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Editorial

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Dear readers:

Welcome to the summer 2014 issue of the **International Journal of Computer Science in Sport (IJCSS).**

The current issue is divided into two parts including six original papers.

The first part contains a research paper, a scientific report, and a project report.

Raine Kajastila, Leo Holsti and **Perttu Hämäläinen** studied, how specific video games can provide empowerment in both the real and the virtual world using a trampoline as part of the human-computer interface.

The scientific report by **Daniel Link** presents three customized observation software tools developed for beach volleyball and suggests five principles for designing of game observation software.

The project report by **Ales Filipcic, Andrej Panjan** and **Nejc Sarabon** compares six machine learning algorithms in order to classify tennis players on the ATP Tour with respect to their playing quality.

Three additional articles are appended thereafter in the second part (“Special Edition”) – a research paper and two scientific reports.

In this “Special Edition” part selected scientific papers presented at the 9th International Symposium on Computer Science in Sport, which was held from 19th-22nd of June, 2013, in Istanbul, are included. The contributions underwent a further review process to ensure the quality of the scientific content. IACSS would like to thank the entire committee under the guidance of Prof. Hayri Ertan for the organization of the conference and the support in the selection process of the papers.

Nicole Bandow, Peter Emmermacher, Christine Stucke, Steffen Masik and **Kerstin Witte** compared the responses of karate athletes to temporally and spatially occluded sequences of attacks shown on a video screen and in a virtual environment and highlight the importance of 3D and, in particular, depth information for the anticipation of karate athletes.

The scientific report by **Mads Møller Jensen, Kaj Grønbæk, Nikolaj Thomassen, Jacob Andersen** and **Jesper Nielsen** presents an interactive football platform (Football Lab), analyses data collected during games using this platform, and discusses challenges during data collection and experiments conducted with the platform.

The paper by **Paul Rudelsdorfer, Norbert Schrapf, Horst Possegger, Thomas Mauthner, Horst Bischof** and **Markus Tilp** presents a custom-made software for handball which allows annotating single actions with accurate manual position information. Furthermore, it evaluates the accuracy of the positional data collected using the software and analyses the data using neural networks.

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

Enjoy the summer!

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PART 1

APPENDED PAPERS

Empowering the Exercise: a Body-Controlled Trampoline Training Game

Raine Kajastila, Leo Holsti & Perttu Hämäläinen

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Abstract

Video games can empower their players beyond reality, giving them extraordinary abilities. We investigate a novel class of games that provide empowerment in both the real and the virtual world, in this case using a trampoline as part of the human-computer interface. We studied whether novice trampoline jumpers can learn trampolining skills while playing a platform jumping game implemented using computer vision and a screen placed near the trampoline. 29 participants were divided into three groups: self-training, a game with a normal jump height, and a game with an exaggerated jump height. Performance was tested in pre, post and follow-up tests. All groups improved their performance significantly. The game was considered more engaging and the mean flow questionnaire (SFSS) result with games was significantly higher than with self-training. The study shows that trampoline games can be fun, intuitive to play and basic trampolining skills can be improved while playing the game. A game is more engaging than self-training and extra empowerment, such as jump height exaggeration, enhances the experience. The exaggeration did not adversely affect jumping performance, and half of the participants did not even consciously notice it, which suggests that there is considerable design freedom for manipulating the player's movements in trampoline games.

KEYWORDS: MACHINE VISION, GAMES, USER INTERFACES, SPORTS EQUIPMENT, EDUCATIONAL TECHNOLOGY

Video games can empower their players beyond reality, giving them extraordinary abilities and letting them use the abilities for exploring fantasy worlds. Curiosity and fantasy have also been identified among the intrinsic motivations of computer games (Malone & Lepper, 1987; Malone, 1981). From this point of view, it is easy to understand how physical exercise and sports might have trouble competing with digital games.

Fortunately, the last decade has brought about interesting developments in combining video games, sports, and exercise. So called motion games (exergames, active video games) have become mainstream thanks to technologies like Microsoft Kinect, PlayStation Move and Nintendo Wii. At the same time, indoor activity parks and fitness centers appear to utilize more and more motion-enhancing equipments such as trampolines, inflatable bouncy surfaces, crash mats or even wind tunnels for indoor skydiving. The equipment can be considered to serve a dual purpose of 1) scaffolding motor skill learning by reducing the impacts of landings on one's joints and giving more time to perform aerial techniques and 2) implementing the power fantasies of action video games in an embodied fashion.

This paper studies the effect of *mixed reality empowerment* on exercise motivation and motor skill learning using a trampoline platform jumping game. Here, mixed reality empowerment is defined as giving extended abilities and empowering the player both on the screen and in the real world. The game is implemented using a depth camera, real-time computer vision software and a screen near the trampoline. The trampoline boosts the players' jumping abilities in the real world, and the game further exaggerates the movement on-screen. Previously, the combination of real-life and in-game motion enhancing has been studied relatively little, although many virtual reality experiments and arcade games have manipulated the user's physical movement to some degree via, e.g., actuated seats or suspending the user in some form of harness (McKenzie, 1994).

We have previously presented the preliminary trampoline game prototypes shown in Figure 1 (Holsti, Takala, Martikainen, Kajastila, & Hämäläinen, 2013). In the previous study, we found the platform jumping game more interesting for novice trampoline jumpers, whereas more advanced practicers preferred less playful augmented feedback (e.g., video delay) that can be used to aid skill acquisition.

The contribution of the present paper is a comprehensive user study of a mixed reality trampoline game with novice users, using a battery of tests: the self-assessment manikin (SAM), flow and perceived competence questionnaires, as well as quantitative computer vision data and semi-structured interviews. We show that at least the basic skill of jumping high with precision can be improved while playing a fun and exhausting game. Furthermore, the combination of on-screen and real world empowerment can be used to enhance a game. We also provide some design guidelines and lessons learned, as mixed reality trampoline games have not been previously studied to this extent. Next, the previous research relevant to this paper is reviewed in more detail.

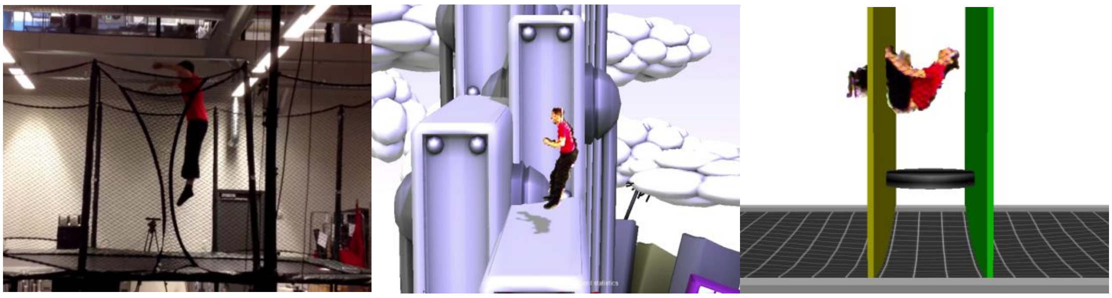

Figure 1 Previous trampoline game prototypes by the authors. Left: Player jumping on a trampoline in front of a Kinect camera. Middle: screenshot of a platform jumping game with the player embedded in the 3d graphics. Right: screenshot of a virtual training space with graphical obstacles.

Full-body human-computer interaction and designing for thrill

Our work is related to Myron Krueger's Artificial Reality, where the video image of the user was embedded inside interactive computer graphics (Krueger, Gionfriddo, & Hinrichsen, 1985). Later on, various research projects as well as commercial motion games have used avatars controlled using body tracking (Ishigaki, White, Zordan, & Liu, 2009; *Kinect Sports*, 2010), but in our opinion, using background-removed video or a 3d mesh obtained from a depth camera, as shown in Figure 1, is often better suited for sports training, since it minimizes the visual glitches caused by tracking failures. In general, various authors have researched physically intensive full-body interaction (Bianchi-Berthouze, 2013; Mueller, Agamanolis, & Picard, 2003).

Although commercial motion games are widely available, they are not always ideal for motor skill learning and exercising. One reason for this is probably the need to optimize the games for an average customer in an average living room with very little space, which limits the movements that can be used. While motion game equipment can be suitable even for the elderly in therapeutic use (Sparrer, Duong Dinh, Ilgner, & Westhofen, 2013) and some games do offer intensive exercise, the health benefits of commercial motion games in general are debatable (Baranowski et al., 2012; Owens, Garner, Loftin, van Blerk, & Ermin, 2011).

Skill transfer from a game to real practice does not always require realistic movements. Fery and Ponserre (2001) found that the skill of golf putting can be improved using a game controlled with a computer mouse. However, games are not always more entertaining than real practice, and a skill learned with commercial exergames might not transfer to real world, e.g., a virtually learned basketball throwing skill does not transfer to real performance (Wiemeyer & Schneider, 2012).

Quantifying the game user experience

In a broader view, our work belongs to the tradition of using computer games as experimental stimulus (Järvelä, Ekman, Kivikangas, & Ravaja, 2012; Washburn, 2003), and measuring game user experience (Brockmyer et al., 2009; Nacke, 2009; Takatalo, Häkkinen, Kaistinen, & Nyman, 2007).

Game user experience can be analyzed from various angles. In this paper, we are interested in the following three aspects:

1) Flow, a state of optimal experience characterized by, e.g., becoming completely absorbed in what one is doing, losing track of time, and finding the activity intrinsically rewarding (Nakamura & Csikszentmihalyi, 2002). Facilitating flow experiences is often considered relevant for good game design (Salen & Zimmerman, 2003; Schell, 2008; Sweetser & Wyeth, 2005). As we have also a no-game group of participants in our study, we use a flow questionnaire instead of a game-specific engagement measure such as the widely used Game Engagement Questionnaire (Brockmyer et al., 2009). Questions related to flow also constitute a part of the GEQ.

2) Perceived competence, which is linked to motivation and adherence of sport and exercise (Cairney et al., 2012; Carroll & Loumidis, 2001; Feltz & Lirgg, 2001; Ferrer-Caja & Weiss, 2000). We hypothesize that the virtually exaggerated abilities of the player may affect perceived competence.

3) The affective dimensions of valence, arousal and dominance, which can be measured using the Self-Assessment Manikin (SAM) (Bradley & Lang, 1994). We consider high positive valence, high arousal, and high dominance as descriptive of the “super hero” experiences that we wish to create using the mixed-reality empowerment approach.

Augmented feedback for motor skill learning

The role of feedback in motor skill learning and performance has been studied extensively (Bilodeau & Bilodeau, 1961; Magill & Anderson, 2012; Newell, 1991; Schmidt & Wrisberg, 2008; Sigrist, Rauter, Riener, & Wolf, 2013). Feedback provides athletes information for regulating action in various forms, e.g., intrinsic proprioceptive feedback, visual feedback, and extrinsic verbal feedback from a coach. The essential type of feedback for this study is concurrent augmented visual feedback, i.e., visual information that is given in real-time during the movement and would not be available otherwise, in this case provided by a computer system.

Compared to training with a video camera or receiving feedback from an instructor, computer generated feedback can be faster and more accurate, letting the student do more repetitions and evaluations of a skill in a short time. Considering the experiential learning cycle of concrete experience (CE), reflective observation (RO), abstract conceptualization (AC), and active experimentation (AE) (Kolb, 1983), the feedback design defines the transition speed from CE to RO and what data is available for RO, and can also provide cues and suggestions for AC and AE. However, while optimizing the experiential learning cycle (a closed loop control cycle) with augmented feedback, one must be aware of the guidance hypothesis that states that the learner may develop a dependency on augmented feedback, especially if it’s provided concurrently or too frequently (Magill & Anderson, 2012; Schmidt & Wrisberg, 2008; Sigrist et al., 2013). Feedback design is also important considering that clear goals and feedback are central prerequisities for flow experiences (Csikszentmihalyi, 1990).

There are several previous studies of computer-generated visual feedback. However, concurrent feedback does not always speed up the learning of a skill, and finding feedback that suits a particular skill can be hard (Chua et al., 2003). Using VR to improve motor control skills especially in ball sports is possible (Miles, Pop, Watt, Lawrence, & John, 2012). Yet, there is no single viable solution, and technical limitations such as latency in high-speed sports and inappropriate haptic feedback can deliver negative efficacy in the training task (Miles et al., 2012). There are also numerous non-VR training systems using computers and screens. Game-inspired elements can be used in dance training, but game environments can be more useful when combined with traditional instruction videos (Charbonneau, Miller, & LaViola, 2011). Also, ballet poses can be learned with concurrent feedback utilizing motion capture, but subtle style differences in movement are harder to detect and display (Marquardt, Beira, Em, Paiva, & Kox, 2012). For a more detailed overview of feedback technologies, see reviews by Lieberman et al. (2002), Magill and Anderson (2012), and Sigrist et al. (2013). According to Sigrist et al. (2013), concurrent visual feedback can especially benefit the initial learning of complex skills. For best results in retention tests without the feedback, no-feedback training or some other form of reduced feedback is usually needed in learning simple skills and refining complex skills. In our game, the player’s movements are exaggerated on the screen. Related to this, Buekers, Magill and Hall (1992) found that verbal knowledge of results (KR) can influence learning and retention even if it is erroneous or conflicting with one’s sensory feedback.

