure 4.

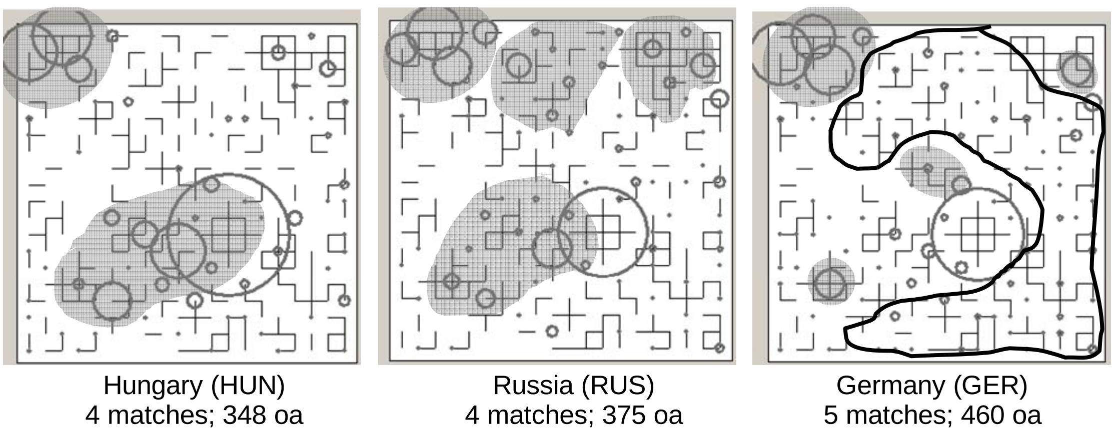
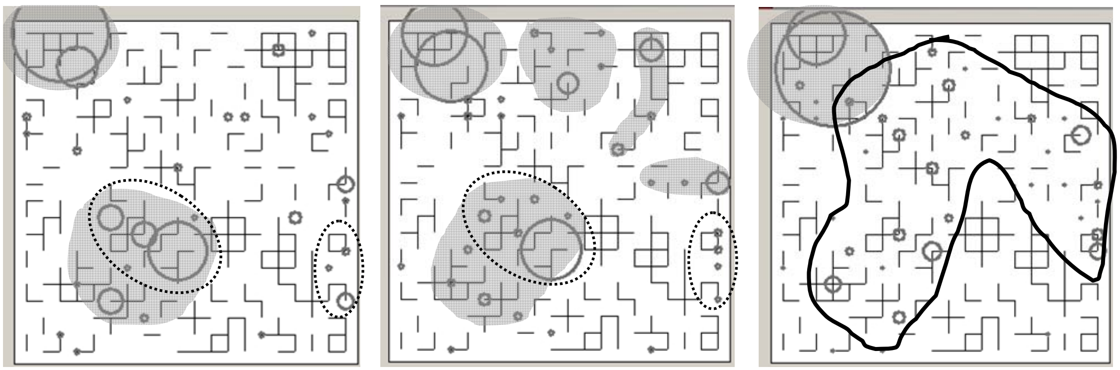


Figure 4. Type pattern of offensive attempts (oa) of the best teams (placement 1.- 3.)

Considering the upper left corner of the pattern, which represents attempts organized in the formation “fast break attack”, it becomes evident that Hungary turned fast break attacks 1 to a similar degree into actions with and without goal throw. In contrast to this, the Russian team more frequently terminates fast break attacks 1 with a goal throw, which at least opens up the possibility to score. For the German team the relation between fast break attack 1 with and without goal throw was unfavorable, i.e. more attempts are finished without a goal throw. However fast break attacks of Germany are characterized by the fact that in the fast break attack 2 the attempts with goal throws were dominating. If we look at the offensive attempts organised in the formation “position attack”, the type pattern of the Hungarian team is dominated by the formation 3:3 and individual tactical concepts. In contrast, for Russia three areas of activity could be identified. As in the tactical concepts of Hungary, individual actions are used, but also transitions and other actions (predominantly blocks) are applied as the first tactical action. The Russian team (as the only of the three teams under consideration) more frequently organised the position attack in a 2:4 formation. Contrary to Russia and Hungary, ranking first and second in the championship, we could hardly identify dominating tactical types in the position attack of the German team. The offensive attempts are distributed over the entire network area, indicating a diversified tactical behaviour. In comparison to the Hungarian pattern, it is striking that attempts without tactical actions predominantly end with a straight shot.

In a second analysis, we separately tested the successful attempts of the three teams, (i.e. those attempts that finished with a goal). As figure 5 shows, the network also identifies different patterns of successful tactical behaviour for the three teams. While the Hungarian team is more successful in the fast break attack 1 (upper, left area), the Russian team scores with both variants of a fast break attack. Germany acts predominantly successful with the fast break attack 2 (figure 5).



Hungary (HUN)
4 matches; 107 oa

Russia (RUS)
4 matches; 113 oa

Germany (GER)
5 matches; 117 oa

Figure 5. Pattern of successful types of offensive attempts (oa) (best three teams)

The Hungarian team does not only use individual tactic concepts frequently (figure 4), but also scored frequently by using these tactics (Figure 5). They were frequently successful by initiating with a feint without accomplishing continuing actions (dotted line). The Russian team acts partly in the same way, but three further areas of successful attempts can be identified by the network. Offensive attempts in the position attack 2:4 are to be emphasised. In comparison to the network pattern of the teams from Hungary and Russia, up to the fast break attacks we could not find dominant clusters of successful attempts in the team of Germany. Successful offensive attempts are distributed over large areas of the network (bold line) and show that Germany scored with a variety of different tactical concepts.

For the interpretation it must be considered that the defensive system of the opponents is not included in the present model of an offensive attempt. From a handball-specific point of view, however, there is an evident connection between the defensive system and the tactics of the offensive play. Therefore, additional information about the behaviour was registered as attributes next to the tactical characteristics, e.g. the defensive system. Hungary organised their offensive attempts more frequently (62% of all attempts) against offensive or half-offensive systems than the other two teams (RUS = 41% and GER = 37%). That could be a reason for the individualised tactical concept of the Hungarian team.

Discussion

The aim of the study was to show that the neural network method can be usefully applied to analyse the complex tactical structures in the field of sports games. In particular, the method provides a worthwhile instrument to investigate the process of the match which is conceived as a detailed process with high structural resolution. In the presented application, a model of an offensive attempt was taken as a structural unit in order to identify typical tactics of three teams aggregated over several plays. It is to be noted that the presented approach is not restricted to the use of the offensive attempt as a structural unit: By defining other appropriate structural units (depending on the particular aim of investigation), different methods of game structure analysis can be implemented. But even if restricted to the presented structural unit, its application can be helpful for tackling a variety of further questions.

If it is of interest to detect the change of tactical concepts within one match, several play phases may be considered separately by comparing the distribution of each phase on the same specifically coined network. Another way to investigate the evolution of the tactics within a match could be to classify the attempts in their chronological order obtaining trajectories over the network.

The structural analysis relies on information which represents the reality of the respective play only in an incomplete and selective way. The representation of the play in the model implies that, of course, not all relevant information can be contained in the data recorded according to this model. It is possible, however, to add potentially relevant information using additional attributes, which can provide important hints useful for the interpretation of results. Finally, analysis could be restricted to those attack attempts which are comparable under the view of corresponding play ideas or play contexts. Moreover, this analysis could be further restricted to those attack attempts which were accomplished against similar defence systems.

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Guidelines for motion control of humanoid robots: Analysis and modeling of human movements

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Abstract

The objective of the interdisciplinary Collaborative Research Center 588 "Humanoid Robots – Learning and Cooperating Multimodal Robots" is the construction of a humanoid robot. To make the robot attractive for services in households and offices the robot should be able to communicate and to interact with humans. Among other topics, this humanization concerns the strategies of motion planning for the humanoid robot. Besides anthropometric resemblance, the motion of the robot must be comparable to human motion. In this work, we analyze trajectories of limbs and develop guidelines for motion planning based on task-specific characteristics. Based on these guidelines we present adaptive models that are trained to classify single motion phases. A new algorithm is presented to compose these elementary models to large models that recognize complete motion trajectories. Finally, we show how to use the motion models to control the movements of a humanoid robot.

KEY WORDS: HUMAN MOTION, MOTION ANALYSIS, HUMANOID ROBOT, MOTION CONTROL

Introduction

Ever since people have dreamt of having automatic helpers which support them in their activities. Nowadays these automatic helpers have penetrated into many areas of human life. For example, robots in the motor industry are used for putting body panels of cars together. Their effectiveness surpasses that of man significantly. Furthermore, robots are used in danger zones. A well known example is the Robonaut of NASA's Johnson Space Center or the use of robot manipulators in nuclear power stations which handle contaminated material. First developments of mechatronical subsystems for humanoid robots have taken place in Japan over thirty years ago. Since then, the technological environment (computing power, power consumption, etc.) has developed dramatically. Consequently, humanoid robotics research was rediscovered within the last few years. Humanoid robots already completed or rather progressed far in their development are mainly found in Japan and the USA. The various research projects in this field have different emphases such as interaction with humans, multimodal communication with humans, learning ability, biped walking, etc. (Becher et al., 2004).
In July 2001, Collaborative Research Center (CRC) 588 "Humanoid Robots – Learning and Cooperating Multimodal Robots" (http://www.sfb588.uni-karlsruhe.de) was established by

the German Research Foundation (http://www.dfg.de). The project is designed for 12 years. More than 50 scientists from “Universität Karlsruhe (TH)”, “Forschungszentrum Karlsruhe”, “Forschungszentrum Informatik”, and “Fraunhofer Institute for Information and Data Processing” are involved in this interdisciplinary research project. The goal of CRC 588 is to generate concepts, methods, and concrete mechatronical components for a humanoid robot, which will be able to share its activity space with a human partner. In order to be a helpful assistant for its human counterpart, the robot system has to have many complex abilities and characteristics:

A humanoid shape: To be accepted by humans and to interact with them, it is advantageous for the robot to have an anthropoid shape. This means that the size, the geometry, and the arrangement of limbs as well as the number of degrees of freedom and the range of movement should be similar to that of humans. Besides anthropometric resemblance, the motion of the robot should be comparable to human motion.

Multimodality: This term includes the communication modalities that are intuitive for the user such as speech, gesture, and haptics (physical contact between the human and the robot), which will be used to interact with the robot system.

The ability to cooperate: Concerning the cooperation between the user and the robot – e.g. manipulation of objects – it is important for the robot to recognize the human's intention, to remember the actions that have already been carried out, and to apply this knowledge correctly in each individual case. Great effort is spent on safety, as this is a very important aspect of man-machine-cooperation.

The ability to learn: What honors humans in comparison with other living beings is their ability to learn. This ability has to be at least rudimentarily transferred to the robot. The reason for this is the possibility to lead the system to new formerly unknown tasks, for example to new terms and new objects. Even new motions will be learned with the help of a human and can also be corrected interactively even by inexperienced users (Becher et al., 2004).

The partially anthromorphic robot system ARMAR is the central component of the CRC 588 and the connecting element of the research endeavors (see Figure 1).

Figure 1. Partially anthromorphic robot system ARMAR

The possible service scenarios of such a robot are manifold. Quite conceivable appears a robot supporting a workman as an intelligent tool by manipulating objects or materials as a third or fourth hand of man, keeping the materials ready for processing. Another example would be the use as an accessory system in so-called smart houses, where such a system could execute inspections, repairs, or supervisions round-the-clock. Another interesting market is certainly the private living quarter since the proportion of elderly people in society rises constantly. Thereby it is not all about replacing trained nursing staff, but to enable elderly or disabled people to stay in their own apartments as long as possible by the use of such a technical support. Moreover, future generations are expected to have a considerably higher technology acceptance than today's generations.

Analysis of Human Movements

To enable a cooperation between a subject and a robot, the robot must have an idea of the motion sequences of the subject as exact as possible. The robot has to know which motion is currently carried out, it has to be able to estimate reliably how the motion is continued, and it has to be able to judge how well the subject can operate due to his anatomical prerequisites in the present situation. If the robot has the ability to detect these parameters in a current situation, it can prepare for the actions of the subject and adapt its movements accordingly. Thus, it must be examined which motion patterns people prefer for mastering prototypical everyday tasks. Personal features such as height, weight, or functional restrictions are going to be taken into account. It has to be elaborated, which degrees of freedom a subject uses at repeated executions of a provided task and which motion patterns are typical for a certain subject. The concept of motion patterns contains the trajectories of the limbs as well as the modeling of different partial motions which are performed by a subject. Finally, it must be evaluated how probable motion patterns are on the level of motion trajectories of the limbs and on the level of the sequence of partial motions. This knowledge serves the robot as a general basis for the recognition of human movements and for the adaptation of its own motion planning and motion execution to the movements of the subjects. Hence, a cooperation between the user and the robot is possible, in which the robot becomes an effective work assistant.