Combining motion-enhancing equipment and digital technologies

One of the disciplines that have traditionally experimented with both digital technology and motion-enhancing equipment is contemporary circus. For example, the show Kà by Cirque du Soleil utilizes wire-flying in conjunction with movement tracking, interactive projections, lighting and set elements (*Kà*, 2004). Circus equipment and arts have also inspired new forms of exercising, e.g., in the case of Jukari Fit to Fly, a trapeze-based exercise program designed in collaboration between Cirque du Soleil and Reebok (Murphy, 2009). Flying has also been simulated in a virtual reality system by suspending the user horizontally in the air using a harness (McKenzie, 1994).

Considering previous experiments with trampolines, computer vision has been used to analyze sport videos, including trampolining (Xian-jie, Zhao-qi, & Shi-hong, 2004), and Mori, Fujieda, Shiratori, & Hoshino (2008) have mapped the motion of the trampoline bed to movement in a virtual world. However, to our knowledge, we are the first to study trampoline games with full body tracking or the player's image embedded in the computer graphics.

It should be noted that trampolines can be dangerous, especially in recreational, unsupervised use (AAP Committee on Injury and Poison Prevention and Committee on Sports Medicine and Fitness, 1999; "Trampolines and Trampoline Safety Position Statement of the American Academy of Orthopaedic Surgeons", 2010). Attempting somersaults is not recommended and only one person should be jumping at a time. We believe that technology can be used to increase training safety, e.g., by using computer vision to monitor that there is only one player in the camera view. In addition to simple monitoring of safety guidelines, we are also trying to design goals and feedback to keep players interested longer in preliminary training before attempting high risk skills.

Materials and Methods

Participants

Thirty-four adult participants participated in the user study, of which 29 completed the experiment successfully. All 29 participants were novice trampoline jumpers, with only little or no experience in trampolining and without physical disabilities affecting trampoline jumping. Participants included 21 males, 6 females and 2 who did not define their gender. All participants had an academic background and were recruited through the university's email-lists. The ages of the participants varied from 21 to 59 (M = 31.9, SD = 7.2) and body mass index (BMI) varied from 19.3 to 34.6 (M = 23.9 kg/m2, SD = 3.1). The participants' mean estimation of their physical condition was a bit above average (M = 4.75, SD = 1.0) on a scale from 1 (very poor) to 7 (very good).

The five participants who were excluded from the study included 3 participants who reported back pain and did not successfully finish the test. One participant quit the experiment during warm-up due to a previous knee injury. Follow-up questions after a week affirmed that permanent injuries did not occur. Furthermore, the data from one participant was excluded because of a malfunction in the motion tracker. All participants volunteered and consented to the study. Two experimenters were always present during the experiment, one of which had professional trampoline experience and first-aid training. The university's ethics committee approved the study.

Apparatus

An Acon Air Sport 16 trampoline with a safety net was used, as shown in Figure 2. The trampoline was located in a large indoor research facility. A 40 inch HD TV was positioned 3.5 m from the center of the trampoline and the lower edge of the screen was 0.33 m above trampoline bed.

Figure 2. Test setup when participants were training with a game with exaggerated jumps (EJ). A screen shot from the TV is shown in the upper right corner.

An Asus Xtion Pro Live depth camera was positioned near the screen, 3.35 m from the center of the trampoline and 0.33 m above the trampoline. The camera and the TV were connected to a laptop running Windows 7. The game prototype including the tracking software were developed using the Unity 3D game engine and a custom plugin that gives Unity access to the RGB and depth images of the camera (containing each pixel's distance from the sensor) as well as skeletal tracking data from OpenNI/NITE middleware. Furthermore, video and audio were recorded from all test sessions.

The total collected data consisted of all jumps in all tests, as well as all jumps during the training. Tracker data was gathered at 30fps using the depth camera. Data was stored on each frame, including the xyz-coordinates of the bounding box corners and the approximate coordinates of the center of volume (COV) of the player's mesh. COV was analyzed from the 3D mesh captured using the depth camera. The COV was calculated as the average of the 3D coordinates of all pixels belonging to the player. The jumps' key points were extracted from the data. Jump height was calculated from the Y-value of the COV, extracting the highest value (jump apex) from the lowest point when the jumper's feet are about to touch the trampoline bed. For jumping accuracy, jump start and end positions were calculated from the X and Z coordinates of the COV.

The game used in the experiment was a very simple platform jumping game where the goal was to jump upwards from one platform to another. The player received points by collecting coins and stars, and jumping high jumps over multiple platforms. The score was shown in the upper left corner of the screen. The player was represented by a textured 3d mesh captured using the depth camera (see Figure 2). The player's moves resulted in vertical and horizontal movement on the screen.

Two versions of the game were used in the experiment: exaggerated (EJ) and normal jump height (NJ) relative to the height of the avatar. In NJ the actual jump height measured from the trampoline was mapped closely to the avatar's jump height whereas in EJ the avatar could jump more than 3 times the height of the actual jump. Jump exaggeration was done by scaling the tracked upward velocity and adjusting the simulated gravity.

The game level was designed to become gradually more difficult by making the platforms narrower and increasing the vertical spacing of the platforms. Level design was the same between NJ and EJ. However, as shown in Figure 3, the spacing between the platforms varied between NJ and EJ in order to equalize the effort needed to jump from platform to platform.

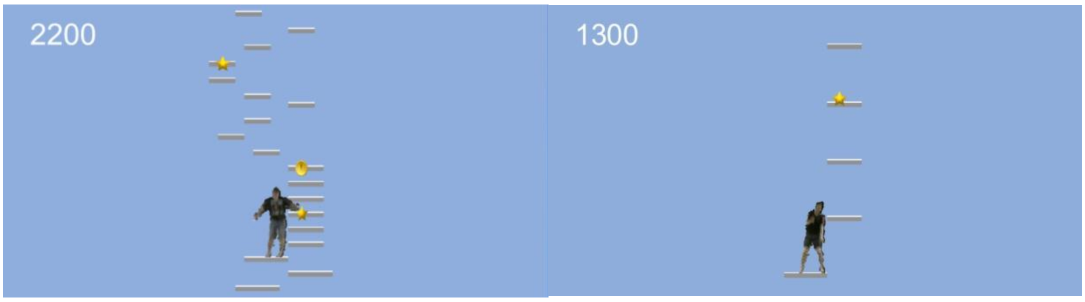

Figure 3. Avatars of two participants on the same platform. Level design was otherwise the same in NJ (left) and EJ (right), but spacing between the platforms was adjusted to the jump height in the game.

Task and Procedure

The whole procedure is shown in condensed form in Table 1.

Each participant performed the task individually. Upon entering the research facility, the procedure was verbally explained to the participants and they signed a release form and filled a questionnaire for background information. The participants were instructed on safe jumping on a trampoline by a professional circus artist/teacher. The participants were free to warm-up and get familiar with the trampoline for about 3 minutes, after which they were asked to try a few high and accurate jumps in middle on the trampoline. After the warm-up, the participants were given a pre-test (PRE) to determine their current maximal jump height and accuracy. The participants were informed that they would have to perform the same test after the training period (POST) and also the next day (NDAY). PRE-test as well as POST-test and NDAY-test consisted of 15 consecutive jumps with the current maximum height 100% (instructed as "the current maximum height that still feels controlled"), and 15 consecutive jumps with a self-assessed 75% and 50% of the maximum height with a short resting period between each jump height. Just before each test the participants filled an adapted perceived competence (PC) questionnaire (Williams & Deci, 1996).

For the training task, the participants were assigned in order of arrival into three groups, who either trained with a game with normal jump height (GN), a game with exaggerated jump height (GE) or self-training with no game at all (ST). An equal number of females were assigned to each group. Note that all the groups can be considered to have used a discovery learning approach, as we gave the participants the goal of learning high and precise jumps, but didn't instruct them how. In the GN and GE groups, the participants saw their body position and posture in relation to a virtual environment, but did not receive any further instruction. In previous studies, discovery learning has been found to lead to slower skill acquisition but better retention than guided instruction (Singer & Pease, 1976), and explicit instruction has yielded a decrease in performance when compared to discovery learning and guided discovery under anxiety provoking conditions (Smeeton, Hodges, Williams, & Ward, 2005). The training time was 6 minutes in total, which was divided into 3 periods of 2 minutes of training with 1 minute of rest in between (performed standing). The experimenter informed verbally the start and end of the training period. The groups with the game (GN,GE) played the game for 2 minutes. The self training group (ST) were instructed to first jump 1 minute in the center of the trampoline and then 1 minute varying their position sideways, thus experiencing a slightly "guided" discovery learning. The ST group was also instructed to vary their jump height according to their preferences. The amount of jumps during the 6 minutes of training was similar between the groups. The mean number of jumps was 324, 330, 344 for GN, GE, and ST respectively. After the training, the participants filled the Short Flow State Scale (FLOW

SFSS) (Csikszentmihalyi, 1990; Jackson, Eklund, & Martin, 2010), self-assessment manikin (SAM) (Bradley & Lang, 1994), STICK-figure, and an open ended questionnaire asking 3 positive and 3 negative aspects of the training. The main purpose of these questionaires was evaluating differences in the training, but SAM and STICK-figure -questionnaires were also administered in the POST-test and the DAY-test to see if any possible effects of the training methods would persist over time.

The STICK-figure questionnaire consisted of questions illustrated with stick figures (see Figure 4). After filling the questionnaires, the POST-test was done by the participants, after which they filled a STICK-figure questionnaire again.

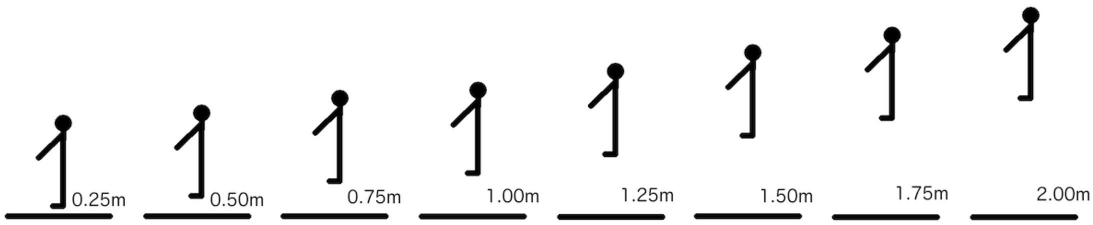

Figure 4 Perceived jump height questionnaire filled after the training and retention tests.

On the second day the participants went directly to warm-up on the trampoline. After the warm-up, the NDAY-test was done, after which SAM and STICK-figure questionnaires were filled again. After the NDAY-test, the participants were asked to play both game configurations for about 1 minute each and semi-structured questions were asked in between and after. A semi-stuctured interview was done only after the actual experiment so that it would not affect the results. The questions were defined beforehand, (e.g., "*How did the game with non-exaggerated jumps feel compared to the exaggerated version?”),* but the experimenter could ask the participant to describe the initial answer in more detailed form. GN and GE groups first played the game they used for training the day before. The ST group started with the game with exaggerated jumps, to assess if they perceived the exaggeration or not. The participants were instructed not to discuss the experiment with other participants.

The main experimental interest for administering each questionnaire**:**

- PC: Does the training method have an effect on the perceived competence? Does the change in perceived competence match the possible learning of a skill?
- STICK-figure: Possible interaction between the in-game motion exaggeration and the players’ perceived real-world jump height.
- FLOW: Assess overall participant engagement and flow during the training. Which components differ between groups with different training methods?
- SAM: Participants’ affective experience of the training and the difference between training methods.

Table 1 Procedure of the trampoline jumping experiment during 2 days.

Day 1	Day 2
1. Verbal and written introduction, pre-questionnaire	1.Warm-up on the trampoline
2. Warm-up on the trampoline and safety instructions (3 min)	2. NDAY-test (PC questionnaire, SAM, STICK-figure questionnaires)
3. PRE-test (PC questionnaire)	3. Systematic testing of both games and a semi-structured interview
4. Training either with GN, GE or ST. (10 min) (FLOW, SAM, STICK-figure questionnaires)	
5. POST-test (PC questionnaire, STICK-figure questionnaires)	

Results

The jump height data of all tests for GE, GN and ST was evaluated as normally distributed. Skewness values were 0.45, 0.30, 0.50 (SE = 0.075, 0.075, 0.079) for GE, GN and ST, respectively. Kurtosis values were -0.17, -0.21, -0.23 (SE = 0.15, 0.15, 0.16), for GE, GN and ST, respectively. The means of 100% jump heights with change between the tests are shown in the Figure 5.

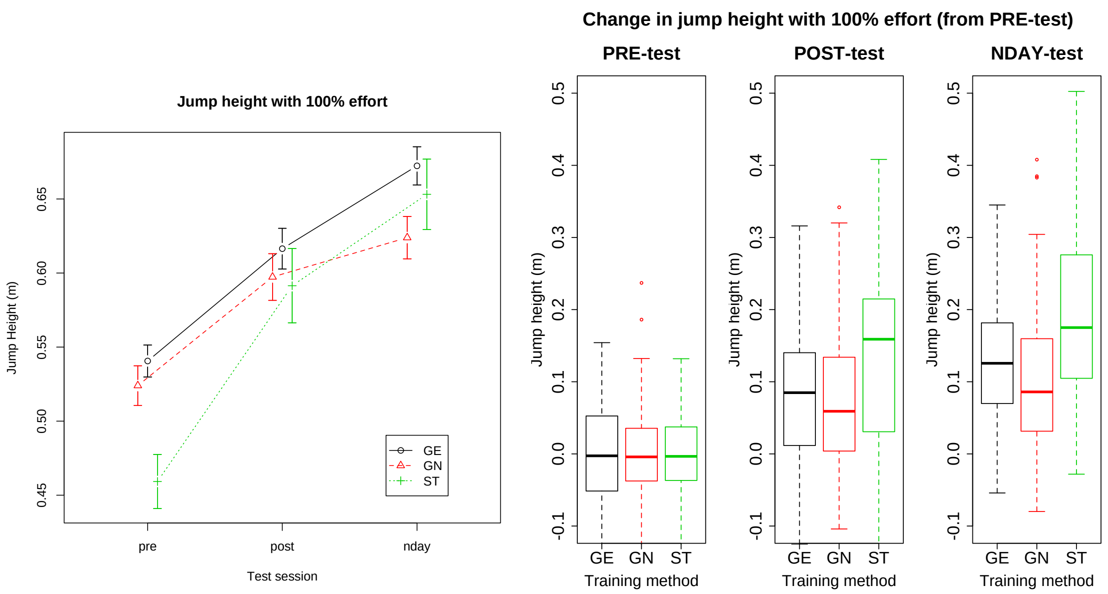

Figure 5. Left: Jump heights with 100% effort. (Error bars represent standard errors) Right: Boxplot of jump heights with 100% effort. Heights are relative to the mean jump height in PRE –test (i.e. change from PRE-test).

A mixed design 3 (training method) × 3 (test session) ANOVA was used with the training method (GN, GE, ST) as the between-subject factor and the three test session time points (PRE, POST, NDAY) as the within-subjects factor. ANOVAs were conducted for gain scores (i.e. change in jump height from PRE-test) in jump height and jump accuracy.

For jump height, analysis revealed a significant main effect of test session ($F(2, 52) = 46.19$, $p < .001$, $\eta_p^2 = .28$). There was no main effect of training method ($F(2, 26) = 2.59$, $p = .094$). The interaction terms were not significant.

Table 2 The means of 100% jump height and accuracy between groups and PRE, POST and NDAY tests.

Group	PRE		POST		NDAY	
	Height	Accuracy	Height (+change)	Accuracy	Height (+change)	Accuracy
GN	0.52 m SD=0.15	0.19m SD = 0.12	0.60m SD = 0.17 (0.07m)	0.20m SD = 0.16	0.62m SD = 0.16 (0.1m)	0.17m SD = 0.13
GE	0.54 m SD= 0.14	0.19m SD= 0.12	0.60m SD = 0.15 (0.08m)	0.19m SD = 0.12	0.67m SD = 0.14 (0.13m)	0.20m SD = 0.14
ST	0.46 m SD= 0.18	0.17m SD =0.12	0.59m SD = 0.26 (0.13m)	0.16m SD = 0.11	0.65m SD = 0.25 (0.19m)	0.18m SD = 0.13

One-way within-subjects ANOVAs were conducted to determine simple main effects. 1 (training method) x 3(time point: PRE, POST; NDAY) ANOVAs were conducted separately for each training method GN, GE and ST. Analysis revealed a significant effect of test session GN ($F(2, 18) = 10.93$, $p < .001$, $\eta_p^2 = .19$), GE ($F(2, 18) = 23.10$, $p < .001$, $\eta_p^2 = .29$), ST ($F(2, 16) = 16.17$, $p < .001$, $\eta_p^2 = .35$). Post hoc comparisons using the Tukey's test showed that there was a significant increase in jump height from PRE to POST 0.073m, 0.076m, 0.132m ($p < .001$) and PRE to NDAY 0.100m, 0.132m, 0.194m ($p < .001$) in GN,GE and ST respectively (see Figure 5). Furthermore, only GE had a significant increase in jump height from POST to NDAY ($p < .05$).

Jump accuracy (measured as the distances between the starting and landing points of jumps) data was skewed to the left and a square-root transform was applied before testing. There was no main effect of test session ($F(2, 52) = 0.13$, $p = .88$) or training method ($F(2, 26) = 1.11$, $p = .32$). The interaction terms were not significant. Jump accuracy varied only slightly in PRE, POST and NDAY tests, as seen in Table 2.

The amount of jumps during the 6 minutes of training was similar between the groups. The mean number of jumps was 324, 330, 344 for GN, GE, and ST respectively. The distributions of jump heights in each group were also similar.

Questionnaire results:

The nine original Likert-style questions of the Short Flow State Scale (SFSS) (Jackson et al., 2010) were used and mean flow values were calculated (M =3.83, 3.72, 3,11 , SD = 0.36, 0.42, 0.35 , for GE, GN, ST respectively). Cronbach's α was 0.7. A Kruskall–Wallis one-way analysis of variance was used to analyze the results and a significant difference between the rank means of the mean flow scores was found ($\chi^2 = 10.7603$, $p < .05$). Nemenyi post-hoc analysis ($p < .01$) of the three conditions shows a significant difference between ST and GE and ST and GN (p < .01, p < .05). A closer analysis of individual Flow scores with Kurskal-Wallis and Nemenyi post-hoc revealed that the largest differences are seen in action-awareness merging (AM), clear goals (CG), unambiguous feedback (UF) and autotelic experience (AE), where a significant difference to ST is in AM (GE and GN, p < .05), CG (GN, p < .05), and AE (GN, p < .05). This is also seen Figure 6.

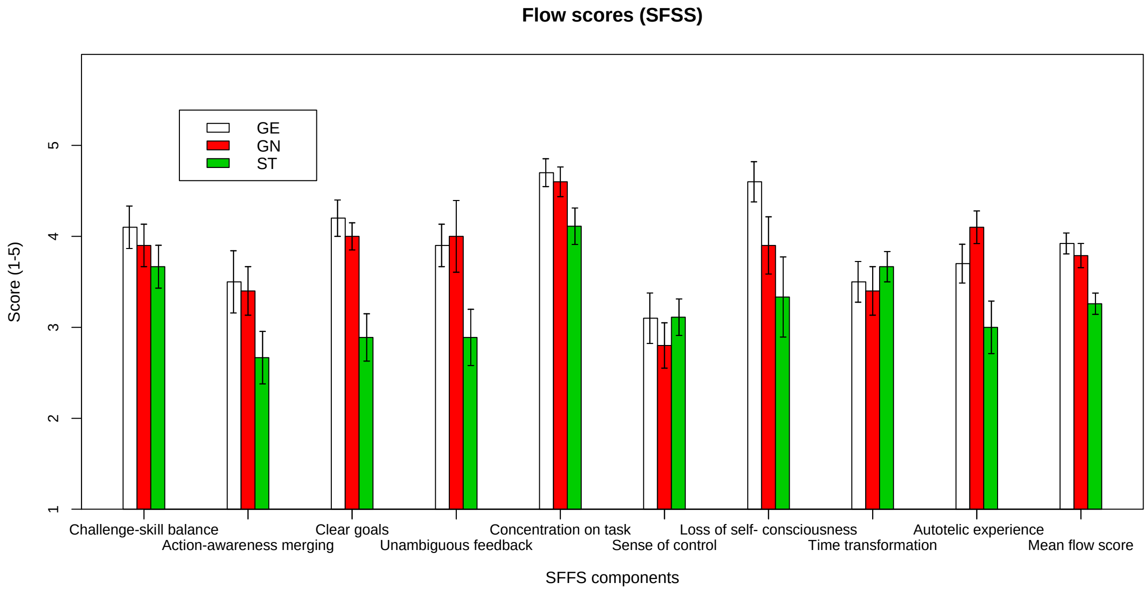

Figure 6. Flow (SFSS) scores for GN, GE and ST after the training show that experience of the ST group differed form GN and GE. (Error bars represent standard errors)

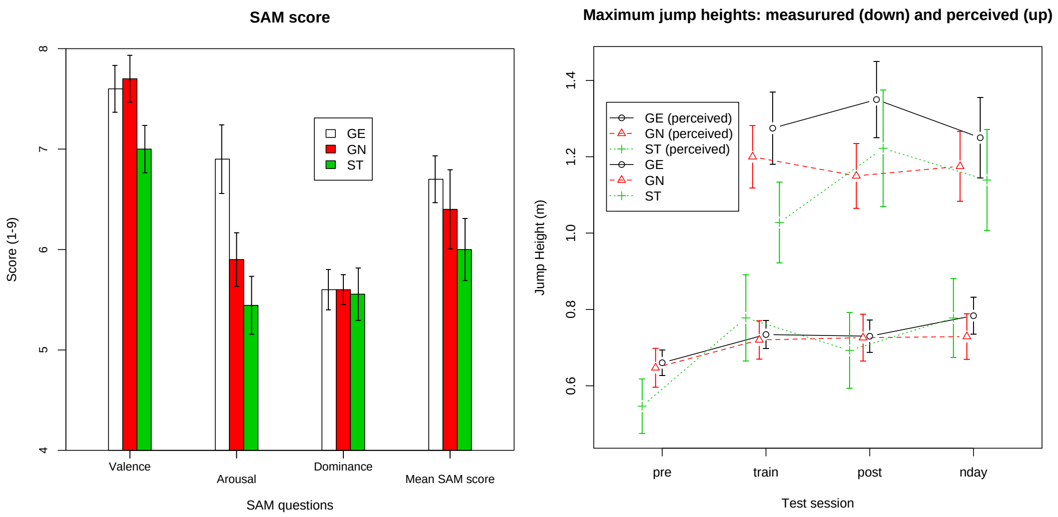

Figure 7 Left: SAM scores for GN, GE and ST after the training. There was a significant difference in arousal between the groups ST and GE (p < .05). The bars are shown between scores 4 to 8. Right: Measured and perceived jump heights in the highest point of the highest jump. (Error bars represent standard errors)

The self-assessment manikin (SAM) questionnaire was also filled after training and NDAY-test. A Kruskall–Wallis one-way analysis of variance and post-hoc analysis was used to analyze the results. The only significant difference between the rank means was found in arousal ($\chi^2 = 6.4741$, $p < .05$) and Nemenyi post-hoc analysis showed that difference was significant between GE-ST ($p < .05$). The results are also seen in Figure 7 (left).

Perceived competence (PC) scores show an overall mean increase of 4.67, 4.93, 5,37 (Cronbach's α = 0.8, 0.9, 0.9) during PRE, POST and NDAY respectively. There were no significant differences found between GN, GE and ST. The perceived maximum real world jump height was asked after the training, POST-test and NDAY-test. The maximum perceived and measured jump heights are presented in Figure 7 (right). The perceived jump height is consistently higher in training, POST and NDAY (M = 1.20m, SD = 0.33) than the measured one (M = 0.74 m, SD = 0.21).

Interview results:

The game with exaggerated jump height (EJ) was preferred over normal jump height (NJ) by most of the participants in the groups GE and ST. GE and ST were introduced to the exaggerated version of the game first. In the GN group, who used the NJ version first, 5/10 preferred the EJ version.

The game with exaggerated jumps (EJ) received positive comments when *compared* to (NJ):

- *“More rewarding, like driving a racecar instead of a scooter”,*
- *“Because the avatar jumps with ease, it creates a feeling that I’m more competent too”,*
- *“The exaggerated game feels somehow like superpowers in a game. Suddenly you get a boost”,*
- *“The exaggeration has a better correlation to the forces and acceleration that one feels on the trampoline”,*
- *“More rewarding. I’m used to exaggeration in games. It feels more natural, and stimulates me to jump higher",*
- *“The feeling of beeing a superhero”,*
- *“The exaggeration is more interesting, but on the other hand it affects the maneuverability“.*

The normal game (NJ) was described more negatively when *compared* to (EJ):

- *“Like jumping in tar”,*
- *“It felt more boring because of small jumps, a lot of platforms close to each other”,*
- *“Does not encourage to jump higher”.*

However, some participants preferred NJ since it felt more like an exercise or it was easier to control:

- *"It felt somehow more realistic and more demanding, and not too exaggerated",*
- *"I was more in control",*
- *"Exaggerated jumps gave a nice feeling, but non-exaggerated jumps gave better control sideways and the pace felt a bit more relaxed".*

The GN group, who trained with the NJ game, was asked if the jump height was underestimated, normal, or exaggerated. 5/10 said that jump height was normal and 5/10 underestimated. The same question was asked from groups ST and GN, who tried the exaggerated version first. Surprisingly, 4/9 (ST) and 5/10 (GE) participants did not notice any jump exaggeration even though they could jump many times their height on the screen. 2 participants realized the exaggeration only after being asked directly about it: "*I did not notice it… or now when asked about it, yes*", "*not exaggerated, but the avatar feels more able*".

The participants were asked about the positive and negative aspects of training with the game. The real-time feedback of the jumps in the game was appreciated by many participants and increased motivation, fun and efficiency of exercise was mentioned often: *"I get instant feedback when trying something different","Exercising comes with the fun".*

Discussion and design recommendations

Results show that all groups GE, GN and ST improved their jump heights while maintaining accuracy, as seen in Table 2. This indicates increasing skill, as more effort usually leads to lower accuracy (Schmidt & Wrisberg, 2008). The learning effect is still seen in POST and NDAY tests, when the real-time feedback (game) was removed from the groups GN and GE. The participants were tired after the training, which may partly explain the higher jumps in in the NDAY test compared to the POST-test. A couple of participants also commented on this: *"My muscles were tired in the end test, so I could not jump so high"*

The ST group increased its performance slighty more than GE and GN (see Table 2 and Figure 5 (left)), although no significant difference was found. However, as seen in Figure 5 (left), the ST group had slightly lower average jump height in PRE-test. Individual differences were big in the PRE-test results and we observed that two participants in the ST group were more intimidated by the trampoline training than the other participants. Their maximum jump height remained considerably lower only in the PRE-test. The training style varied between the participants in the ST group. Some jumped maximum jumps for the whole training period, whereas some settled for minimum effort jumps. It should be noted that all groups had some kind of training either with game or without a game. Overall improvement of the skill cannot be evaluated, because a no-treatment group is missing and part of the improvement can be due to a simple repeated-measures effect.