The research objective in this case is to analyze and to judge prototypical everyday movements for different groups of subjects. The motion data came from different subjects. They were asked to repeatedly perform different types of predefined object manipulations. Our analysis considers inter- and intra-individual variations in performance and timing. Based on the obtained results, principles of human motions were extracted. The motion data is used to train adaptive models that can be used to classify and thus to identify human motions. This classification enables the robot to estimate the intention of the subjects as well as to humanize its own movements.

Data Acquisition and Processing of Human Motion Data

Comparative studies of human motion and the extraction of typical motion characteristics require kinematic data of motion sequences from different subjects. We analyzed 10 subjects whose ages ranged from 21 to 28 years. In this study, we focused on the coordination of arm, hand, and fingers during simple object manipulations such as grasping, displacement, and rotation of wooden cuboids, bottles, and cups. The model of the human arm with hand and fingers comprised 28 marker points. Further on, eight additional markers were used to track the object’s positions. The 3D coordinates of skin markers were determined by video analysis. Six cameras were installed around the subject to ensure that all markers could be detected by at least two cameras at any time (see Figure 2). Since DV cameras do not have an option for an electronic synchronization of frame switch, an exact synchronization of the cameras was achieved by ten running LEDs visible in each view. The LEDs were switched with a frequency of 500 Hz, which yields a resolution of 0.002 s.

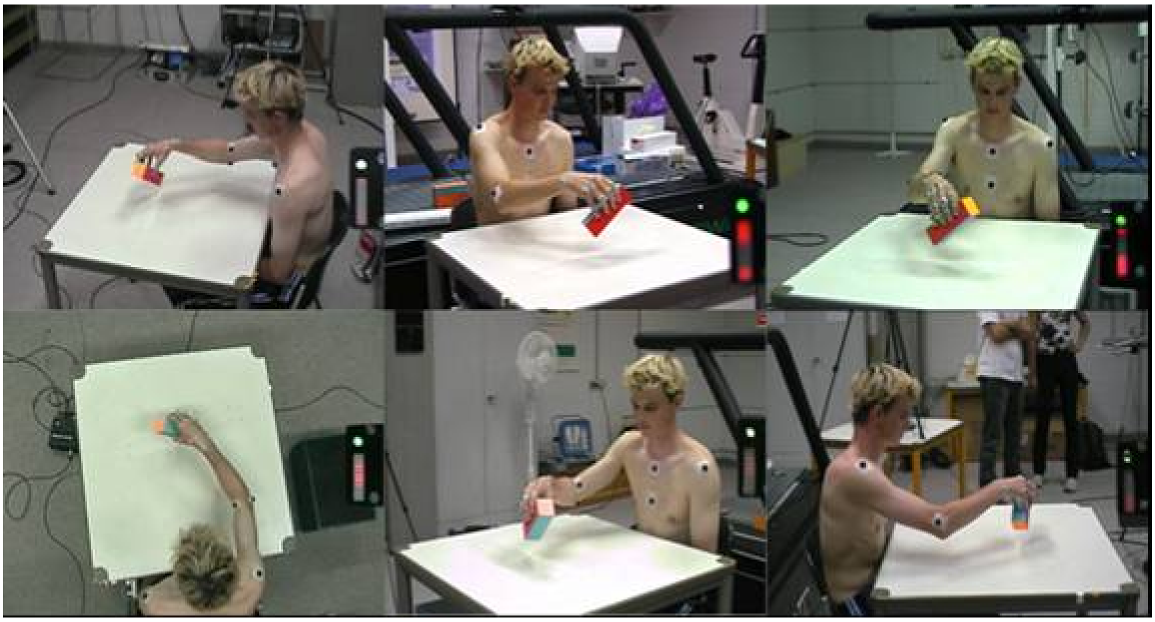

Figure 2. Views from six different camera perspectives

The data of the six cameras were registered by PC via an IEEE 1394-interface. For digitization of the video data and reconstruction of spatial coordinates we used a coordinate capturing software (SIMI-Motion 6.0, see Figure 3). The 3D coordinates were calculated according to the algorithm of Abdel-Aziz and Karara (1971). Although the marker picture coordinates were scanned on a sub-pixel level systematic errors occurred when identifying the centroids of the markers in the video frames. We used a special tool to de-interlace the video data and to improve the quality of the pictures. However, there were still some discontinuities in the images after interpolation and thus the 3D data was degraded by noise. The transformed 3D coordinates were exported into a specific software for kinematic analysis and smoothed with a cubic spline approximation (Reinsch, 1967). To be able to compare the repeated execution of a predefined motion task of one subject or the motion data of different subjects, the time series of trajectories and joint angles had to be normalized in time. After that, the mean trajectories and joint angles with standard deviations were calculated.

Intra- and Inter-Individual Variations in Human Movements

In the following, we present some results of the intra- and inter-individual comparison of the different motion tasks. Thereby, we focus predominantly on one of the 6 analyzed object manipulations: grasping a cuboid on a table and putting it on a heightened rack (see Figure 3). The reader is referred to Wank et al. (2004) for a more detailed discussion of the intra- and inter-individual spatiotemporal variations in human movements.

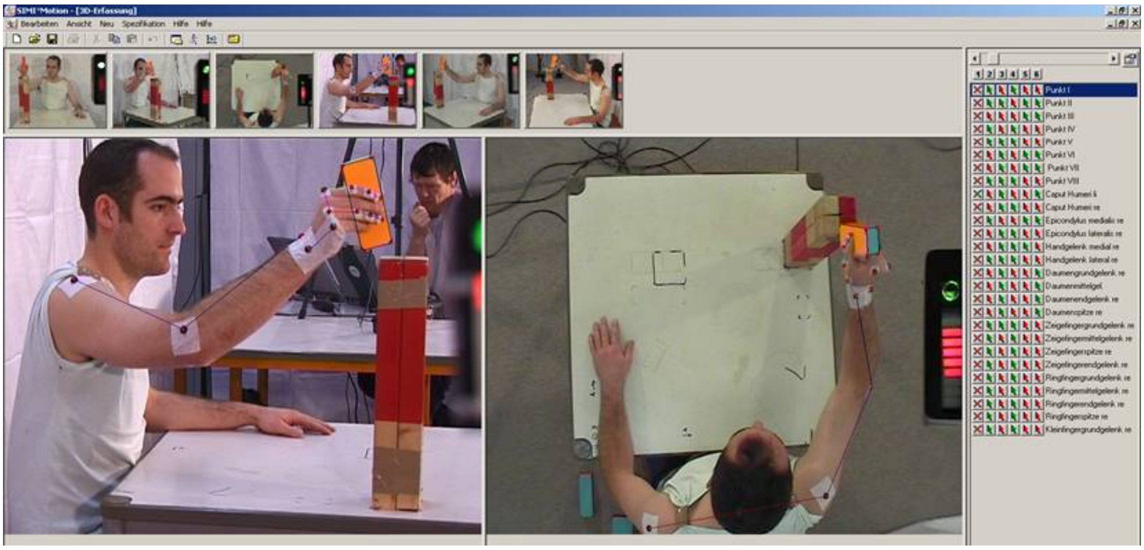

Figure 3. User interface of the SIMI-Motion software for the manual registration of marker coordinates in different camera views

In the sagittal plane, the trajectories of the manipulating hand showed permanent curved paths. Some subjects did not put the cuboid directly from the starting position to the target. Sometimes the subjects first moved the object towards their body and then to the target position (see Figure 4, left).

In the horizontal plane, human movements are performed more linearly following to the principle of the shortest path. This was observed even in those cases in which the objects had to be rotated during their displacement (see Figure 4, right).

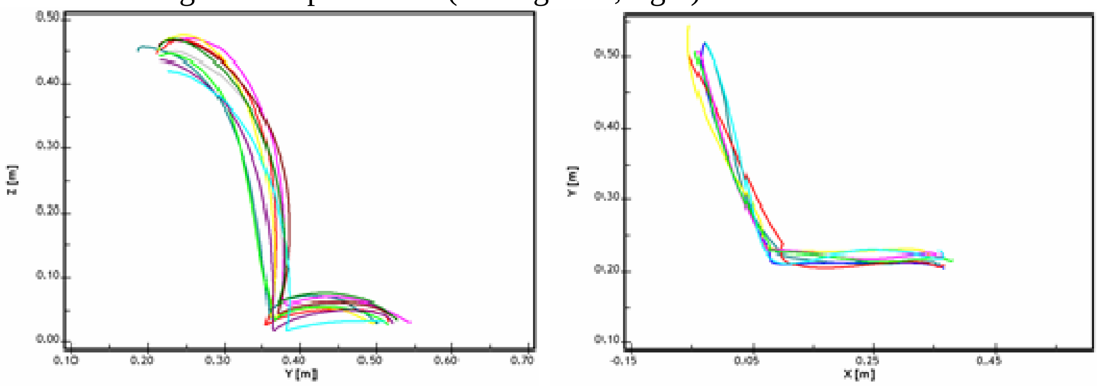

Figure 4. Left: Side view of hand trajectories of 10 subjects grasping a cuboid on a table and putting it on a heightened rack. The hands move from the starting position y = 0.50 m to the object at y = 0.35 m and then putting the object to the target position (y = 0.20 m, z = 0.40 m). Right: Top view of hand trajectories of 7 subjects moving from the starting position (x = -0.05 m, y = 0.50 m) to the object (x = 0.10 m, y = 0.20 m) and putting it with a rotation of 90° clockwise to the target position (x = 0.40 m, y = 0.20 m). All values are given in global coordinates.

The intra-individual variations during repeated actions of a subject are substantially lower than inter-individual variations. This was predominantly caused by differences in the body height of the subjects (between 1.60 m and 1.93 m) and the resulting variation in the limb length. However, it has to be mentioned that the trajectories of the hand or the object were quite similar almost independently of the body height of the subjects. Because of described differences in the length of limbs, the varieties in the joint angles of different subjects were very high in the course of time. In principle one can observe that relatively measured the differences of the joint-angle courses are fundamentally higher compared to the differences in trajectory courses (see Figure 6). Therefore one could suppose that the movement is mainly controlled by the trajectory of the periphery (hand and object) and not by the joint positions. In most cases, the subjects moved their eyes to the target position immediately after grasping the object. A permanent visual tracking of the object while performing the predefined object manipulations was never observed in our tests.