The questionnaire data shows that perceived competence was on the same level in all groups and exhibited a steady increase during PRE, POST and NDAY tests. All participants in all groups had fun in the experiment, which is not surprising because trampoline jumping is regarded as exciting in general. However, small differences between groups can be seen in the questionnaire results. The game with the exaggerated jumps (EJ) was more arousing than no game or NJ as seen in Figure 7.

Also differences in flow scores show that the ST group did not have as positive an experience as the GE and GN groups. This can be seen in the lower score for the question "I found the experience extremely rewarding" (AE). Self-training also received a lower flow score for spontaneous and automatic behavior (AM), knowing what to do (CG) and receiving feedback on one's own performance (UF). The participant's comments also complement this ***"****I don't pay so much attention to the jumping, it comes automatically when focusing on the game".*

Overall, NJ was reported to be more accurate with sideways jumps, although there was no exaggeration sideways in either of the games. The exaggerated jumps may affect horizontal aiming, because the target platforms are further away on the screen. However, more research is needed to confirm this.

It seems that jump height exaggeration makes the game more engaging and fun without affecting most players' performance. The exaggeration can also feel so natural that the player does not even notice it. A couple of participants asked if the jump height could be relative to the effort: "It would be nice if the jump height would be mapped to my effort and not to my actual jump height".

The game directs the player's attention to the game, which was mostly seen as a positive aspect. The player might use more extrinsic feedback, where as intrinsic feedback might be used more while jumping without the game:

- *"I don't pay so much attention to the jumping, it comes automatically when focusing on the game", "*
- *"I forgot how I was jumping and concentrated on the result".*
- *"More concentration to the body, because I do not have to look at the screen. However, it still lacks the real-time feedback.".*

The screen could be seen well through the safety net. In trampoline jumping, it is common to keep the eyes focused on one spot. It seems that focusing the eyes on a screen while jumping does not cause problems. One participant mentioned that: *"It feels harder to jump accurate jumps without the game. I had to find a focus point for the eyes. With the game it came automatically".*

Although care was taken that the participants had a proper warm-up, there were still people reporting back pain in all groups, although the pain had subsided when we checked back a few days later. Also muscle pain in the calves, thighs, neck and feet was reported. Two subjects even said that their hand muscles got a workout. Although trampoline jumping alone without attempting any tricks is regarded as relatively safe, it also appears to be so engaging that at least adult office workers may use too much effort and get hurt. All our participants reporting back pain were also initially among the most active jumpers. Trampoline training games should clearly include a proper warm-up and safety-instructions. Furthermore, it could also be possible to match the difficulty level of the game to the fatigue level of the player and design breaks as part of the game.

Many participants noted that jumping accurately sideways was difficult before getting used to it. This appears to be an unanticipated result of the trampoline enabling high jumps that travel a long distance. When landing on a platform that is high and to the side in the game world, the player will still continue moving downwards and sideways in reality. This may result in the avatar sliding off the platform if there is a one-to-one mapping between the horizontal positions of the player and the avatar. The design could be changed so that the platforms would slide sideways with the avatar and add an elastic vertical movement to imitate the movement of the trampoline bed.

It should be noted that in our previous computer vision game experiments, we have found it quite easy to exaggerate the player's jumps by simply boosting the tracked upwards velocity and adjusting gravity. We didn't initially realize that the exaggeration is more difficult in the case of trampolining where the user is jumping constantly. The player should not land on the ground later in the virtual world than in the real world, because otherwise the player starts to move back up before landing in the game, which can cause missed or mid-air jumps, depending on the game mechanics. In the platformer used in this study, gravity is exaggerated so that the player lands early enough even when jumping down from a high platform, but this seems to add a sticky feeling to small jumps, because the player stays on the ground longer than in the real world.

Overall, trampolining was seen as an interesting sport and many participants stated that balance challenges, effective full-body workout, and high jumps make it intriguing. On average, the participants positioned the exhaustion level of the trampoline training in this experiment between jogging and running. The exhaustion level was also compared to aerobic, football, zumba, biking uphill, badminton, interval training, dancing and rope skipping. Safety, velocity and increased abilities were also mentioned by several participants: *"Scary but safe at the same time"*, "*Euphoria from the velocity*", *"Illusion that I'm stronger than in reality, which is not an everyday feeling"*.

Conclusion

We studied how playing a simple body-controlled game while jumping on a trampoline affects the exercise experience, and whether the game enables the learning of basic trampolining skills. The platform jumping game was implemented using computer vision and a screen placed near the trampoline. The results show that improvement in high and precise jumps on a trampoline is similar between the group playing a game and the group without a game. Although trampoline training was regarded as fun by itself, the game made it more engaging. Focusing on the game did not disturb the participants' jump training and many participants considered the real-time feedback beneficial. Extra empowerment in the game, as jump height exaggeration, did not affect the performance adversely. Most of the participants preffered the exaggerated version of the game. The exageration felt natural and half of the participants did not even notice it. This suggests that extra empowerment may be used to make the training more engaging without affecting the results negatively. In light of these results, we suggest that mixed reality empowerment should be studied more to understand better its impact on exercise motivation and motor learning. We are currently investigating what abilities beyond jump height can be exaggerated, and how it affects motivation, interaction, and the social context of play, e.g., the skill attributed to the player by an audience.

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A Toolset for Beach Volleyball Game Analysis Based on Object Tracking

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Abstract

User acceptance of observation tools for game analysis highly depends on the quality of respective user interfaces. The paper presents three customized, non-commercial tools which were developed for the German national beach volleyball teams. BeachScouter enables coaches to capture live game data via touch screen. BeachTracker uses methods from computer vision in order to track the players and the ball automatically. Additionally, BeachViewer is designed for the quantitative analysis using this positional data, subsequently structuring video footage for further qualitative analysis. Based on the experiences while developing these tools, five design principles for game analysis software are suggested, (a) separating data collection and analysis, (b), minimizing input load during data collection, (c), provision of at least two levels of analysis, (d) using computer vision to reduce the amount of manual inputs, (e) orientation on specific questions of coaches and players.

KEYWORDS: USABILTY, GAME ANALYSIS, BEACH VOLLEYBALL, POSITIONAL DATA, SOFTWARE

Introduction

The quality of user interfaces is crucial for the acceptance of software products. Besides Apart the importance of visually appealing to the user, simplicity and operability are fundamental qualities. In terms of computerized game analysis two issues need to be put to the forefront: first the easy and efficient collection of data and second the extraction and analysis of sport relevant cues. Both tasks need to be reflected in the user interface to optimize the analysis procedure.

This article aims to illustrate how an intelligent interface design combined with the use of image detection can significantly improve collection and analysis of performance data. We present three customized, non-commercial tools that have been developed for the German beach volleyball national teams called BeachScouter (data collection), BeachTracker (automated player detection) and BeachViewer (data analysis). BeachScouter and BeachViewer were integral part for the game analysis during the 2012 Olympic Games in London. BeachTracker intends to improve the speed of the game observation process in the next Olympic cycle. The paper intends to present ideas and suggestions that can be applied to other sports to enhance efficiency in the data analysis.

Background

Game Observation Tools can be distinguished in general observation tools, which can be applied to any sports (i.e. SportsCode, Data Video Pro, SimiScout) and more specialized tools for one specific kind of sport (i.e. DataVolley, Sportstec Mercury or Mercury Beach). Although these of-the-shelf products are well established and have been successfully applied by various coaches and scientists (Patsiaouras et al., 2009, Turpin et al, 2008), their usefulness has yet to convince coaches and players from the German beach volleyball. Four reasons come to mind that can essentially be applied to every tool by varying degrees:

1. Complexity: Basically, these products are complex database tools that have grown over the years. The functionality is a mix, stemming from various requests to the manufacturer. Experience indicates that users require only a small part of the functionality, but still need a good overview of much of the product to work with.
2. Lack of efficiency in collecting data: It is essential to minimize user input for live scouting, and also for post editing of video footage. Although most tools allow adapting their interfaces to a certain extent, but the need to adapt these to any monitoring systems quickly sets limits. Without changing the source code relations between sport-specific features can hardly be implemented.
3. Inadequacy of options for data analysis: Not just any sport, but also coaches have their particular research interests. Tools need not only add up features, but also reflect the sport-specific relations. In particular, possibilities arising from the analysis of data in the position of beach volleyball are not yet sufficiently supported.
4. Design of interfaces: Evaluation modules are often designed similarly to the logic of office applications and its corresponding database structures. In practice, however, simple interfaces are necessary that allow for quick and easy performance analysis.

These deficiencies led to the complete abandonment of specific tools in German Beach volleyball, and the reliance on simple video players. To improve this situation, in particular in view of the 2012 Olympic Games, the Technical University Munich developed three new software solutions. The design priority was set on usability criteria. Subsequent sections should illustrate how efficiency and effectiveness of the game observation process was achieved.

Game Observation Process

The primary architectural decision in the design process of game observation software concerns the modularization of required functions. We hold the position that data collection and data analysis should be carried out with separate tools. These work processes are independent of each other regarding both content and timing. Additionally, the related tasks are being carried out by different users. Using separate tools advocates the simplicity of each individual program. Particularly, coaches and players ask to extract information from data analysis without needing to acquire in depth understanding on the processes of the data collection. Against this background, three separate tools were developed: While data is collected via BeachScouter and BeachTracker, BeachViewer is the presentation and analysis platform of that collected performance data. Figure 1 illustrates the basic work processes and interplay of the three tools.

BeachScouter is the tool for collecting match data. A key requirement for data acquisition is to provide basic evaluations immediately after the competition. That allows timely analysis and provision of that information to players. However, more complex analysis should also be possible, which might be more time intensive, and therefore might only be done after a tournament. For this purpose, Beach Scouter operates on two levels: In live mode, the start and end point of the rally are noted, as well as the most important observational characteristics (e.g. server, reception players, outcome, score). The first annotation can be supplemented in Review mode by more detailed features. If data must be provided very quickly to athletes, the live annotation is used immediately.

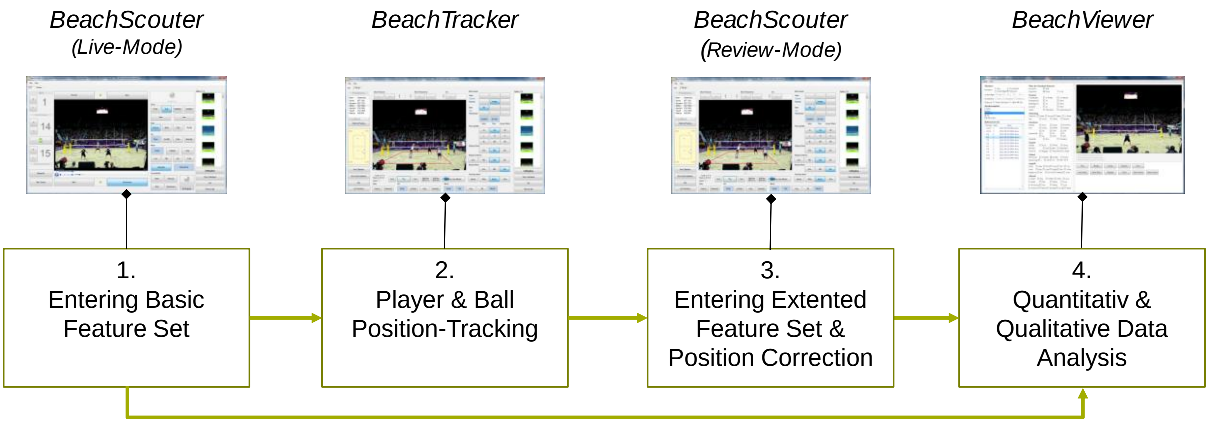

Figure 1. Schematic illustration of the workflow with BeachScouter, BeachTracker, and BeachViewer. The observer records the match data, depending on the time available in two levels of detail: live mode provides basic information on rallies, in review mode detailed recordings are being made. The BeachTracker is used to collect player and ball positions, which also can be corrected in review-mode if necessary. The annotation files along with video footage is uploaded to the file server and used by coaches and players for the data analysis in the Beach Viewer.

BeachTracker uses the annotation file created in BeachScouters live mode and extends it with the positional data. It uses methods from computer vision in order to detect the player and the ball position. It is important to know that tracking results are never 100% correct and must be reworked. This is done in BeachScouters Review-Mode manually. The resulting XML-based annotations file is read together with the video file from BeachViewer. Depending on available data, varying options for detailed analysis are possible.

A precondition for this process is the availability of video recordings. On competitions on the FIVB World Series they are recorded by scouters, which are on the spot. Parallel to the match a basic annotation of the game is created that is later uploaded to the file server together with the video. Players and coaches can download these files and use for their analysis. Generally, over the course of a tournament the second detailing is skipped, and one rather aims to capture as many games as possible. If live capturing is not possible due to parallel games, the annotation is done afterwards via the recorded video material.

If a detailed annotation is demanded following a tournament, games are being reworked by the Olympic training center in Germany. At the Olympic Games 2012 several detailed annotations of opponents were available from previous competitions. These were supplemented by new data at the Games. An additional scouter, located in Germany has been introduced considering the significance of the Games. That scouter had also access to the file server and was also able to edit the games and upload the completed annotations. This approach has been adapted in other major games during the World Series.

On the youth development level at the German Volleyball Federation it is generally not possible that a scouter or coach accompanies players at international competitions. In those instances players themselves record their opponents and upload the video footage on the file server for analysis. Sometimes games are uploaded by the organizer or by betting companies. Coaches can then use these streams for their basic annotation and record the video file. After the primary game analysis, players can download the BeachScouter file, and receive feedback supporting their preparation for upcoming competitions.

BeachScouter

Similar to any other sport, beach volleyball aims to collect as many performance relevant data as possible, while carefully weighing the cost benefits. The Beach Scouter fulfills these requirements through the use of four features, which in this combination or specificity have not been implemented in other tools:

1. Support of a live and a review mode
2. Collection of positional data from video footage
3. Derivation of features from the game and rally course
4. Optimized user interface for touchscreens

The following sections describe how these concepts are practically implemented. Logic and design of the interfaces in both cases are focused on minimizing the required manual input.

Live Mode

The interface in live mode is divided into four major components (fig. 2). The left panel (A) contains the configuration of the rally (formation, score, service player). Video image and video control (B) are only available when a video file is available. If no video signal is present, the user starts a timer to start the game, so that the annotation can be synchronized with the video image afterwards. Input of features of rallies (C) is carried out via control panel preferably via touch screen. The right panel (D) contains the list of previously collected rallies.

Prior to the rally

Prior to each rally a configuration is annotated. This is based on the configuration and the result of previous rallies, automatically calculated by the program and pre-assigned to the graphical control elements. Thus on the basis of the score the system automatically assigns side changes, and does this also for the serve once it has been dedicated. From that information further automatic assignments regarding possible reception players as well as serve order are being calculated. Hence scouts only need to enter data in specific cases (i.e. if a player attacks on the atypical side, or if a time out was taken). A crucial rally for example after a spectacular point, a discussion with the referee or between the teams can be marked as a stress point. BeachScouter automatically suggests this when a team has 12 points in the third set with a distance of no more than a break more than 18 or, the previous rally lasted longer than 15 seconds or more than one counter-attack arises. The above features are automatically assigned, while serve technique and receiving player may be estimated. That information may be extracted since players often follow a specific serve tactic. These parameters remain relatively constant during the game.

During and after the rally

During the rally the starting time is recorded either via a control button or a click in the video. In the second case, this coordinate is already stored as a serve position (see review mode described in the next subsection). After the serve the rally lasts usually between 5 and 15 seconds. During that time serve technique, receiving players, set technique, attack technique, outcome, and the end time is collected. If an attack does not occur, due to direct serve win or errors, less user action is required.

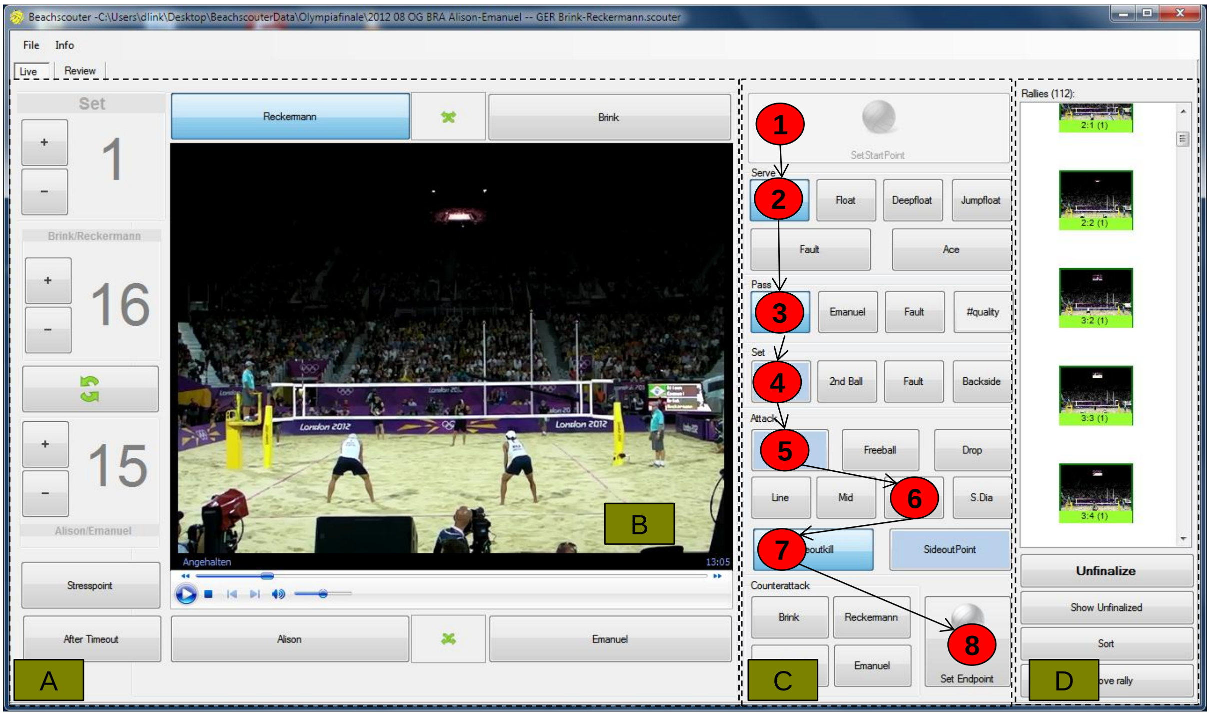

Figure 2. User interface of the Beach Scouter in live mode. The buttons set up follows an intelligent logic and are in relation to one another to reduce the number of inputs. On average, instead of the eight inputs represented, only five are needed.

The controls are arranged in a way that the path between them is as short as possible and operation can be done in a fluid motion from top to bottom. If a complete recording by the end of the turn should not be possible, one must at least enter the ending time correctly. Until the next rally, at least 15 seconds remain to update missing information. Also special cases such as attack without block, joust balls, free balls or possible counterattacks from field defense are recorded then. Upon completion of the rally, it is stored in a list, the user interface resets, and then calculates the states of the user controls for the next rally.

The software follows the game logic, where certain inputs on the user interface results in changes of button states. Some of these inputs are:

- An ace, a reception error or a setting error leads to a point by the serving team (break).
- A break automatically rules out a direct attack success of the receiving team.
- A direct attack success or a serve error automatically leads to a point for the receiving team (sideout-point).

- A free ball and a counter-attack rules out a successful direct attack success by the receiving team (kill).
- A successful counter attack determines the winner of the rally.
- Serve error and aces are mutually exclusive.

In addition to the above basic data, the quality of reception and the direction of the attack can be entered optionally. In the latter, fielding areas are being differentiated and also displayed on the control panels depending on the technique applied. If these two parameters are not explicitly specified then they are calculated based on the positional data entered in the review mode.

As shown in Figure 3 (area C), a maximum of eight clicks is necessary for scouts to mark the features in live mode of a standard rally (plus two more to mark ball stress points and time outs before). Due to pre-allocations and the implemented dependencies, the effort in the statistical average is reduced to about five clicks. In a counterattack, yet again up to four clicks are added, three clicks or less necessary in the event of a failure in the playmaking. Experience from initial tests showed that this input can be made by a scout with little exercise between two charges. A detailed breakdown of the observational features and their attributes can be found at Link & Ahmann (2013).

Review Mode

Purpose of the review mode is the annotation of positional data and some further quality characteristics that are not sufficiently well identified in real time. The interface for the review mode is shown in Figure 3. It is similar to the live mode and contains video control (B), a list of previously collected rallies (D) and some controls for entering the features of a rally (C). This part involves somewhat more controls, because the features of the first wave of the survey must also be editable. The positional data is collected via tipping directly on the video control. Further editing of the positions is done in the right area of the screen (A).

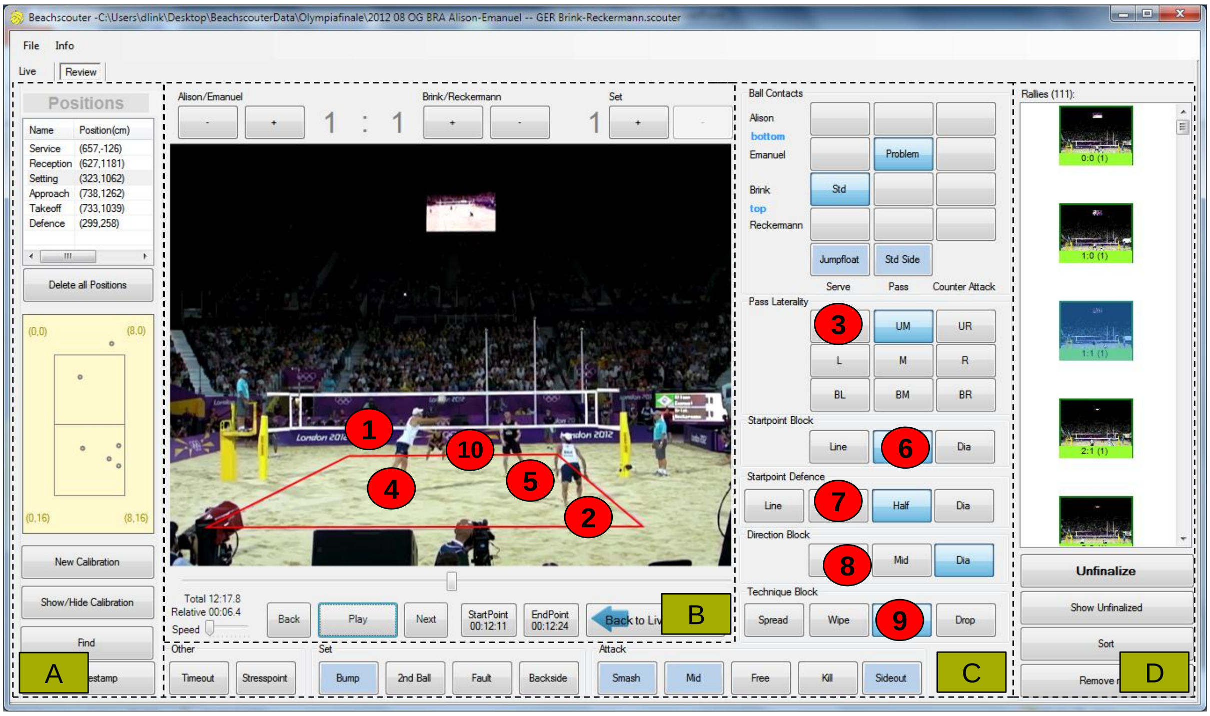

Figure 3. User interface of the Beach Scouter in review mode. The red cycles symbolize the order of user inputs By collusion of the video player, the number of required user actions can be reduced.

The data collection is carried out in a defined order, whereby scouts mark the positions of serve, reception, set, approach, take off and field defense directly in the video footage (see fig. 3). The positions are complemented by the qualitative assessment of the laterality of the reception, the position of defensive and blocking players and block technique and block direction. The starting position of block and field defense player (line, diagonally, middle) could be derived in principle from coordinates. However, in that case qualitative assessments of scouts are needed as an automatic differentiation between attribute levels did not produce the desired error rate.

Buttons and video image inputs are tuned with the video controller, that way users no longer need to worry about play or pause, thereby reducing the number of manual inputs. For example if the video image is stopped after entering the reception position and started again after entering the laterality of the adoption. After eleven clicks of the second analysis wave, the four qualitative characteristics, positional data of the rally emerge. From the latter not only visualizations are created, but also ten other features are automatically calculated, which would have to be entered manually in the use of standard software. The time for data entry takes roughly the gross game time. If the BeachTracker is used, the software already suggests positions of the players. In this case, the observer only has to confirm the tracked position.

In sum over both rounds with BeachScouter - depending on the counting method - approx. 32 observation items per rally are raised, or are algorithmically derived. For this purpose, approx. 17 clicks per rally are necessary depending on the outcome of the rally. The elevation is about the double of the season possible. With a classic game observation tool, with freely definable category system with no sport specific logic, such a data acquisition multiples takes longer (up to 50 clicks on an established commercial tool). Just this efficiency made possible the evaluation at this level of detail in London 2012.

BeachTracker

The BeachTracker is a tool, which takes the data produced by BeachScouters live mode. It uses the starting and endpoint of a rally and the manual entered configuration of the players on the court. The tracking of beach volleyball players uses particle filters (Gordon, Samond & Smith, 1993). For each of the four players, a particle cloud is created that tracks one player over the entire game. Particle filters consist of particles having intrinsic properties such as the particle's position, its weight, and for the current work the colour histogram of a defined region in the image associated to the particle. The particles' weights are calculated frame by frame using different hints such as a distance measure between a particle's histogram and the player's histogram, which is calculated in the first frame after selecting the player with a mouse. The entire algorithm is described in detail by Gomez et al. (2012).

Figure 4. Example for used video. In video A (left), the conditions are challenging, due to two reasons. Firstly, the perspective complicates the tracking, since, as can be seen, the players of the back appear too small. The lighting condition is also challenging since it is not homogeneous where in some regions there are shadows and in others there is light. Video B (middle) gives a view of the field from a greater height, which a sufficient size of all objects, but the illumination in this case is also homogeneous. Video C (right) allows the best tracking, because of a good contrast between the ground and players appear bigger.