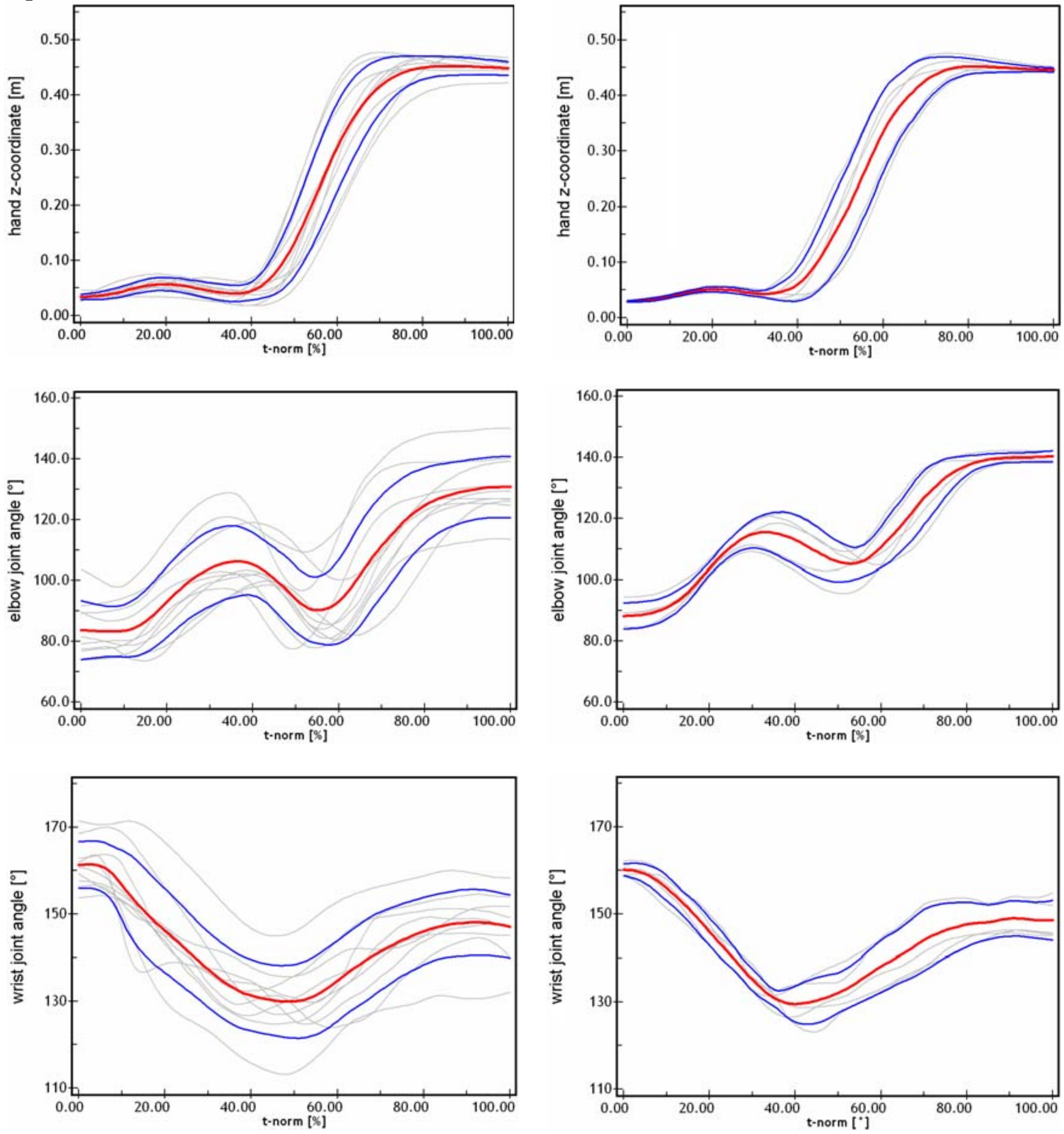

Figure 6. Top row (putting a cuboid on a heightened rack): Mean (red), standard deviation (blue), and individual time series (light gray) of the vertical coordinate z(t) of 10 subjects (left) and 5 trials of the same subject (right). All values are given in global coordinates. Middle and lower row (putting a cuboid on a heightened rack): Mean (red), standard deviation (blue), and individual time series (light gray) of elbow joint angles and wrist joint angles of 10 subjects (left) and 5 trials of the same subject (right). All values are given as solid angles between adjacent limbs.

The subjects were urged to execute the predefined movements as they would in their daily life. This led to partly huge differences in movement speed and therefore in movement duration, too. Almost constant movement durations were measured for each subject except one. These results indicate that the mean movement duration is characteristic for each subject. It describes the mentality of the subject ranging from fast and imprecise to slow and precise.

Building the Motion Data-Base

Based on the results from the analysis of intra- and inter-individual human movements, we created a first universal model for the characteristics of human movements. The model should be adaptive and thus able to learn the characteristic features from a set of given motion trajectories. Since all adaptive models require a large set of training data, we started to build a motion data-base. For that purpose, we used a magnetic motion tracking system (Motionstar by Ascension) (see Figure 7). This system is equipped with a long range transmitter and 6 sensors to track the entire right arm and allows the acquisition of motion data with only minor manual interaction.

The sensors were placed on the sternum, the acromion, the middle of the humerus, the middle of the ulna, and the dorsum manus. Using our algorithm for the reconstruction of joint centers (Beth et al., 2003) we could determine the joint angles for the shoulder, the elbow, and the wrist. To get the joint angles of the right hand, the subjects wore a data glove (CyberGlove by Immersion) with 18 DOFs. The positions of the hand and finger segments could be determined by the position of the wrist and a direct kinematical model of the hand.

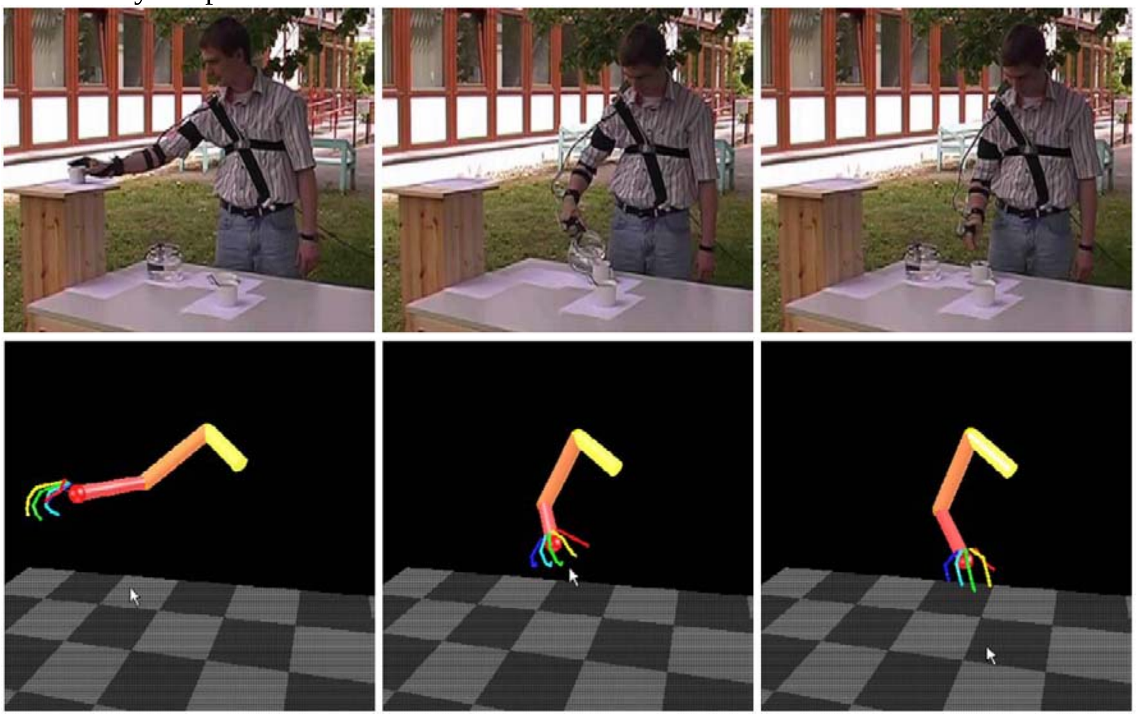

Figure 7. Acquisition of motion data from a subject wearing a magnetic motion tracking system and a data glove (upper row). 3D visualization of the reconstructed trajectories (lower row).

Our first set of trajectories comprises 140 motions from 7 subjects performing a complex motion sequence. Each motion sequence consists of 13 major motion phases:

1) Movement of the hand and arm from the starting position to the saucer.
2) Lifting the saucer, putting it on the table, and opening the hand.
3) Moving back the arm and grasping the cup.
4) Lifting the cup and positioning it on the saucer.
5) Moving back the arm, grasping the coffeepot, and contracting the muscles for lifting.
6) Actual lifting of the coffeepot and bringing it to the cup.

7) Pouring the water into the cup.
8) Putting the coffeepot back on the table.
9) Moving the hand to the spoon in the sugar bowl, including grasping.
10) Movement of the spoon and lowering it into the cup.
11) Stirring the content of the cup, lifting the spoon.
12) Putting back the spoon.
13) Moving the hand back to the starting position.

In contrast to absolute spatial coordinates the joint angle trajectories contain relative information to fully describe human motions. While the angle trajectories of the fingers are highly characteristic for certain applications (Wank et al., 2004) our experiments show that it is sufficient to use the shoulder, the elbow, the wrist, plus two flexions and the abduction of both thumb and index finger in our test scenario. The angle trajectories of these 9 joints and the corresponding angular velocities are the basis for all subsequent trainings and evaluations.

Modelling the Characteristics of Human Movements

There are two main research interests in the field of motion control for humanoid robots: first, to identify a subject from its movements and second, to identify motion phases that come from different subjects. While the identification of a subject is straightforward because of the restricted number of subjects, the classification of motion phases within a complex movement is still a challenging problem. Since our motion data-base has 140 trajectories with 13 motion phases each, the models have to deal with 1820 data sets and thus have to learn the corresponding classification by abstracting from the individual subjects.

In previous work, we demonstrated how to automatically train an adaptive mathematical model and make it learn the characteristics of human movements (Boesnach et al., 2005; Moldenhauer et al., 2005). In a first approach, we used recurrent neural networks called Elman network (EN) (Elman, 1990) and Hidden Markov Model (HMM) (Rabiner, 1989) to classify human movements by time series of joint angles and angular velocities. In both studies, a model was trained to identify a certain motion phase and the classification was performed using a winner-takes-all strategy. The ENs reach an average recognition rate of approx. 66 %, the HMMs perform significantly better with approx. 86 % of correctly classified points in time. In particular, HMMs have proven to serve well for the analysis of complex time series.

HMMs can be defined as probabilistic models for stochastic processes or as probabilistic automatons $\lambda = \left(S, \boldsymbol{\pi}, \mathbf{A}, \mathbf{B}, V\right)$ with N states $S = \left\{s_1, ..., s_N\right\}$, an initial state distribution vector $\boldsymbol{\pi} = \left(\pi_1, ..., \pi_N\right)$, and a stochastic state transition matrix $\mathbf{A} = \left(a_{ij}\right) \in \mathbb{R}^{N \times N}$, where a_{ij} are the probabilities for the transitions from state s_i to state s_j. In our work we use Bakis-models (see Rabiner, 1989) with an upper-triangular transition matrix. This family of transition matrices makes the models run through a strict sequence of states. Additionally, observation probabilities $\mathbf{B} = \left(b_j\left(v_k\right)\right) \in \mathbb{R}^{N \times K}$ define the probability of having an output v_k out of the set of K observable symbols $V = \left\{v_1, ..., v_K\right\}$ when the automaton is in state s_j. For discrete HMMs a codebook $o_t \mapsto v_k$ maps the elements of an observation sequence $O = o_1 o_2 ... o_T$ to the symbols in V over the time steps $t = 1, ..., T$. For our purpose we use HMMs with continuous observation densities. In this case, the observation probabilities are directly calculated from real vector observations with dimension n by the following equation using mixture densities:

$$b_j\left(o_t \in \mathbb{R}^n\right) = \sum_{m=1}^{M} w_{jm} \mathcal{N}\left(o_t, \boldsymbol{\mu}_{jm}, \mathbf{U}_{jm}\right).$$

The *M* mixture components $\mathcal{N}$ are weighted by the coefficients $w_{jm} \in [0,1]$. Generally, we use Gaussians for $\mathcal{N}$, where $\boldsymbol{\mu}_{jm} \in \mathbb{R}^n$ and $\mathbf{U}_{jm} \in \mathbb{R}^{n\times n}$ are expectation vectors and covariance matrices. Figure 8 shows a general model unrolled over the time. The upper row represents the state sequence $Q = q_1 q_2 ... q_T$ and the transitions of the automaton. The lower row shows the corresponding observation sequence $O = o_1 o_2 ... o_T$. Note that only the observations in *O* can be seen from outside the automaton. The inner states in *Q* must be estimated via probabilities and are thus called hidden states.

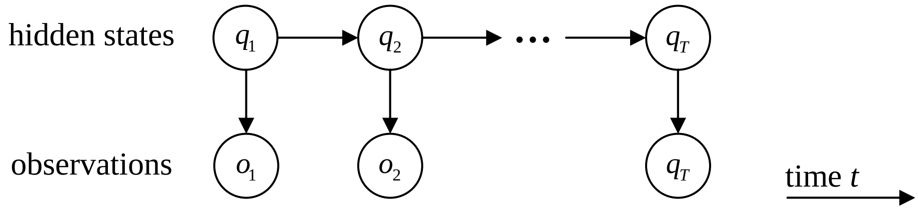

Figure 8. A general HMM

To find proper parameters for the transition probabilities in **A** and the observation probabilities in **B**, HMMs are trained with sequences of example observations. Typically an expectation maximization by the so-called Baum Welch algorithm is used for this task. Then, the so-called forward algorithm can calculate the probabilities $P(O \mid \lambda)$ for an observation sequence *O* that has to be analyzed given the model *λ*. If there are several HMMs $\lambda_1, ..., \lambda_C$ for *C* different classes of observations then the model $\lambda_{c_{\max}}$ with the best probability and hence the class $c_{\max}$ of the current observation can be found:

$$c_{\max} := \arg\max_{c=1,...,C} \left\{ P(O \mid \lambda_c) \right\}.$$

This method is the so-called winner-takes-all strategy. In our first work, we used one model λ_p for each of the motion phases $p = 1, ..., P$ and time-shifted windows $O_{t,W} = o_t o_{t+1} ... o_{t+W}$ from entire motion trajectories *O* as observation sequences.

As another approach we developed a new algorithm for the composition of motion models. This algorithm uses a set $\{\lambda_1, ..., \lambda_P\}$ of the HMMs trained to identify simple motion phases $p = 1, ..., P$ and concatenates them to a new HMM $\tilde{\lambda}$ for a complex movement. The objective is to define a catalogue of motion phases, to train an elementary HMM λ_p for each phase, and to analyze a very complex motion consisting of certain elementary motion phases from the motion catalogue by the complex HMM merged from elementary HMMs.

The parameters of such a complex HMM $\tilde{\lambda} = \left(\tilde{S}, \tilde{\boldsymbol{\pi}}, \tilde{\mathbf{A}}, \tilde{\mathbf{B}}, V\right)$ can be automatically constructed from the parameters of selected elementary HMMs $\lambda_1, ..., \lambda_P$ by a context-free grammar or an adjacency matrix defining the succession of motion phases. The parameters of these models are once determined by the methods in Boesnach et al. (2005) and stay constant in the motion catalogue. To compose an HMM from the elementary HMMs we first combine the state transition matrices $\mathbf{A}_1, ..., \mathbf{A}_P \in \mathbb{R}^{N\times N}$ of the models to a large matrix $\tilde{\mathbf{A}} \in \mathbb{R}^{NP\times NP}$ for an extended state space $\tilde{S} = \{s_1, s_2, ..., s_{NP}\}$. Again, Bakis-models produce proper HMMs for phase detection. Following this design principle, the complex model is constructed to run through a desired sequence of elementary motion phases. Thus, also the transition matrix of the complex model has the structure of an upper triangular matrix. In contrast to elementary HMMs, the entries on the diagonal are not transitions for single states but for the submatrices of the elementary models:

$$\tilde{\mathbf{A}} = \begin{pmatrix} \ddots & & & & \\ & \boxed{\mathbf{A}_p} & & & \\ & & a_p & & \\ & & & \boxed{\mathbf{A}_{p+1}} & \\ & & & & \ddots \end{pmatrix} \mathbf{n} .$$

Additionally, the elementary matrices are connected by transition probabilities $a_p = 1/(1+\bar{T}_p)$ between the motion phases which depend on the mean lengths $\bar{T}_p$ of the elementary motion phases. The final multiplication by a normalization vector $\mathbf{n}$ guarantees the stochastic constraints for HMMs. The initial state distribution $\tilde{\boldsymbol{\pi}} \in \mathbb{R}^{NP}$ and the parameters $\tilde{\mathbf{w}} \in \mathbb{R}^{NP\times M}$, $\tilde{\boldsymbol{\mu}} \in \mathbb{R}^{NP\times M\times n}$, and $\tilde{\mathbf{U}} \in \mathbb{R}^{NP\times M\times n\times n}$ for the output probabilities in $\tilde{\mathbf{B}} \in \mathbb{R}^{NP\times K}$ are determined by a corresponding composition of the parameters from the elementary models.

The proposed construction can be extended to allow not only strict sequences of motion phases but branches in motion parts. These alternative motion parts are required, e.g., if the motion contains significant intra-individual differences during the performance of the motion and if we want to detect these differences. The differences in the motion phases during the manipulation of the coffeepot are a typical example in our motion catalogue. Transitions to the additionally introduced artificial phases allow the distinction of the fill level of the coffeepot.

Classification of Phases in Human Motion

The composition of complex HMMs from elementary HMMs of single motion phases leads to a new method of motion analysis. The information about the sequence of hidden states

$$Q_{\max} := \underset{Q\in\{q_1q_2\ldots q_T \mid q_t\in\tilde{S}\}}{\arg\max} \left\{ P(Q \mid O = o_1o_2\ldots o_T, \lambda_c) \right\},$$

which is calculated by the Viterbi algorithm (Rabiner, 1989), is explicitly used to detect certain motion phases. If $q_t = s_z \in \tilde{S}$ holds for the state variable then the phase index is $p = \lfloor z/N \rfloor + 1$ at time *t*. Typically, the information about *Q* is only used to calculate a better model probability in dependence of the Viterbi path. However, usage of the full capacity of the state sequence leads to more efficient and robust classification methods with high recognition rates (see Figure 9). Even the difficult problem of constraint recognition can be solved with excellent recognition rates. The reason for this is that the model regards the entire motion and the motion phases in their context. Furthermore, the composition of the complex HMMs is automated. The composition algorithm is generic and can be used to concatenate any elementary models to a complex one. Thus, it is possible to build up a model library with elementary HMMs and to combine them to the required model for a special classification task comparable to a construction kit. This is an important step towards an interactive extension of the robot’s knowledge data-base, which is one of the primary demands for a purposeful cooperation between the human and a learning humanoid robot.

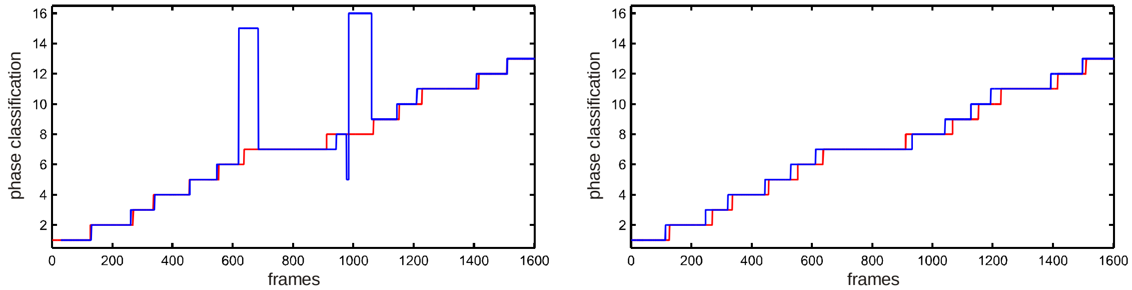

Figure 9. Classification of phases with HMMs (blue) in comparison to optimal classification (red). Left: conventional method with 16 HMMs and winner-takes-all strategy. Right: more robust results with the new algorithm using a complex HMM and state sequence.

Motion Control of a Humanoid Robot

The algorithms for motion control of a humanoid robot highly depend on the field of its application. Most of the methods in literature are either pose or task oriented. The pose oriented approaches optimize the robot’s movements with respect to the pose of the robot in order to look as human-like as possible. These robots are not meant to deal with objects or even to interact with people. In addition to these animation tasks, we consider actions like walking, running, dancing, and some simple manipulation tasks as pose oriented, because they do not require a precise positioning of the robot’s end effectors. Of course, these actions must be performed correctly, e.g. the robot must not loose its balance. However, there is a considerable difference to task oriented motions.
An exact control of the robot's end effectors is indispensable for a humanoid robot that is supposed to interact with people and assist them in everyday life (e.g. Asfour et al., 2000). A very simple solution known from industrial robots is to use inverse kinematics and to solve a set of equations to reach the desired positions. Of course, these movements do not look human-like and thus are not adequate for a humanoid robot. The commonly used methods for the generation of pose and task oriented motion can be divided into methods that map a given human motion trajectory to the robot and model based approaches. The essential difference is that model based methods fall back on the knowledge of human behavior that allows them to generate trajectories from scratch while the mapping of human motions requires some explicitly given trajectories from motion capture data. In general, the mapping of human motion trajectories comprises the following steps:

1) defining a skeleton model for the robot,
2) defining a skeleton model for humans,
3) capturing raw motion data,
4) mapping raw data on the model of the human skeleton,
5) mapping the data on the robot’s skeleton model,
6) applying the robot’s joint angle limits,
7) applying the robot’s joint velocity limits and torque,
8) applying other constraints, e.g. dynamic balance.

For detailed information on the mapping of human motion data to robots we recommend Pollard et al. (2002), Zordan et al. (1999), Nakaoka et al. (2003), Riley et al. (2000) and Riley et al. (2003) which also give a good overview of that area of research.

Some new approaches use model based methods that do not map tracking data from a human to some given constraints. Thus, they must create motion trajectories from scratch using a model that contains the characteristic motion features of humans. So far, model based methods for generating motions are only used for biped walking and running of a humanoid robot. Both motions require a control method that comprises whole body dynamics. As an extensive discussion of this topic would go beyond the scope of this article we refer to Yamaguchi et al. (1999) for walking or Löffler et al. (2002) and Kajita et al. (2002) for running. The latter algorithms use adaptive models that are considerably more flexible than hard-coded models. They can be used for the autonomous control of full-body motions of a humanoid robot. A comprehensive approach that includes navigation, grasping and manipulation, footstep placement, and dynamically-stable full-body motion is published by Kuffner et al. (2003). Further information can be found in Zöllner et al. (2004) or Schaal et al. (2003).

The open question with regard to generating a task oriented trajectory is whether the motions look human-like or not. There is no extensive study dealing with this question so far. The desirable motions of a future humanoid robot are a combination of the task oriented and the pose oriented approach. We call this combination *context oriented* because it must accomplish a given task that is part of the motion context and the trajectory should look as human-like as possible whereas the definition of human-like depends on the motion context, too. In other words, the motion context consists of a concrete action, e.g. the exact positions and orientations of the robot's end effectors and a formal description of the motion called pose, e.g. a motion class like ”grasp book” or ”grasp plate”. From the task oriented view, the trajectories for grasping a book and grasping a plate are very similar. In both cases, the robot must move its hands to the object and pick it up. From the pose oriented view, the motions are totally different because they are located in quite different motion contexts. Some optional style parameters may additionally characterize the motion, e.g. ”fast”, ”precise”, ”female”, or ”young”.

Our new approach uses a context specific motion classifier to select an appropriate trajectory. The scheme for the generation of context oriented motions consists of four parts (see Figure 10). First, the motion context must be defined by the motion planner. The motion context consists of three components: the task, the pose, and the style of a motion. From the motion context, the motion generator creates a set of trajectories that fulfill the given task. Since our approach does not depend on the type of the motion generator, any implementation can be used as long as it creates a set of task oriented motion trajectories. Each trajectory thus may be used by the robot to perform well but there is no information which trajectory would match a human performer best. For this purpose, the set of trajectories is processed by the motion classifier from the previous section. It is used to classify the generated trajectories with respect to the pose and style given from the motion planner. The trajectory that matches these constraints best is finally executed by the motion control. This scheme is only slightly modified compared to a classical approach for generating humanoid robot motions, i.e. the motion generator returns a set of motions instead of a single motion.

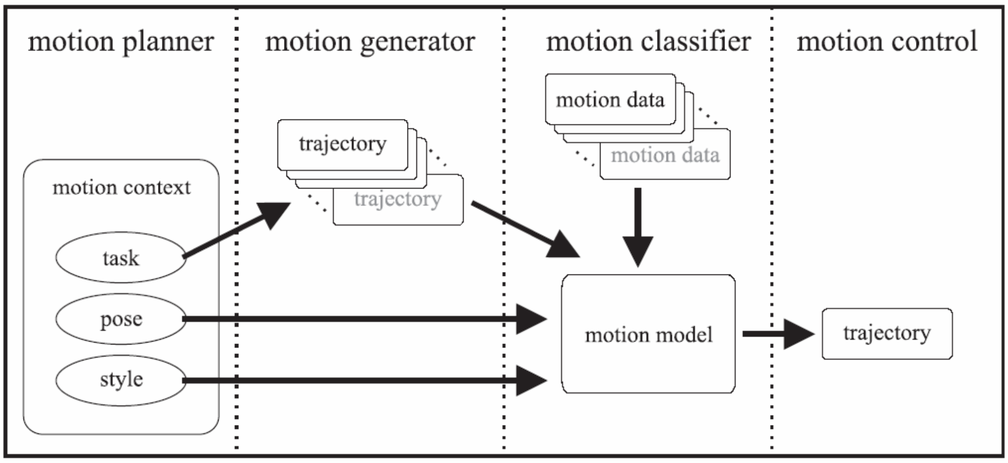

Figure 10. Scheme for generating context oriented motion. Our new approach uses a context specific motion classifier to select an appropriate trajectory.