The quality of tracking results highly depends on the quality of the video recordings (Fig. 4). We evaluated the tracking quality by comparing the tracked coordinates with the coordinate gathered by hand using BeachScouter's review mode. A tracked position was called correct, when is not more than one meter away from the manually annotated one. The recognitions rate ranges for the back player from 25 to 70% and for the players in the front from 36 to 86% (with increased quality from left over middle to right video). As a consequence the tracked positions must always be checked and sometimes corrected manually. This process is typical for all visual based tracking systems – even for the advanced multi camera systems used in professional soccer (Randers et. al, 2010). However, if high quality videos are available BeachTracker helps scouters to save annotation time in many cases.

BeachViewer

The analysis of the collected data aims to reveal strengths and weaknesses of potential opponents. For this purpose, a range of routine questions and spontaneous impressions on the basis of the video recordings will be evaluated. These paint a characteristic image of the opponent on the basis of his own serve, field defense or attack strategies.

The underlying methodology of BeachViewer is in line with qualitative game observation (Hansen & Lames, 2001), which is divided into three separate steps. These are (1) querying of game footage, (2) followed by quantitative pre-analysis and (3) the qualitative main analysis both based on the number of hits resulting from querying. These steps are guided by following software functionalities and illustrate the specific characteristics of BeachViewer:

1. Using a minimalist user interface
2. Classification of rallies on the basis of positional data
3. Provision of beach volleyball-specific querying options
4. Reports for the quantitative pre-analysis

BeachViewer provides a simple interface (fig. 4). The program consists of a window, query options (A), list of rallies (B) as a result of querying, as well as a video window with some basic controls (C). There is only one single menu item for loading one or several data files of BeachScouter.

Based on the uploaded positional data, BeachViewer calculates subsequent features. Some of these include the serve zone, approach length, area and quality of reception, setting angle, takeoff zone, attack direction and many more. Features, such as serve sector and take off zone are calculated canonically from one position. Others follow from the relationship between two positions (e.g., approach direction, setting angle). Calculating the quality of reception is somewhat more complex (details at Link, 2011). Additional functionality of BeachViewer as well as the implementation of above concepts are further discussed in the following section.

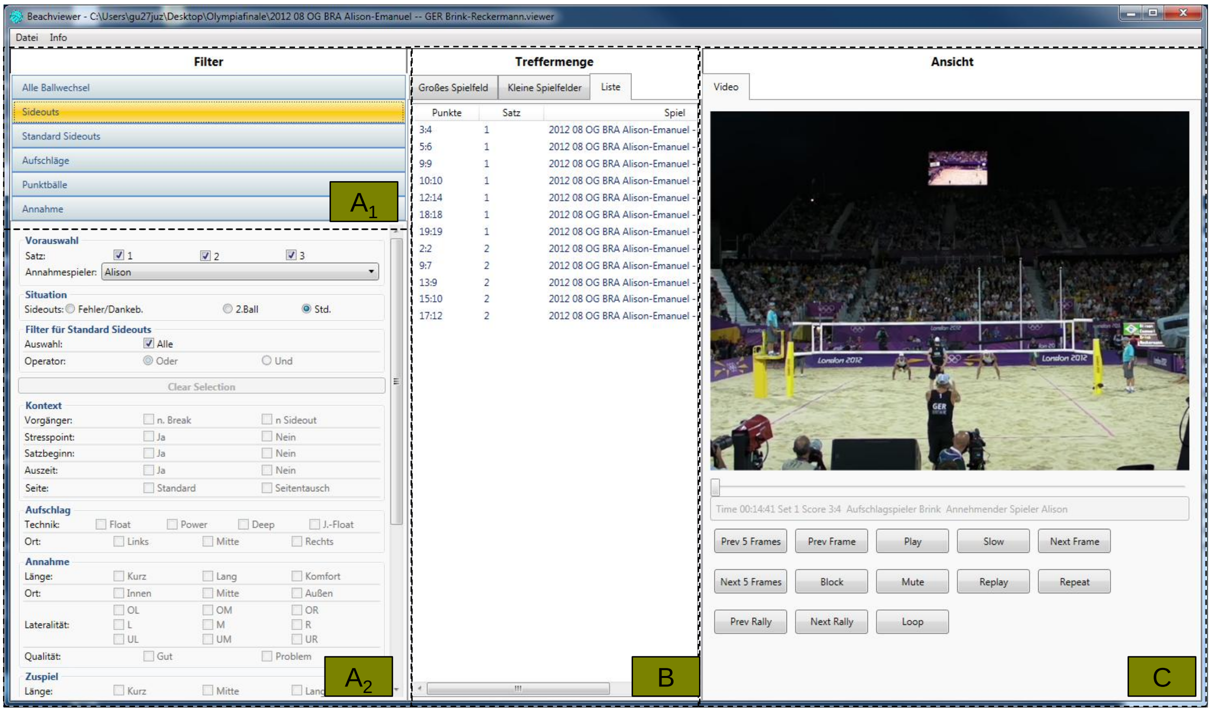

Figure 5. User interface of BeachViewer. The program consists essentially of a window query options (A), list of rallies (B) as a result of the query, as well as a video window with some elementary controls (C). The queries are arranged according to the game logic in beach volleyball.

Querying for situations

Contextual queries are essential for adequate performance analysis. In BeachViewer these queries are organized according to the evaluation logic in beach volleyball. First, the user chooses whether analysis of sideout-, break-, reception-, defence and serve- situations should be run (A1 in Fig. 5). In dependency of this selection the BeachViewer provides different advanced filter options. For example sideout querying differentiates amongst three basic types; sideouts with errors, attacks on the second ball, as well as standard sideouts with three ball contacts (A2 in Fig. 4). Standard sideouts can be further distinguished according to various characteristics into the categories; service technique, reception quality and setting parameters. Querying according to contextual information is also possible (e.g. "rally after a break"). Values within a feature can be ascribed with an “or” operation ("rallies with short or medium length pass"). Furthermore, features can be combined with “and” and “or” operators ("rally with start-up to the middle and shot").

The definition and the order of the queries are essential in querying. It is useful to query rallies initially by attacking directions and then to consider the outcome ("What is the success rate of reception in mid field?"). It is also possible to first query by outcome and then examine the similarities within these results ("Which situation is the least effective?").

Another factor is the specificity of the query. Narrowing searches too much, by clustering several classifiers (e.g. "all successful, hard attacks of a player on the non-standard side") results in a diminutive and unrepresentative sample of game situations. Querying too broadly (e.g. "all side-outs of a player") also hampers systematic analysis. Querying appropriately is challenging and cannot be prescribed through stringent rules. Individual experiences, preferences, and understanding of the game refine the quality of the analysis.

Quantitative pre-analysis

The second step is the quantitative pre-analysis of the queried plays. BeachViewer supports so-called reports to visualize moves and to show statistics such as for example the distribution of attack technique (shot or smash) and attack direction. The design of the reports depend on the selected primary query. For example in the sideout and the serve report, rallies are superimposed and depicted in a single image (fig. 6). These can be colored either by outcome of the turn or a hit technique. Other reports show the impact behavior or the behavior from attacks on the second ball. From a performance diagnostic point of view, the intention is to be able to detect a possible relation between the spatial/temporal constellation of one turn and follow-up action. This allows identifying situations, where a player shows the attack behavior stereotypes.

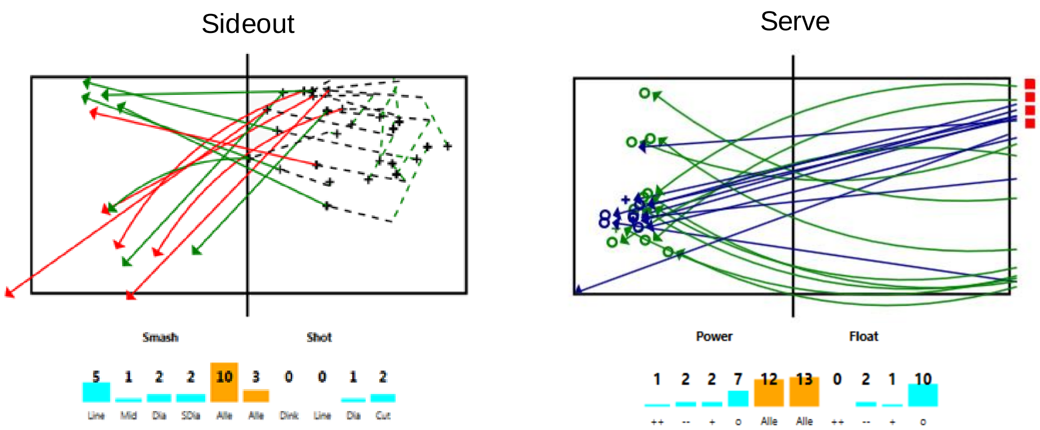

Figure 6. Exemplary report based (left) on the hit list from querying (attacks after low reception quality by Emanuel Rego (BRA) during Olympic semifinal). Besides elementary statistics on outcome, hit technique and the direction of the distribution moves are visualized based on positional data. A tendency can be seen for cross court hits from Rego. The right report shows serve characteristics of Rego. He seems to forgoes on long line power serves.

As an example this principle can be shown in the preparation of the Olympic Final 2012. This was the attack behavior of Emanuel Rego (BRA) examined after low quality receptions. Rego appears increasingly attacking cross court (fig. 6). When he attacks at the line direction he always chooses a smash and forgoes on shots. This information can be used in circumstances for the development of its own strategy.

Qualitative main-analysis

It is essential to understand the reports as a means to detect abnormalities. The results must be substantiated by a qualitative analysis of the video material. Therefore, the third step involves the qualitative analysis of the video material. Various techniques, such as still images, slow motion, and replays of approach sequences or entire plays are commonly applied. Experience has demonstrated that replaying subsets of game situations, and focusing each cycle on different behavioral characteristics best serves that purpose. Routine questions can be answered by comparing fixed observed features. Rapidly changing clips enhances the "layering" effect for each scene, thereby extracting behavioral analogies

Elite players are distinguished by being highly adaptable to emerging situations. Moreover, due to the small sample size one cannot expect quantitative proof of any such profiles. Although it would be nice from a scientific perspective, its relevance for practical purposes is less noteworthy. Simply winning individual plays with information gained from game observation suffices in practical terms.

Summary & Conclusion

The tools described in this paper were not only developed for academic purpose, but they are an essential part in the supporting strategy of the German beach volleyball federation. The presented interface design and the interaction logic for beach volleyball represent several evaluation and development cycles during the FIVB World Tour 2012 and 2013. The basic ideas can be interpreted as best-practice recommendations and are summarized as follows:

- Separation of data collection and data analysis, to reduce the complexity of the individual tools (here BeachScouter and BeachViewer)
- Minimization of the user input data collection through the integration of sport specific simplification mechanisms (here position and dependencies between characteristics).
- Use of different collecting depth, in order to have a quick evaluation available shortly after the event (here live and review mode).
- Consistent orientation of the analysis components on game observation procedure used by the coaches and athletes (here quality game observation).

These principles are complementary to general usability style guides for dialogs (ISO 2011). Essential for the development of software for game analysis is the integration of sports knowledge in the user interfaces. Each sport is defined by its own logic, rhythm, particular dynamic. Hence off the shelf products hardly suffice. The full potential of game analysis can only be realized with the addition of sport-specific software solutions that minimize input loads and produce relevant performance diagnostic cues.

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Classification of top male tennis players

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Abstract

The main objective of this study was to define different quality groups of tennis players based on their position on the ATP ranking list. Ranking data on the top 300 players from 1990 to 2008 were used to conduct the study. The classification into quality groups was performed using six machine learning algorithms suiting such a task. Quality groups were formed better for each year separately than for all years together. Three clustering algorithms (k-means with a Euclidean metric, MDBC with a Euclidean metric, and Xmeans) were equally successful in the classification according to the criteria function. All three algorithms also created very similar quality groups. They are thus equally suitable for classifying tennis players into quality groups based on their ranking scores. Changes in the ranking system (in the year 2000) were also reflected in the differences in classification success between the two periods (before and after 2000). The boundaries between the quality groups were more stable for the period after 2000, and less stable for the period before 2000.

KEYWORDS: SPORT, CLASSIFICATION, RANKING, QUALITY GROUP, MACHINE LEARNING

Introduction

One of the most objective measures of an athlete’s competitive success is the annual ranking list used in many individual sports (golf, car racing, alpine skiing, tennis etc.). The Association of Tennis Professionals (ATP) was formed in 1972 and the first world ranking list was published in August 1973. The ATP publishes weekly rankings of professional players, the ATP Entry Ranking, a 52-week rolling ranking and, up until 2009, the ATP Race, a-year-to-date ranking. Every player starts collecting points from the start of the season.

Tennis players collect ATP points at different tournament levels: Grand Slam (4), ATP Tour Finals (1), ATP World Tour Masters 1000 (9), the ATP World Tour 500 and 250 series, ATP Challengers, and ITF Futures tournaments. A player’s position on the ATP ranking list is defined by the number of ATP points collected and allows entry to and competing on different levels of tournaments.

A player’s competitive success is determined by three groups of indirect factors (Crespo & Miley, 1998):

1. player (playing standard, tactical understanding, technical competence, physiological development, mental characteristics, experience, game-style and training level, level of tournament);
2. opponent (same as for the player, but also ball trajectory, shot selection, position of the player, tactical intentions, and an opponent's tactical strengths and weaknesses); and
3. environment (court surfaces, weather conditions, other environmental factors: spectators, umpires, time, psychological considerations etc.).