Further research

The experimental studies carried out so far are restricted to the analysis of the movement of the shoulder, the right arm as well as the right hand and fingers of a few subjects. In future studies the motion data-base has to be extended and more complex movements have to be analyzed. For that purpose, we use an infra-red motion tracking system by VICON with a set of 80 markers (see Figure 11) for whole body motion capture. Consequently, a skeleton model with 50 DOFs will be used in the following studies.

Among other things, our analyses will focus on the kinematics of the upper part of the body, both arms, both hands, and fingers. We are interested in the reduction of the DOFs at the interplay of limbs as well as the change of movement patterns during fine coordination or pressure of time. Another interesting issue is the consideration of the environmental context, i.e. the reaction to environmental changes and suddenly appearing restrictions of the possible motion trajectories. In other words, the essential questions are: how do humans react if something crosses their movement path, how do they adapt to the new situation, and how do they modify their movement in such a case. Besides the kinematical appraisal of human motion it is important to consider dynamic aspects, too. Thus, we are going to do tests for dynamic analyses of fetch and carry tasks such as grasping a coffee cup and carrying it from one place to another. These tests are very important for the improvement and advancement of the hands of the robot.

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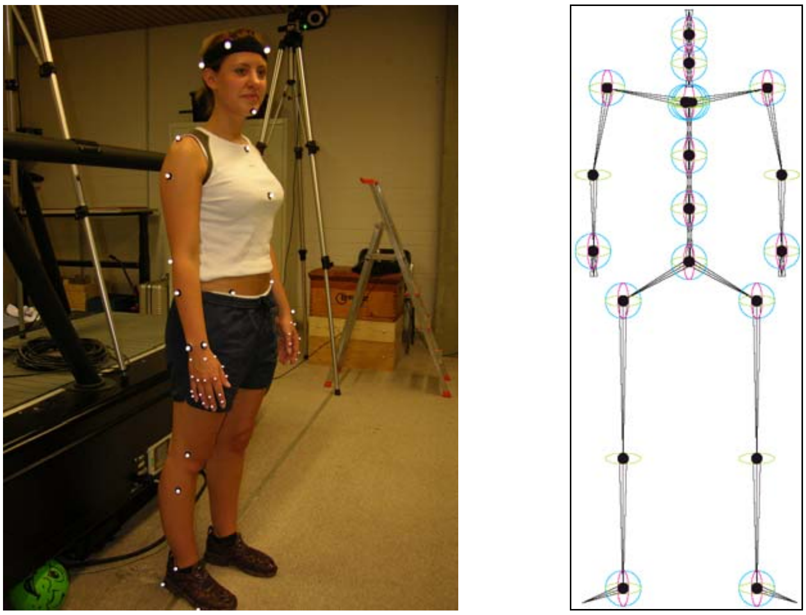

Figure 11. Subject in our motion lab wearing 80 markers that allow whole body motion tracking using a camera system from Vicon (by Vicon Motion Systems). Skeleton model with 50 DOFs for the mapping of full-body motion capture data. All joints have three degrees of freedom except the elbows and knees (1 DOF each) and the clavicles (2 DOF each).

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A dynamic approach for modelling and simulation of motor unit discharge behaviour using recurrent fuzzy-techniques

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Abstract

A dynamic approach for modelling and simulation of motor unit discharge behaviour using recurrent fuzzy-techniques is presented. The model is able to generate a nominal force-time curve by means of the discharge behaviour of a single motor unit pool using the knowledge of various seemingly isolated findings that have been reported.

In several simulations, it has been shown that recurrent fuzzy systems are able to approximate dynamic behaviour in terms of nominal/actual force value regulation.

First results suggest that there might be optimal motor unit co-ordination patterns relating to a given task: in first MVC-simulations variation of about 10% has been shown.

In spite of the difficulties to verify the model experimental examination is necessary to confirm the results. This kind of research is fundamental to understand mechanisms that yield to increased muscle performances in sports.

KEY WORDS: MOTOR UNIT DISCHARGE, MODELLING, SIMULATION, RECURRENT FUZZY TECHNIQUE, ISOMETRIC MUSCLE CONTRACTION

Introduction

Human skeletal muscle is a classic example of a biological structure-function relationship. At both macro- and micro-scopic levels, muscle is exquisitely tailored for force generation and movement. A muscle consists of certain numbers of different motor units with individual characteristics. Force production and force regulation within a muscle is realized by recruitment and rate coding of these motor units. There has been a lot of research in motor control which has provided insight into the recruitment order of motor units, the interaction between recruitment and firing rates and the interaction between the force output of the muscle and the firing rate of motor units (for reviews see De Luca & Erim, 1994; Enoka & Fuglevand, 2001). However, the basic principles underlying system's overall operation still remain poorly understood (De Luca & Erim, 1994). Beside Henneman's well-known size principle (Henneman et al., 1965), there exist a few general concepts for the control of motor units, for instance the concept of common drive (De Luca et al., 1982). It suggests that the activation of motor units is controlled by the same source (CNS) as the net sum of excitatory and inhibitory inputs to the motoneuron pool without monitoring and regulating each motor unit separately (De Luca & Erim, 1994). Research about the influence of interaction between motor units on force production mainly focuses on motor unit synchronization as a measure of the correlated discharge of action potentials. Motor unit synchronization is supposed to contribute to larger force fluctuations in simulated force (Yao et al., 2000) and to increase the rate of force development during rapid contractions (Semmler, 2002). Furthermore it is discussed as a mechanism to coordinate the activity of multiple muscles to promote skilled muscle synergies (for a review see Semmler, 2002).

The exploration of certain principles of motor-unit pool organization is very difficult to examine experimentally. Therefore, some authors developed models of recruitment and rate coding organization in motor-unit pools. Fuglevand et al. (1993) presented an inductive approach simulating isometric muscle force and surface electromyogram from a model that predicted recruitment and firing times in a pool of 120 motor units under different levels of excitatory drive to analyse EMG-force relations. The authors emphasised the exactly known input to muscle which allowed the exploration of some issues of motor-unit pool organization. Unfortunately, neither effective nor efficient interaction between the motor units were discussed.

Summarized, it is still remain unclear whether exist optimal motor unit co-ordination patterns for a given population relating to a given task under specific constraints. Indeed, mechanisms of motor unit synchronization are supposed to be important for the rate of force development during rapid contraction (Semmler, 2002) and it is generally assumed that neural adaptations to strength training consist of newly recruited motor units and higher firing rates (Sale, 1992). But the very fact that motor units have different contractile properties (e.g. contraction times, peak amplitudes, firing rates to tetanise) arises the question of intended purpose.

This work examines a dynamic approach of an isometric muscle model that demonstrates control properties of a single motor unit pool.

Methods

Control properties of the neuromuscular system are responsible for the regulation of muscle force and depend on central and peripheral factors. According to task specificity, the neuromuscular system is a cybernetic system with a more or less of activation and regulation mechanisms.

The model presented in the following part is a fuzzy logic control system and comprises two elements: an isometric force model for single motor units and a fuzzy logic component.

Isometric force model for single motor units:

If isometric force production in motor units is assumed as a linear process (important nonlinearities are discussed afterwards), the twitch can be regarded as the impulse response of the motor unit system and well approximated by a critically damped, second-order system (Stein et al., 1972; Milner-Brown et al., 1973; Fuglevand et al., 1993; see Figure 1). Thus the tension g(t) in response to an impulse is given as a function of time by

$$g(t) = \frac{P \cdot t}{T} \cdot e^{1-(t/T)} \qquad (1)$$

g(t): impulse response as a function of time
P: peak amplitude of twitch force
T: rise time (contraction time)
e: natural constant

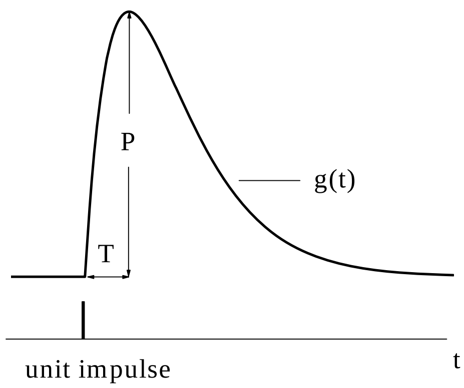

Fig. 1. Simulated impulse response of a motor unit system approximated by a critically damped, second-order system. T: contraction time, P: peak amplitude. Mathematically, a unit impulse is referred to as a Dirac delta function applied over a very short period of time. In practice, an impulse is a postsynaptic action potential, which leads to a motor unit discharge.

But in practice, there is not only a single impulse: recruitment of a single motor unit can be described as a process, where the output of the linear system is a cumulated response to random trains of action potential stimuli with different mean rates.
The most straightforward way to solve linear differential equations and determine the system response is to use the Laplace transform. The Laplace transform is an integral transformation, which maps a large class of original functions u(t) in the time domain unambiguously reversible into image functions U(s) in the s domain (Lutz & Wendt, 1998). This mapping is performed via the Laplace integral of u(t), that is

$$U(s) = \int_0^{\infty} u(t) \cdot e^{-s \cdot t} dt \tag{2}$$

S = $\sigma + j\omega$ (complex variable),
U(s): image functions in the s domain
u(t): original function in the time domain

Instead of solving the differential equation with the initial conditions directly in the original domain, the detour via a mapping into the frequency domain is taken, where only an algebraic equation has to be solved. Thus solving differential equations is performed according to Figure 2 in the following three steps:
1. L-Transformation of the differential equation into the mapped space,
2. Solving the algebraic equation in the mapped space,
3. Back L^{-1} transformation of the solution into the original space.

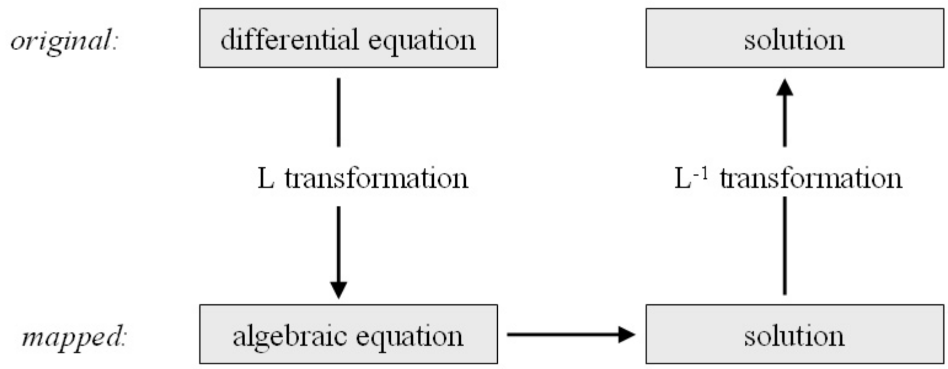

Fig. 2. Schema for solving differential equations using the Laplace transformation (from Schmid, 2004)

The linear differential equation describing the behaviour of a motor unit system with a unit impulse input is

$$\ddot{y} + 2D\omega_0\dot{y} + \omega_0^2 y = K\omega_0^2 u \tag{3}$$

y(t): output variable,
D: damping ratio,
ω_0: natural frequency (frequency of the undamped oscillation),
K: gain factor,
u(t): input variable

The quotient of the Laplace-transformed output and input of such a type of system is a rational fraction. The coefficients of this fraction depend only on the structure and parameters of the system. Such a type of function G(s), which describes completely the transfer behaviour of a system, is called the transfer function of the system:

$$G(s) = \frac{Y(s)}{U(s)} \tag{4}$$

With such a transfer function G(s) the output Y(s) can be immediately calculated for a known input signal u(t), and therefore U(s).
The transfer function that is used in the current model is the 2nd-order lag element (PT_2 element) having damping properties and lag behaviour.

$$G(s) = \frac{Y(s)}{U(s)} = \frac{K\omega_0^2}{s^2 + 2D\omega_0 s + \omega_0^2} \tag{5}$$

The inverse Laplace transform of G(s) is the function g(t). This function is generally known as the weighting function of the system.
Summarised, if the unit impulse is taken as the input signal u(t) for a system described by the transfer function G(s) in Eq. 5, the output y(t) is the impulse response with a defined magnitude of the frequency response conditioned by the constant coefficients. Figure 3 shows

simulated impulse response of a single motor unit after a train of stimuli with different interpulse intervals.