In recent years, we have witnessed a rapid increase in the volume of data in digital form. It is impossible to gain useful information from such a vast data set. We therefore obviously need tools that can effectively search for interesting information in large databases. Machine learning is an artificial intelligence field which deals with discovering knowledge in data. It is becoming an important tool for transforming such data into useful information. The growing expansion of machine learning is also reflected in a rising number of commercial systems within the industrial, medical, economic, banking, etc. sectors. The main principle of machine learning is the automatic modelling of data. Learned models attempt to interpret the data from which models were constructed. They can assist in making decisions when it comes to studying the modelled process in the future (predictions, diagnosis, control, verification, simulations etc.).

Many practical problems entail a need to classify given data into groups. Groups are formed based on certain criteria. In fact, this is one of the most primitive activities of human beings. In order to learn about a new phenomenon, people always try to identify descriptive features and further compare these features with those of known phenomena, based on their similarity or dissimilarity. Naturally, people have limited processing power and memory and are therefore unable to effectively classify large databases. Fortunately, we can use advanced machine learning tools that are suited to such tasks. Clustering is a process of identifying a finite and discrete set of 'natural' data structures from a finite, unlabeled set of data (Xu & Wunsch, 2009). Derived data structures are called clusters. In general, clustering techniques are classified as partitional clustering and hierarchical clustering, based on the properties of generated clusters. Hierarchical clustering groups data point into tree-like, nested structure partitions, while partitional clustering directly divides data points into a pre-specified number of clusters without a hierarchical structure.

In this study, the main objective was to define different quality groups of tennis players based on their position on the ATP ranking list. We were interested in discovering the borders between the quality groups, and the common characteristics of players in each group. This was performed for each year separately, and for all years together.

Methods

In the framework of our project the data for rankings, players, tournaments and matches were collected from the ATP webpage (ATP World Tour, 2009). All individual rankings for the years 1973 through 2008 were collected for the best 300 players. Rankings with ATP points information were available from 1990 on. We selected tournaments from 1968 to 2008, including Grand Slams, the ATP World Tour Masters 1000, the ATP World Tour 500, and the ATP World Tour 250. All matches collected were from 1991 to 2008 for all ATP tournaments previously mentioned. All of the collected data was stored in a specially designed database running on a MySQL 5.1 community database server. A custom-made application was used to store the data in the database which was designed in a way that allows quick and easy queries across players, rankings, tournaments and/or matches.

For the purpose of this article, we used the following variables:

- ranking variables: points and position;
- match variable: round; and
- tournament variables: type of tournament and surface.

The quality groups were determined for every year separately and for all years together using different machine learning clustering algorithms based on rankings (points). We chose points over position because that reflects a real quality difference between players, whereas position only gives the order. There are many possible clustering algorithms (Xu & Wunsch, 2009). Since we had already anticipated having five desired clusters, we used partitional clustering algorithms: k-means with a Euclidean metric (KME) (Forgy, 1965), k-means with a Manhattan metric (KMM), MDBC with a Euclidean metric (Law et al., 2004), Xmeans (Pelleg & Moore, 2000), EM (McLachlan & Krishnan, 2008) and FarthestFirst (Hochbaum & Shmoys, 1985). The metric, or distance function, is a function which defines the distance between elements of a set. Both Euclidean and Manhattan metrics are well known and frequently used. The K-means algorithm is a very simple method for grouping data into *n* clusters, and tries to minimize the within-cluster sum of squares. It starts with *n* randomly positioned clusters. All instances are then assigned to the closest cluster according to the chosen metric. Next, the centroid (mean) of the instances in each cluster is calculated. The whole process is repeated with new cluster centers. Iteration continues until the same instances are assigned to each cluster in consecutive rounds. But K-means does not guarantee that its solution is a global minimum. To increase the chance of finding a global minimum, the algorithm is run many times and the best solution is chosen (the one with the smallest total squared distance). The EM (expectation-maximization) algorithm is an iterative method which alternates between performing an expectation (E) step – which computes the expectation of the log-likelihood evaluated using the current estimate for the latent variables – and a maximization (M) step that computes parameters, maximizing the expected log-likelihood found in the E step. These parameter-estimates are then used to determine the distribution of the latent variables in the next E step. The algorithm iterates until the difference between the successive log-likelihood values is below a pre-defined, small value. The EM algorithm also does not guarantee that its solution is a global minimum. The same procedure employed with the k-means algorithm can be used to overcome this problem.

The quality of the clusters generated by each algorithm was estimated with the criteria function (CF) that most effectively separates the types of tournaments according to quality groups. First, the overall performance of the players in each quality group (QGP) was calculated as the average of the highest round played in tournaments of a specific type. Next, the CF was defined as the average of QGP differences between consecutive quality groups. Finally, the algorithm with the highest CF most effectively separates players into quality groups. In addition, differences in classification success between the two periods (before and after the year 2000) were examined due to changes in the ranking system.

Results

According to our criteria function, quality groups were formed better for each year separately than for all years together (Table 1). The best clustering algorithms for each year separately were KME, MDBC, and Xmeans, whereas for all years together the best clustering algorithms were MDBC and Xmeans. Differences based on the criteria function between KME, MDBC, and Xmeans were minimal, thus the quality groups formed with these algorithms were very similar. The CF standard deviation was considerably smaller for all years together than for each year separately, indicating that the quality groups were formed better for each year separately. All algorithms (except KMM) had greater CF values for the period after 2000 compared to the CF values for the period before 2000 for each year separately. Thus, quality groups were formed better for the years after 2000. In contrast, there were no pronounced differences in the algorithms' success within the two periods (before and after 2000) for all years together, except for the FarthestFirst algorithm.

Table 1. Evaluation of the derived quality groups with the criteria function (CF) for each year separately and all years together

	Algorithm	**CF**	**CF SD**	**CF after 2000**	**CF before 2000**
YEARS ALTOGETHER	KME	0.76	0.15	0.78	0.75
	MDBC	0.84	0.16	0.84	0.84
	XMeans	0.83	0.16	0.83	0.83
	FarthestFirst	0.76	0.40	0.84	0.69
	KMM	0.65	0.09	0.64	0.67
	EM	0.47	0.09	0.49	0.46
YEARS SEPARATELY	KME	0.84	0.25	0.91	0.77
	MDBC	0.84	0.25	0.91	0.76
	XMeans	0.84	0.25	0.91	0.77
	FarthestFirst	0.78	0.39	0.82	0.75
	KMM	0.54	0.09	0.54	0.55
	EM	0.50	0.23	0.49	0.43

The average quality group profiles were similar for the KME, MDBC, and Xmeans algorithms (Figure 1), as were the differences between the quality groups for each year separately. On the other hand, the average quality group profiles across years of the other three algorithms (EM, KMM, and FarthestFirst) differed significantly.

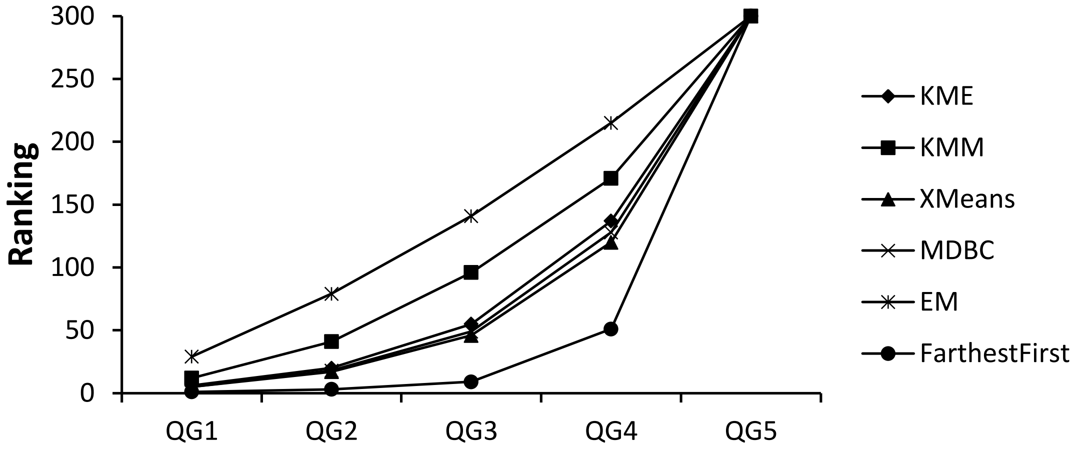

Figure 1. Average quality groups profile for each algorithm for each year separately

The output of each algorithm was a set of quality groups divided by the boundaries between them. The boundaries for KME are plotted in Figure 2. The first quality group (the best players) contained the lowest number of players, while the fifth quality group contained the most players among all quality groups. The number of players in the other quality groups increased from the first to the fifth quality groups. Fluctuations of the boundaries between the quality groups were greater before the year 2000 and considerably smaller after that (Figure 2).

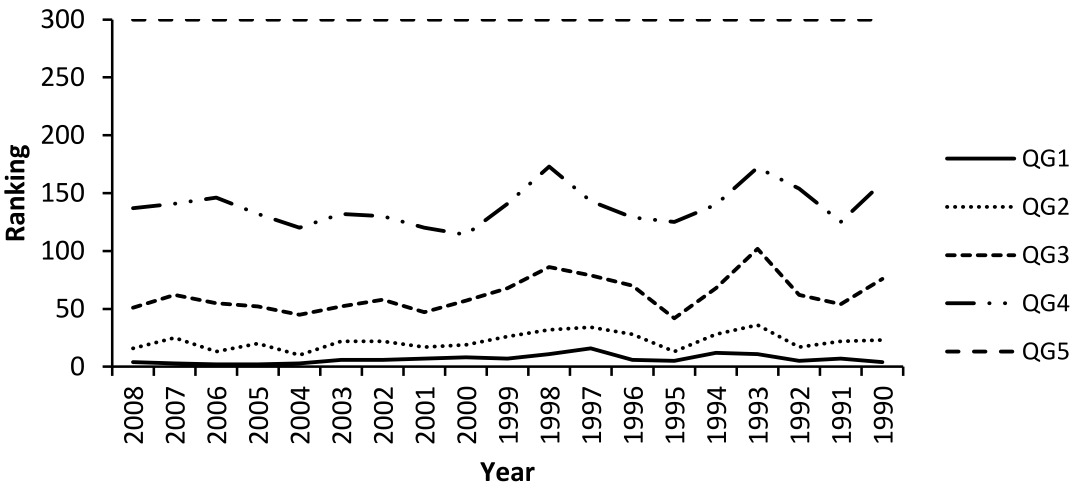

Figure 2. Profile of the quality groups produced by the KME algorithm

Discussion

When comparing the performance of clustering algorithms for each year separately and for all the years together, there was an evident difference between these two approaches. All algorithms, except the KMM, classified players into quality groups better for each year separately (Table 1). Such results were expected because quality groups can be more effectively adjusted for each year separately than they are independent from other years in this case. The adjustments are made as an adaptation of one quality group to adjacent ones. Hence, a boundary between two quality groups affects the adjacent boundaries so that all quality groups formed are the most compact regarding the selected metric function. In contrast, the classification into quality groups based on all years together yielded the same quality groups for all years. The boundaries between quality groups for all years together were very similar to those we obtained as an average of all of the boundaries between the quality groups for each year separately. The differences between boundaries were in ±3 ranking positions. Regarding the classification for each year separately, three clustering algorithms (KME, MDBC, and Xmeans) were equally successful according to the CF. All three algorithms also created very similar quality groups (Figure 1), which was expected because they are based on the same foundations and differ in the selection of the initial clusters. Thus, they are equally suitable for classifying tennis players into quality groups based on ranking scores.

The differences in classification success between the two periods (before and after 2000) were of interest due to changes in the ranking system designed to force top players to play in all the grand slam events and "Super 9" tournaments, or else suffer in the rankings (Mallett, 2009). The changes described here were also detected in our study. The boundaries between the quality groups were more stable for the period after 2000 and less stable for the period before 2000 (Figure 2). Moreover, the CF values were greater after 2000 than before, indicating the better formation of quality groups after 2000. We can therefore conclude that the ranking system changes in 2000 led to a more accurate ranking of tennis players. Moreover, no differences in the success of the clustering algorithms were detected between the two periods for each year separately, which means no algorithm is more suitable for one period than another.

The number of players in each quality group grows with decreases in quality. This behavior is completely natural and can be observed in all other sports. For example, only a few tennis players are able to perform on the highest level, while the number of players grows exponentially (the exponent is typically > 0) with decreasing quality. This behavior depends on the structure of tournaments (the exponential relation between the number of tournaments and prizes) that consist of a few tournaments with big prizes, thus all highly ranked players can participate in these tournaments. If highly ranked players had not been able to participate in all big prize tournaments, the relationship between the number of players and the quality would have moved towards a linear relation. Among all algorithms, it was the EM that had the most linear profile, while the FarthestFirst had an exponent with the highest exponential. All other algorithms were in between these two. The best three clustering algorithms had a similar profile, indicating they are equally suitable for classifying tennis players into quality groups.

Conclusion

The composition of individual quality groups is associated with a player's performance at a specific level of tournaments (Grand Slams, ATP World Tour Masters 1000, ATP World Tour 500 and 250, Challengers, and Futures tournaments) and indirectly with their position on the ATP ranking list. Higher levels of tournaments or rounds of a tournament mean bigger prize money, more ATP points, and more competent opponents. The present findings suggest that each quality group of players is defined by specific tactical, technical, mental, and fitness competencies. Therefore, players must improve those competencies in order to be able to play on the level of the next quality group.