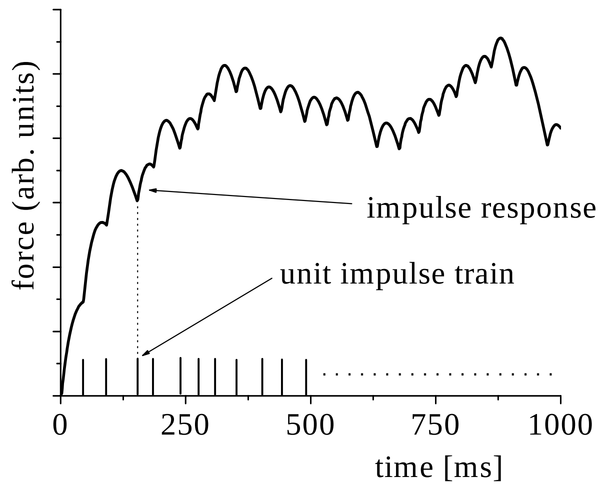

Fig. 3. Simulated impulse response of a single motor unit after a train of stimuli with different interpulse intervals.

A whole motor unit pool consists of a user-defined number of certain single motor units with individual characteristics, which can be chosen from empiric or hypothetic assumptions (see Figure 4). The total force output of the whole model was determined as the algebraic sum of single motor unit forces.

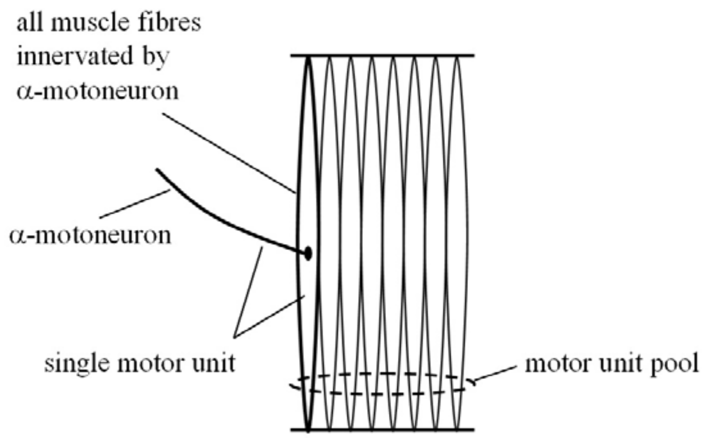

Fig. 4. Abstract muscle model.

Fuzzy logic component

The fuzzy part of the model is embedded in a recurrent fuzzy system. Recurrent fuzzy systems are useful for specific dynamic systems where the state of a dynamic process is usually not only depending on the current input but also on its prior states and inputs (Nürnberger, 2004). Both aspects fulfil the conditions of a motor unit system. The main idea of the fuzzy approach is to use various seemingly isolated findings that have been reported in neuromuscular research as knowledge base to generate a fuzzy rule base (see Kruse et al., 1994).

As fuzzy domains are used Input x_1 to describe the nominal/actual force value comparison of the abstract muscle and Input x_2 for time of the last discharge of each motor unit. The possible values of the input terms are small, medium, large and very large respectively. The resulting output variable z of the model is the excitatory drive. Possible values of the terms are defined as small, medium and large. If z_i reaches the recruitment threshold of the i^{th} MU, an unit impulse will be generated and leads to the force behaviour which was described shortly before. All terms are defined by fuzzy sets and shown in Figure 5.
The rule base describes the relation between the input and output variables. The rule base for the model is defined as shown in Table 1. It has been composed by generally assumed principles of neuromuscular research (mostly referring to Basmajian & De Luca, 1985). Interpretation of the values in the input vectors and, based on the user-defined rules, assignment of the value to the output vector together is called a Fuzzy Inference System (FIS). The model includes two FIS for fast and slow twitch fibres only varying in partitions of the fuzzy set of Input x_2.

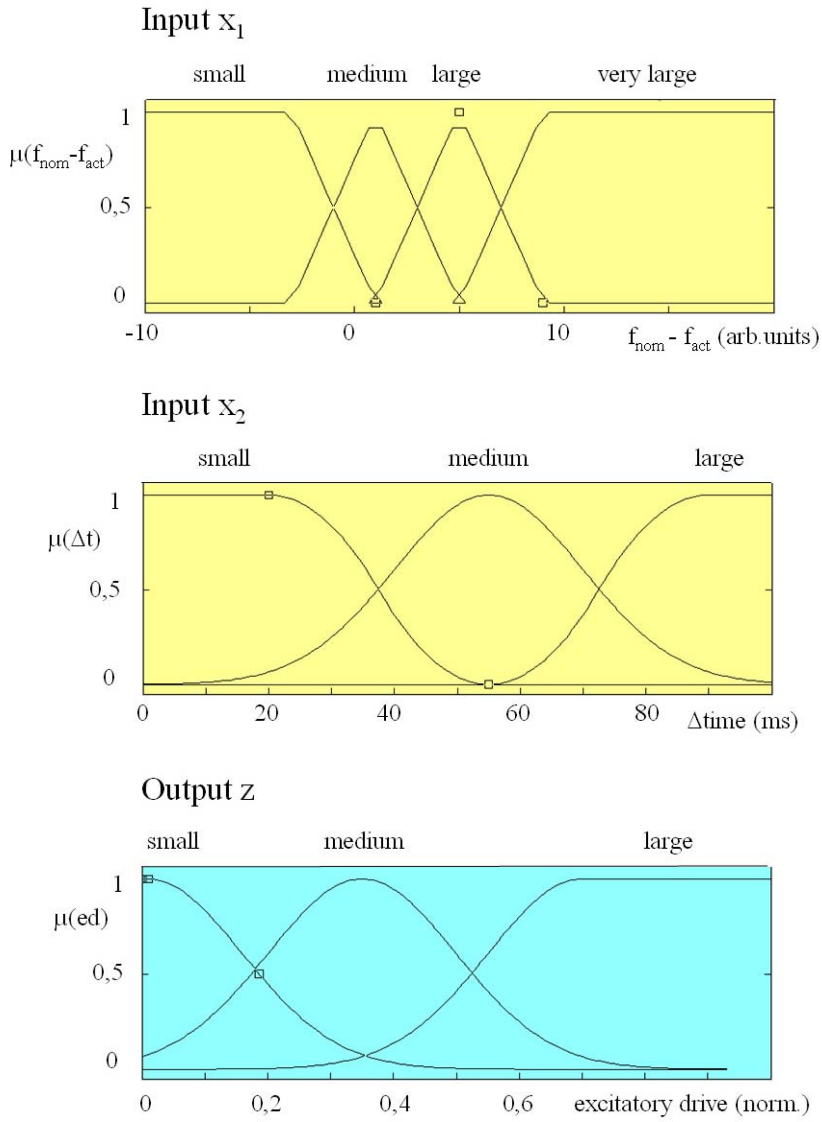

Fig. 5. Fuzzy sets fort he description of input and output variables (see text for more details).

Additionally, the variability of time intervals between the discharges of a motor unit, which seems to be a random process with a Gaussian probability distribution function (for references see Fuglevand et al., 1993), was considered by adjusting the times of the last discharge continuously.

Tab. 1. Fuzzy rule base representing the discharge behaviour of a motor unit. The rule base was defined manually (see text).

IF x_2 IS small		THEN z IS small
IF x_2 IS not small	AND x_1 IS large OR very_large	THEN z IS large
IF x_2 IS large	AND x_1 IS small OR medium	THEN z IS medium
IF x_2 IS not large	AND x_1 IS small	THEN z IS small

Figure 6 shows a schematic of the complete fuzzy control model. The values of the motor unit characteristics vary across population of the motor unit pool. The figure describes nominal/actual force value comparison using recurrent fuzzy techniques. The reference input variable ($f_{nominal}$) can change dynamically.

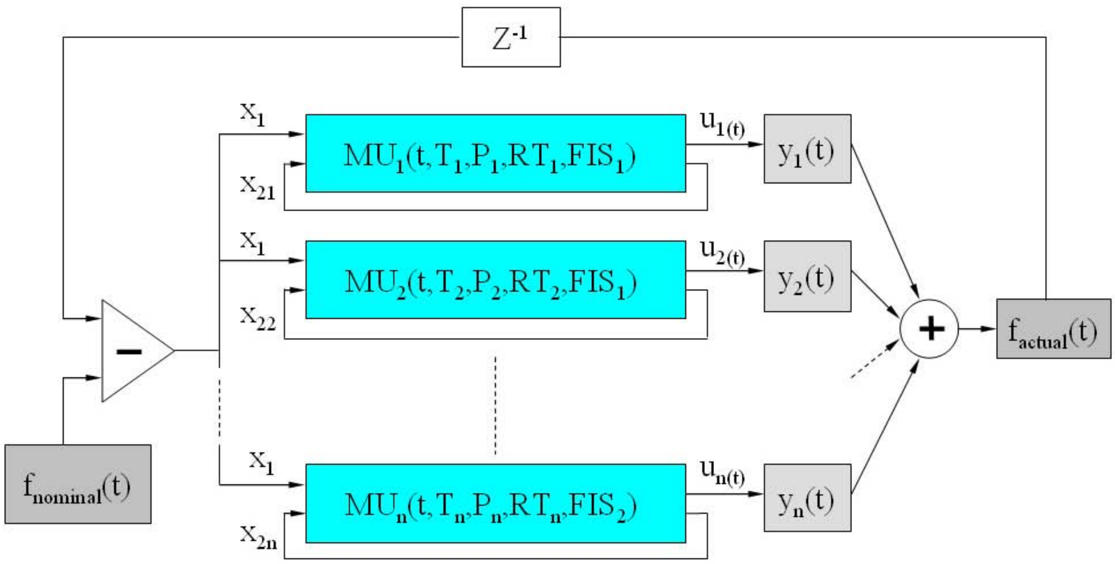

Fig. 6. Schematic of the complete fuzzy control model. MU_i: i^{th} motor unit (i = 1 ... n); t: time-discrete samples (1 sample per millisecond); T: contraction time; P: peak amplitude; RT: recruitment threshold, FIS: Fuzzy Inference System; $x_{1,2}$: input variables for the FIS; u(t): input variable for the impulse response; y(t): output, impulse response of the motor unit; $f_{nominal}$: reference input variable; f_{actual}: control variable (algebraic sum of all MU); Z^{-1}: Sample and hold with one sample period delay.

Simulation procedures

Several task specific conditions and populations of motor units were tested in simulations. Ramp as well as stepwise isometric contractions at different levels of MVC were simulated. As an example simulation of maximum value capacity (MVC) is demonstrated as follows. Mechanical properties of the demonstrated motor unit pool are shown in Table 2.

Tab. 2. Characteristics of the motor unit pool. Further explanation in text.

MU_i	**contraction time T (ms)**	**FIS**	**damping ratio D**	**gain factor K (a.u.)**	**recruitment threshold (a.u.)**
1	90	typ I	1,250	100	0,350
2	85	typ I	1,275	200	0,375
3	80	typ I	1,300	300	0,400
4	75	typ I	1,325	400	0,425
5	70	typ I	1,350	500	0,450
6	65	typ IIb	1,375	600	0,500
7	60	typ IIb	1,400	700	0,550
8	55	typ IIb	1,450	800	0,600
9	50	typ IIb	1,500	900	0,650
10	45	typ IIb	1,600	1000	0,700
variation	twofold	-	-	tenfold	twofold

Results

Figure 7 shows a typical result of a simulated muscle force in order to reach a maximal force output. Single motor units show characteristically superimposed responses to trains of stimuli. Algebraic summated force-time-curve varies over the time. For further analysis, the simulation procedure was repeated ten times under same conditions (results from five simulations are shown in Figure 8). The values of f_{actual} range about 10%.

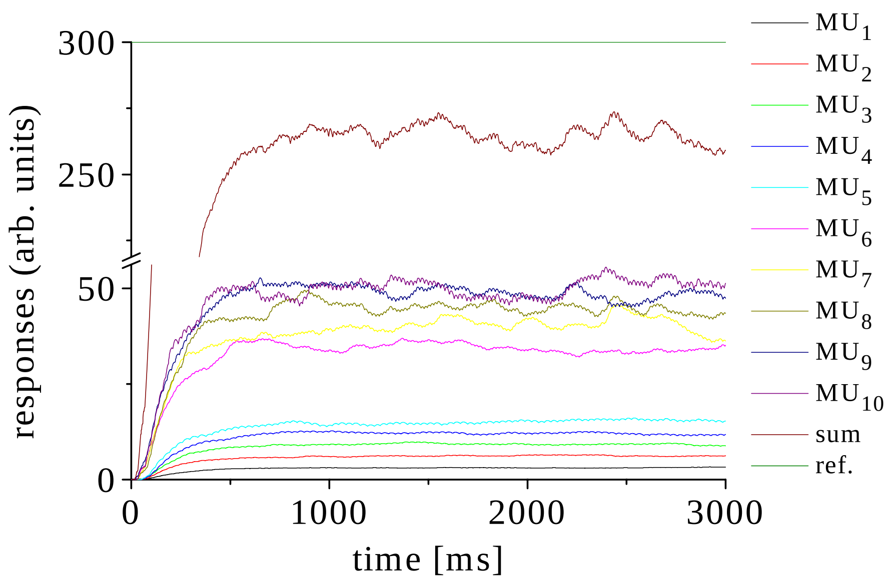

Fig. 7. Simulated muscle force f_{actual} from the motor unit population described in Table 2. The reference input variable was set to 300 so the task for the pool was to reach a maximal force output (MVC – maximum value capacity). Notice the break in vertical axis! Calibration for responses in arbitrary force units (arb. units).

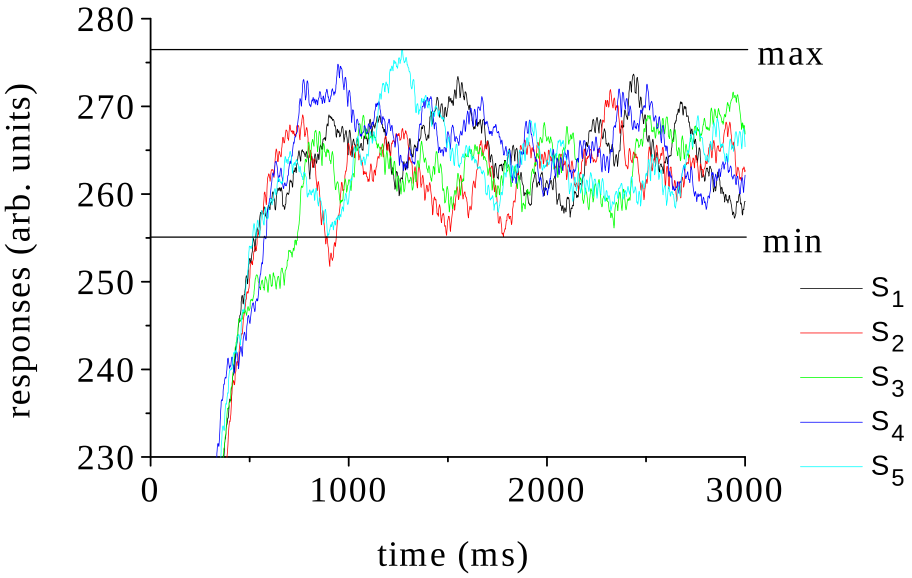

Fig. 8. Simulation results from five simulations (S_1…S_5) under same conditions (reference input variable: 300 arb. units). Minimum and maximum value of f_{actual} between 1000 and 3000 ms is marked. The values range about 10%.

Discussion

A crucial point in modelling and simulation is to verify the results experimentally. An association between muscle function and motor-unit organization has been difficult to verify because recruitment and rate coding behaviours can be monitored for only a small fraction of the motor units participating in voluntary contractions (Fuglevand et al., 1993). In this work, there was no direct comparison with experimental data. The main focus was to design a deductive approach from rule to example that accomplishes possible mechanisms for mechanical responses of motor unit co-ordination patterns. An accurate prediction of experimentally observed single motor unit responses was not included in the model. However, further developments will focus on the validation of the isometric force model against different types of motor units.

Just as nearly all muscle models and most motor control concepts it was assumed that forces from individual motor units sum in an additive manner. Recent studies demonstrate significant nonlinear interactions between small numbers of motor units, where mechanical coupling plays a major role (see Perreault et al., 2003). For the most part, motor unit force summation is superadditive with the actual force sum during simultaneous stimulation of the units being greater than the algebraic sum of each unit’s force measured in isolation (Clamann & Schelhorn, 1988; Emonet-Dénand et al., 1990; Powers & Binder, 1991; Troiani et al., 1999). In contrast, some authors report from subadditive summations with the actual sum being less than the algebraic sum in larger portions of the muscle (Brown & Mathews, 1960; Hunt & Kuffler, 1954; Sandercock, 2000). Perreault et al. (2003) investigated motor unit force summation in cat soleus muscle examined from approximately 0 to 25% of tetanic muscle force and noticed a modest, but clear transition from predominately superadditive to predominately subadditive summation occurred in the range of 6-8% of tetanic force. Because nonlinear summation was small (approximately 1%) and became subadditive already above approximately 10% of tetanic force, the assumption of an algebraic sum of single motor units as a part of a whole muscle simulating 100% of tetanic force has been supported.

A number of authors report from other important nonlinearities in the force response of motor units due to activation history, e.g. posttetanic potentiation (Burke, 1981); the marked enhancement of twitch responses occurring with short-duration inter-stimulus-intervals (doublet firing) (Burke et al., 1970); the serial dependence of twitch responses (Stein & Parmiggiani, 1981) or fatigue (Bigland-Ritchie & Woods, 1984). These aspects are not included in the model yet. But the flexible structure of the model allows modifications, particularly in the fuzzy component.

To the authors' knowledge, systematic investigations of interaction effects within a motor unit pool model are not yet available. So it is not possible to compare the results obtained with pre-existing research. Besides that, the results presented here only have a sample character in order to test the model. A future task is to devise specific experiments with reported muscle properties under various experimental conditions to determine possible magnitudes of enhanced muscle performances. Further analysis of these patterns is necessary too.

The specific mechanisms underlying the assumed optimal discharge patterns remain unclear. It is not well-known whether central command of the muscle (brain control) or certain reflex responses may play a major role. It also might be per se a random process in terms of biological variability without any command. In principle, the presented approach makes a contribution towards understanding the control of isometric force production in skeletal muscle.

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Two tests for synergy of player in basketball games

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Abstract

In the analysis of the strength or efficiency of players in a game it is usually assumed that there is no interaction between the strength or efficiency of players against the alternative that players display synergy, i.e a group of players work together better than would be predicted by just considering their individual strengths or efficiencies. This paper deals with two tests for synergy when considering the strength or efficiency of a triplet of players in a game.

KEY WORDS: INDIVIDUAL AND GROUPS EFFECT, SYNERGY, BASKETBALL

Introduction

The subject of our elaboration is the analysis of synergic effects generated by highly qualified players during a team sports game. Our methodological assumptions are based upon the theory of a team sports game (Naglak 2001, 2005), theory of efficient activities – praxiology (Kotarbiński 1973, Pszczoowski 1978) and theory of complex systems (Morawski 2000) and mathematical methods of determining the reliability of complex structures (Barlow, Proschan 1975). Tendencies to acquire synergy constitute a significant essence of all forms of social life. Such tendencies are with us most of the time of our everyday life, virtually in all its domains: in industry, economy, politics, sports, religion, etc. Hubert (2000 p.23), among others, writes: synergy is considered to be at a relative scale called: micro, mezzo and macro. Scale micro – it is a synergy obtained by a small number of people (family, group of friends etc.). Scale mezzo – it is a synergic effect which is realised in medium size groups such as: company, factory, institution, sports club, etc. Scale macro – it is the scale of city, country, region, continent. According to the a/m author, synergism is concerned with more numerous groups of population (societies) whereas synergy is the effect of mutual development and stimulation of a group composed of few persons. Synergism was defined as ‘science of cooperative phenomena’ which is a science of phenomena of interaction and cooperation (Haken, Graham 1971, Haken 1978). This science attempts to formulate some rules and regulations underlying the creation of the phenomenon of cooperation, coherence between the particular elements of the system, as well as the conditions in which coherence disappears and chaos comes along. Synergism, when applied to human systems which create an international community, becomes a science of stability and possibilities of development for these systems. The prefix ‘syn-‘ here conveys the meaning of synchronization of activity in time of the particular parts of the complex system. Etymologically, the second part of the word refers to Greek ‘ergon’ which means activity. Generally speaking, the word ‘synergism’ is connected with activity and with action of the system as a whole. In some particular cases, synergy may assume minus values, i.e. the particular elements weaken one another. In its basic meaning, synergy (plus value) constitutes cooperation of two or more elements in order to achieve a global effect which is more than the total of effects caused by each of these elements separately, i.e. in a situation where they do not have contact with each other (Pszczołowski 1978 p.236). Social synergy is the energy of action and development released by a group of people, and it may be bigger than the total of action energy which might be released by each of these human beings separately (acting in complete isolation). The difference stems from the fact that between the particular members of the team there might be a plus coupling which reinforces the energy and information processes taking place in each of these individuals.

In the accessible literature, both in Polish and in other languages, we have not found any publications that would allow us to estimate the size of cooperation in multi-subject activities in the range of team sports games. Multi-subject activities (collective and team) are to be understood in a distributive aspect, not in a collective one, i.e. an activity is performed by each subject separately (Pszczołowski 1978 p.57). A description of cooperation or effects of this cooperation called synergic effects in human activity is something we can find in publications: Zajonca (1983), Huberta (2000), Panfila (2006) however, this description does not let us estimate (assess) the size of the effects of the cooperation. Therefore, we have made an attempt to elaborate some methods which would allow us to assess the size of the effects of the cooperation.

The problem

The assessment of the effect of individual players and groups of players on the final score in a game, for example of basketball, may concern the game as a whole, as well as particular sections of a game. There are a few approaches to such a problem. One approach takes into account the strength and efficiency of players and groups of players. The strength of a player may be described by the number of points scored in some time interval of a game. This characteristic is additive with respect to the association of players into groups and unions of time intervals. Another approach to the problem is to consider efficiency during a specified action in a game (e.g. an attack). From the point of view of an approach based on reliability theory it is useful to characterise the structure of a game.

In the analysis of the effect of individual players on the performance of a team as a whole, it is normally assumed that the efficiency of players is independent of the efficiency of other team members. However, synergy between players should be considered in such a way that the effectiveness of the team differs from the effectiveness of the individual parts considered independently. This paper deals with tests for synergy and two approaches are used to illustrate these methods. Note that synergy within teams in the Polish basketball league was considered in Dembiński, Kopociński (2004).

The synergy of strength

Let a suitably indexed X denote the strength of a player in a monitored time interval of a game. Consider three players A, B, C. Assuming that the strength of players is additive, we define the strength of the triplet ABC and the strengths of the three pairs composed of two of these three players:

$$W_{ABC} = X_A + X_B + X_C$$

$$W_{AB\bullet} = X_A^{(1)} + X_B^{(1)},\ W_{A\bullet C} = X_A^{(2)} + X_C^{(2)},\ W_{\bullet BC} = X_B^{(3)} + X_C^{(3)}.$$

The expected strength of the triplet ABC in which strength is defined by pair wise interactions is given by the formula

$$W^*_{ABC} = \tfrac{1}{2}(W_{AB\bullet} + W_{A\bullet C} + W_{\bullet BC}),$$

which can be rewritten as

$$W^*_{ABC} = \tfrac{1}{2}(X_A^{(1)} + X_B^{(1)} + X_A^{(2)} + X_C^{(2)} + X_B^{(3)} + X_C^{(3)}).$$

In the test for synergy, the null hypothesis assumes that the random variables describing the strength of three players in a given section of the game $X_A^{(i)}, X_B^{(i)}, X_C^{(i)}$, $1 \le i \le 3$ are independent and identically distributed (with respect to both player index and i, the section of the game) random variables normally distributed with expected value m and variance $\sigma^2\left(X_\bullet^{(i)}\right) \sim N\left(m, \sigma^2\right)$, where • denotes one of A,B,C. Under these assumptions we have:

$$W_{ABC} \sim N(3m, 3\sigma^2),$$

$$W_{AB\bullet}, W_{A\bullet C}, W_{\bullet BC} \sim N(2m, 2\sigma^2),$$

$$W^*_{ABC} \sim N\left(3m, \frac{3}{2}\sigma^2\right).$$

The test for synergy of strength

Suppose that we have four sets of data. Let n denote the number of observations of the model triplet, n1 is the number of observations of the incomplete triplet AB•, n2 is the number of observations of the incomplete triplet A•C, n3 is the number of observations of the incomplete triplet •BC. The data are denoted as follows:

$w_1, w_2, \ldots, w_n$ - observations of the model triplet,

$w_1^{(1)}, w_2^{(1)}, \ldots, w_{n_1}^{(1)}$ - the observations of the incomplete triplet *AB*•,

$w_1^{(2)}, w_2^{(2)}, \ldots, w_{n_2}^{(2)}$ - the observations of the incomplete triplet *A•C*,

$w_1^{(3)}, w_2^{(3)}, \ldots, w_{n_3}^{(3)}$ - the observations of the incomplete triplet •*BC*.

We use the following notation for the averages and variances $\overline{w}$, $\overline{w}^{(1)}$, $\overline{w}^{(2)}$, $\overline{w}^{(3)}$ in these subsets of data:

$$S_0^2 = \frac{1}{n}\sum\left(w_j - \overline{w}\right)^2,\ S_0^{(1)2} = \frac{1}{n_1}\sum\left(w_j^{(1)} - \overline{w}^{(1)}\right)^2,$$

$$S_0^{(2)2} = \frac{1}{n_2}\sum\left(w_j^{(2)} - \overline{w}^{(2)}\right)^2,\ S_0^{(3)2} = \frac{1}{n_3}\sum\left(w_j^{(3)} - \overline{w}^{(3)}\right)^2.$$

For the triplet ABC, whose effectiveness is defined by pair wise interactions, we define the mean strength

$$\overline{w}^* = \frac{1}{2}\left(\overline{w}^{(1)} + \overline{w}^{(2)} + \overline{w}^{(3)}\right) \qquad (1)$$

Proposition 1

Under the assumptions of the null hypothesis, the random variable

$$t = \frac{\overline{w} - \overline{w}*}{S} \sqrt{\frac{n + n_1 + n_2 + n_3 - 4}{\frac{3}{n} + \frac{1}{2}\left(\frac{1}{n_1} + \frac{1}{n_2} + \frac{1}{n_3}\right)}},$$

where

$$S^2 = \frac{1}{3} n S_0^2 + \frac{1}{2}\left(n_1 S_0^{(1)2} + n_2 S_0^{(2)2} + n_3 S_0^{(3)2}\right),$$

has the Student distribution with $n + n_1 + n_2 + n_3 - 4$ *degrees of freedom.*

Proof. Note that:

$$\overline{w} \sim N\left(3m, \frac{3\sigma^2}{n}\right),$$

$$\overline{w}^* \sim N\left(3m, \left(\frac{\sigma^2}{2}\right)\left(\frac{1}{n_1} + \frac{1}{n_2} + \frac{1}{n_3}\right)\right).$$

Hence,

$$\overline{w} - \overline{w}^* \sim N\left(0, \sigma^2\left(\frac{3}{n} + \frac{1}{2}\left(\frac{1}{n_1} + \frac{1}{n_2} + \frac{1}{n_3}\right)\right)\right).$$

The random variable S^2 / σ^2 has the chi-square χ^2 distribution function with n+n1+n2+n3 – 4 degrees of freedom. Finally, note that these two random variables are mutually independent.

The synergy of players in a game action

Let us consider three players from the attacking team. We consider the defending team as one player. Consider the structure of each single offensive action with pair wise interactions. The problem is to test the hypothesis that one pair out of the three pairs of attackers demonstrate synergy: i.e. more effective play than expected on the basis of results of individual actions.

The model

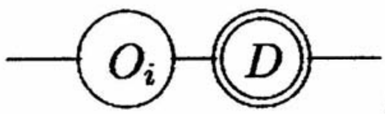
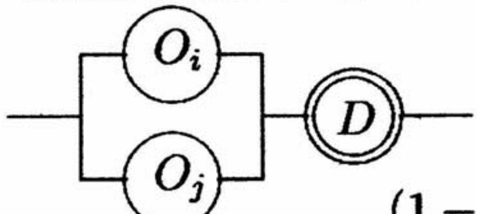
Let us assume that a player may be efficient or inefficient in an action. The efficiencies of individual forwards are denoted by Oi, $1 \le i \le 3$, the efficiency of the defender is denoted by D. Efficiency is assumed to be a binary 0-1 random variable: 1 denotes efficiency, 0 - inefficiency. The complementary variables are denoted $\overline{O_i}$ = 1 – Oi, $\overline{D}$ = 1 – D. The probability of efficiency is called the reliability. We introduce the notation: P(Oi) = pi, $\overline{p}$ i =1– pi, P(D) = q, $\overline{q}$ = 1 – q, $1 \le i \le 3$.

Assume that one attacker and the defending team form a series structure. The efficiency of this structure is expressed by the Boolean function Oi $\overline{D}$ for $1 \le i \le 3$. Two forwards form a parallel structure and this structure together with the defending team form a series structure. The efficiency of such a structure is the Boolean function:

$$(1 - (1 - O_i)(1 - O_j))(1 - D) = (1 - \overline{O_i}\,\overline{O_j})\,\overline{D} \text{ for } 1 \le i < j \le 3 .$$

Table 1 illustrates these structures, the Boolean function describing structures, the reliability functions and notation for the estimates of reliability from the data, which can be calculated on the basis of a monitored game. Random variables O1, O2, O3, D are virtual values, also observable are Boolean functions presented in Table 1. Assuming null hypothesis, the random variables O1, O2, O3, D are independent. The alternative hypothesis assumes that they are dependent (synergy exists).

Tab. 1. Description of the structure of a game: in the example considered 1 i < j 3 .

Structure	Boolean function	Reliability	Data
	$O_i\bar{D}$	$p_i\bar{q}$	x_i
	$(1-\bar{O}_i\bar{O}_j)\bar{D}$	$(1-\bar{p}_i\bar{p}_j)\bar{q}$	x_{ij}

The estimation of parameters

Markings i,j = 1, 2, 3 are indexes of players. In order to describe the data assume that x_i, x_{ij} are the appropriate estimators of the probabilities p_i, p_{ij}, of reliability in the corresponding Bernoulli trials. Let Var(x_i) = $\sigma_i^2 = \dfrac{p(1-p)}{n_i}$, where $p = p_i\bar{q}$, Var (x_{ij}) = $\sigma_{ij}^2 = \dfrac{p'(1-p')}{n_{ij}}$, where $p' = (p_i + p_j - p_ip_j)\bar{q}$ and n_i, n_{ij} be the number of observations used to estimate these probabilities. Random variables x_i and x_{ij} have only an approximately normal distribution. In our applications we assume that it is cut and it is conditioned by $x_i > 0$ and $x_{ij} > 0$ because the matches are observed for such a long time until a particular phenomenon occurs at least once (or a certain number of times). In the model we have four parameters p_1, p_2, p_3, q and six empirical probabilities (reliabilities) x_1, x_2, x_3, $x_{1,2}$, $x_{1,3}$, $x_{2,3}$. In order to find estimates of the parameters, we equate the expected values to the observed reliabilities and obtain the following system of equations:

$$p_1\bar{q} = x_i,\ (p_i + p_j - p_i\,p_j)\bar{q} = x_{ij},\ 1 \le i < j \le 3\ .$$

An approximation to the solution of this system of equations can be obtained by finding the minimum of the function

$$L(p_1, p_2, p_3, \bar{q}) = \sum_i n_i(p_i\bar{q} - x_i)^2 + \sum_{i<j} n_{ij}((p_i + p_j - p_ip_j)\bar{q} - x_{ij})^2.$$

Totals for i, j extend to the domain from 1 to 3. We intend to solve this numerical problem using a sequential method. An initial solution may be found in the following way. The three equations which do not take interaction into account reduce the other equations into the form:

$$x_i + x_j - \frac{x_i x_j}{\bar{q}} = x_{ij}, \ 1 \le i < j \le 3 \ .$$

Using the least square method, we obtain an estimator for $\frac{1}{\bar{q}}$ of the form:

$$\frac{1}{\bar{q}^*} = \left(\sum_{i<j} x_i^2 x_j + \sum_{i<j} x_i x_j^2 - \sum_{i<j} x_{ij} x_i x_j \right) / \sum_{i<j} x_i^2 x_j^2 .$$

and next we obtain $p_i^* = x_i (\bar{q}^*)^{-1}, \ \ 1 \le i \le 3.$

The test for synergy

Let us suppose that, given the background of the remaining players. Players 2 and 3 demonstrate synergy. In order to test whether this effect is significant, we first estimate the parameters of the model from the condition:

$L(p_1, p_2, p_3, \bar{q}) = \min \left\{ \left[\sum_i n_i (p_i \bar{q} - x_i)^2 \right] + n_{1,2}((p_1 + p_2 - p_1 p_2)\bar{q} - x_{1,2})^2 + n_{1,3}((p_1 + p_3 - p_1 p_3)\bar{q} - x_{1,3})^2 \right\}.$

Having obtained the solution $p_1^*, p_2^*, p_3^*, \bar{q}^*$ to this problem of estimation, we now consider the residual $r_{2,3} = x_{2,3} - (p_2^* + p_3^* - p_2^* p_3^*)\bar{q}^*$, that is to say $r_{2,3} = x_{2,3} - x_2 - x_3 + \frac{x_2 x_3}{\bar{q}^*}$.

A positive residual demonstrates that synergy occurs. In order to calculate its variance, we make some approximations. The estimators given by the method of least squares are asymptotically unbiased and for large ni the variance of $\bar{q}*$ may be neglected. We assumed that the estimator $\bar{q}*$ of the parameter $\bar{q}$ is not burdened and its variance is neglected. Taking into consideration the expansion in a series:

$$\frac{1}{\bar{q}*} = \frac{1}{\bar{q}} \sum_{i=0}^{\infty} \Delta^i \approx \frac{1}{\bar{q}} \left(1 + \Delta + \Delta^2 \right),$$

where $\Delta = \left(\bar{q} - \bar{q}* \right) / \bar{q}$, assuming $|\Delta| < 1$, we get

$$\mathrm{E}\left(\frac{1}{\bar{q}*} \right) \approx \frac{1}{\bar{q}} + \frac{1}{\bar{q}^3} D^2 \left(\bar{q}* \right).$$

The estimate $\mathrm{Var}(X_i X_j) \approx (p_i \bar{q})^2 \sigma_i^2 + (p_j \bar{q})^2 \sigma_j^2$ may be used. It follows that

$$\mathrm{E}(r_{2,3}) \approx 0, \quad \mathrm{Var}(r_{2,3}) \approx \ \sigma_{2,3}^2 + (1 + p_2^2)\sigma_2^2 + (1 + p_3^2)\sigma_3^2 .$$

Assuming the residual has a normal distribution, we have an instrument for testing the null hypothesis of a lack of synergy against the alternative that synergy exists.

Example

In order to establish the amount of data required in order to test for synergy, we consider an example. Under the assumption of the null hypothesis let p1 = 0.4, p2 = 0.5, p3 = 0.6, q = 0.5, x1 = 0.2, x2 = 0.25, x3 = 0.3 x1,2 = 0.35, x1,3 = 0.38. Suppose that the observed value of x2,3 is equal to 0.5 instead of 0.4 as expected from the null hypothesis (indicating synergy between players 2 and 3). Estimation of the parameters of the model give the following results: $\hat{p}_1 = 0.180$, $\hat{p}_2 = 0.277$, $\hat{p}_3 = 0.327$, $\hat{\bar{q}} = 0.913$.

The example illustrates what kinds of accuracy can be expected when the model parametres are estimated and using the techniques that hale been used In the course of the very work. This result demonstrates the high sensitivity of the estimates to the data. It seems that in practice the reliability q of the defending team should be taken from another experiment. The residuals in the solution of the basic system of equations are equal to -0.036, 0.003, -0.001, 0.022, 0.029, -0.031, respectively. Therefore, this example also shows that the residuals certainly do not indicate synergy between Players 2 and 3. Hence, the hypothesis regarding the pair exhibiting synergy should be stated explicitly in the alternative.
The example enables to show what size the empirical data are indispensable when practically using the work's results. It should be noted that the expected errors due to sensitivity do not exceed the sampling errors indicated by a confidence interval when $n2,3 \geq 92$. In this case the number of observations are too large (they cannot be made within the course of a game).

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