The performance of players can also be defined with an analysis of performance indicators. In the future, we want to determine the following: differences in performance indicators through different time periods, and differences between quality groups in performance indicators in specific game situations. In this study, we classified players into five quality groups where the number of groups was chosen based on experts' knowledge. However, we are aware that some other classification approaches could result in different conclusions.

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PART 2

SPECIAL EDITION

Comparison of a Video and a Virtual Based Environment Using the Temporal and Spatial Occlusion Technique for Studying Anticipation in Karate

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Abstract

Perception and anticipation are important determinants in karate sports. Using the temporal and spatial occlusion technique in video presentations is a common method to determine anticipatory cues but the lack of information about depth in video presentations seems to affect the results. The aim of this study is to compare the responses of karate athletes to occluded attacks shown on a video screen and in a virtual environment. Five expert karate athletes were filmed by two synchronized high-speed cameras while responding to nine temporally and spatially occluded sequences of a competition relevant attack at first in a CAVE (Cave Automatic Virtual Environment) and then on a life-size video screen. Their responses were rated as 'correct' or 'incorrect'. The results of the Wilcoxon test show significant differences ($Z = -2.325$, $p < .05$) in regard to the number of 'correct' responses for these scenarios. It is concluded that the higher number of 'correct' responses in the virtual environment is caused by depth information, which evokes a more realistic feeling about the environment and is therefore seen as more beneficial for research of anticipation. Also, first anticipatory cues based on the results of the virtual environment could be determined.

KEYWORDS: ANTICIPATION, KARATE, OCCLUSION, VIRTUAL REALITY

Introduction

Anticipation is a performance-dependent factor in sports. In general, it is defined as a person's ability to "foresee an action, an effect of an action or a dynamical changing environmental condition" (Munzert, 2003); in sports this can be the movement of a ball, a team mate or an opponent. Anticipation of human movements is based on the perception and recognition of cues within kinematic patterns, which are commonly learned by experience and training. Recent studies revealed that an early recognition of anticipatory cues depend on the level of expertise (e.g. Blake & Shiffrar, 2013; Jones, & Miles, 1978; Williams, 2004). Anticipation is especially important in fast ball sports, such as racquet sports, since the initiation of an appropriate movement must occur before racquet-ball contact, in order to achieve an on-time and successful response (Abernethy, 1987; Cauraugh, 2002; Goulet, Bard, & Fleury, 1989; Savelsbergh, Williams, Van der Kamp, & Ward, 2002; Williams, Ward, Knowles, & Smeeton, 2002; Williams, 2009).

A common method to identify anticipatory cues is the usage of video presentations combined with the occlusion technique (Davids, Savelsbergh, Bennett & Van der Kamp, 2002). Two different types of occlusion methods can be distinguished: the temporal and the spatial occlusion. The temporal occlusion method crops visual presentations completely at certain points in time, while the spatial occlusion method only masks specific sections of a display covering up parts of the human body or objects. The method's general purpose is to withhold specific visual information of the presentation to which the participants have to respond, either verbally, in written form or physically. The aim of this method is to detect which occluded information is important, based on the participant's responses. Bad or out-of-the-order-responses at specific occlusions are seen as indicator for important information being withheld covering up an anticipatory cue. The number of correct responses to the temporal occlusions allows the detection of the occurrence of cues over time and the responses to the spatial occlusions of the location of the cues (Abernethy, 1987; Clatworthy, 1991; Jones & Miles, 1978; Mori, Ohtani, & Imanaka, 2002; Panchuk & Vickers, 2009).

One of the first studies using the temporal occlusion method was conducted by Jones & Miles (1978) and Isaacs & Finch (1983) in tennis. In their studies the participants had to verbally predict the ball's landing position based on slides revealing information about a tennis serve before, during and after ball contact. The results are the same in both studies: unlike novices, expert tennis players are able to perceive and use early cues to predict the ball's landing position. Abernethy & Russell (1987) also used the temporal occlusion method for presenting badminton serves on a video screen. While they were able to identify the point of time of anticipatory cues, they were unable to determine its location, e.g. body part or specific movement. In another study in squash, Abernethy (1990) used both, the temporal and spatial occlusion method, to identify the time and spatial location of cues of a serve. The results show that only experts are able to pick up information of the opponent's arm movement before ball contact in order to anticipate the stroke direction. Savelsbergh, Van der Kamp, Williams, & Ward (2005) analyzed anticipatory skills of novice and expert soccer goalkeepers to temporally occluded penalty kicks on a video screen. The goalkeepers had to predict the ball's landing position in the goal using a joystick. It showed that experts predicted the direction the ball flies concerning height and side better than novices. Williams (1997) and Williams, Davids, Burwitz, & Williams (1994) came to similar results in previous studies. The occlusion method has also been used to analyze anticipation in cricket (Müller & Abernethy, 2006; Müller, Abernethy, & Farrow, 2006), field hockey (Clatworthy, 1991) and fencing (Hagemann, Schorer, Canal-Bruland, Lotz, & Strauss, 2010).

Anticipation in karate has hardly been examined in sports. One of the first studies analyzing perception and action coupling in karate was by Scott, Williams, & Davids, (1993). In the first part of the study participants had to verbally identify the attacking body part and in the second part they had to respond with a physically appropriate movement. Experts performed better than novices in the second task, but not in the first. In another study Mori et al., (2002) examined novice and expert karate athletes' anticipation using temporally occluded karate attacks presented on a video screen. The attacks were stopped at specific times before fully performed and the athletes had to verbally predict which part of their body would be hit. In comparison to the novices, the experts showed superior anticipatory skills in being able to predict the target area at early stages of the attack. Since only the temporal occlusion was used the point of time of the cues could be identified, but not the cues' spatial locations.

All presented studies used two dimensional presentations as visual stimulation. It is assumed that the lack of depth information in these studies affected the participant's perception and anticipation skills and consequently the results' ecological validity (Abernethy & Russell, 1987; Mori et al., 2002; Savelsbergh et al., 2002; Williams et al., 2002). Depth information is very important in sports in order to act and react appropriately. A two dimensional environment lacking depth information is not able to create a feeling of immersion which evokes realistic responses from athletes (Farrow & Abernethy, 2003).

One of the first studies using a three dimensional environment for sports was conducted by Bideau, Multon, Kulpa, Fradet, & Arnaldi (2004). The aim was to develop and evaluate the ecological validity of a virtual environment for sports. They were able to show that a virtual environment with animated virtual athletes, based on motion capture data, could be used for scientific research in sports. A virtual environment provides many advantages such as standardization, highly controllable environmental set-ups, repeatability and the possibility to manipulate human movements in a certain manner. Bideau, Kulpa, Vignais, Brault, Multon, & Craig (2010) carried out two experiments using a virtual environment to examine anticipation skills in rugby and handball: In the first experiment the novice and expert rugby players' ability to perceive an attacker's deceptive movements were analyzed. A HMD (head mounted display) was used to provide stereoscopic view of an attacker's movements which was temporally occluded. The rugby players had to predict the attacker's movement direction at the end of each occluded scene by pressing a button. The results show that rugby experts have a better ability to predict an attacker's movement direction, based on the attacker's kinematic information. In the second experiment a spatially occluded virtual handball penalty throw, animated by motion capture data, was presented on a stereoscopic screen. The handball goalkeepers had to react physically to the virtual penalty throws as if intercepting the ball in reality. The throws were modified to provide three different sorts of information: the ball trajectory, the thrower's movements and both together. The results show that the highest number of successful interceptions is achieved when seeing the thrower's movements and the ball trajectory.

This last study points out the abilities and advantages of using virtual environments in sports and furthermore the possibility to examine anticipation skills in conditions close to reality. In order to use these advantages and to analyze anticipatory skills in karate Bandow, Witte, & Masik (2012) developed a virtual environment in a CAVE. To provide realistic movements the virtual attacker was animated by motion capture data. The virtual environment was evaluated positively in regards to realism and immersion by karate athletes responding to karate attacks as well as by non-karate athletes viewing the attacks and answering a questionnaire (Bandow, Stucke, Trebeljahr, Masik, & Witte, 2012; Witte, Emmermacher, Bandow, & Masik, 2012). In order to compare the effects of a two dimensional and three dimensional virtual environment on expert karate athletes, one aim of this study is to compare the athlete's responses towards occluded attacks in each environment. The other aim of this study is to identify the relevant anticipatory cues of the attack.

Methods

Defining the temporal and spatial occlusions

To analyze differences between the expert karate athletes' responses in front of a two dimensional video screen (2D) and in a three dimensional environment (3D) the karate technique Gyaku-Zuki was chosen. The Gyaku-Zuki is the most often used technique in competitions and is characterized through its fastness and surprise effect (Figure 8).

Figure 8: The karate technique Gyaku-Zuki is accomplished by punching the opposite arm straight forward towards the opponent's body. In detail: Stable stance. Rotation of the hip and shoulders. Beginning of stretching the back leg. Shifting the center of gravity forward. Moving the arm forward. Stretching back leg and punching arm forward until fully stretched, center of gravity is on the front leg.

To define the specifics of the temporal and spatial occlusion, a movement analysis of the Gyaku-Zuki was conducted by a karate expert athlete. Although the movement is performed slightly differently by each athlete, key movement characteristics can be defined. Based on these, three phases for the temporal occlusion were defined (Table 3).

Table 3: Phases of temporal occlusion based on visible movement characteristics.

	Phase 1	**Phase 2**	**Phase 3**
Movement characteristics	• exposure of the back leg • taking the punching arm to the body • beginning of lateral rotation of the torso • big step forward with the front leg	• positioning of the punching arm for attack • lateral rotation of the torso • beginning to lift the front leg	• end of lateral rotation of the torso • beginning to stretch the punching arm • moving the front leg forward

For the spatial occlusion the following body parts were chosen: *hip, punching arm, front leg*.

In order to define the time and the location of the anticipatory cues the temporal and spatial occlusions were combined into nine sequences (3 temporal x 3 spatial occlusions).

Development of two and three dimensional stimulus footage

The two dimensional stimulus footage was created by video recording of a female karate athlete who had international competition experience with an analogue video camera (Sony HDR FX7; resolution: 1080p) at a distance of 10 meters while performing the Gyaku-Zuki. The video was transferred and digitized with Adobe Premiere Pro CS4 (Adobe Systems, San Jose, California, USA) without loss of quality. The spatial occlusions were created by replacing the hip, punching arm and front leg by each frame with the background using Adobe After Effects CS4 (Adobe Systems, San Jose, California, USA). The temporal occluded sequences were created from the already spatially occluded sequences by cutting the video when each phase ended. To avoid that the athletes only responded at the end of the presentation, the last 800-1000 ms of each phase was rewinded and attached to the end of each phase (Figure 9).

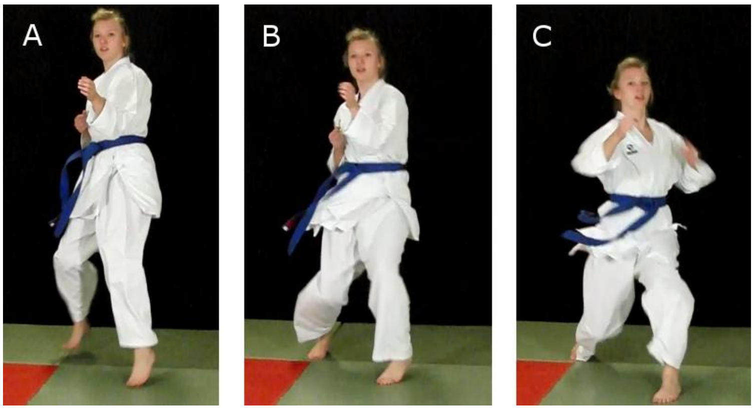

Figure 9: Shows the last frame of the Gyaku-Zuki in phase 1 (A), phase 2 (B) and phase 3 (C) of the video presentation before the rewind.

The attacker's movements for the virtual three dimensional environment was created by capturing the same female performing the attack with the VICON Tracker motion capture system (Oxford Metrics, Oxford, UK). The recorded motion capture data were imported through a specific plug-in into the software Review3D which was developed by the Fraunhofer Institute for Factory Operation and Automation Magdeburg. This software allows adjusting the three dimensional karate model to the motion capture system's model segments for the animation. The spatial occlusion is achieved by turning the model's body segments invisible during the presentation. The duration of the presentation was predefined through an editable timer value, which allowed the exact presentation of each phase in combination with defined occluded body limbs.

The 2D and 3D virtual footage was presented in a special ordered sequence. The results of a pre-test from Zerbe, Kirbach, Bandow, Emmermacher, & Witte (2013) revealed an influence of presenting all phases in a random order, e.g. showing a phase 3 sequence before a phase 1 sequence, so that an order was defined where phase 1 sequences were shown first, then phase 2 and finally phase 3 sequences, but within one phase in random order. The analysis of the athlete's anticipation skills to the Gyaku-Zuki was only one of four techniques performed by two attackers that are presented in this paper. Overall, the participants had to respond to 79 different sequences that were repeated three times, resulting in 237 sequences which the participants had to respond to. As in a normal round in a karate competition the sequences were presented in blocks over 2 – 3 minutes.

Participants and experimental procedure

Five male expert karate athletes with experience in national and international competitions (15.4(±1.67) years of age) responded physically to 27 sequences of the Gyaku-Zuki in each environment. They were instructed not to attack without a reason or to start an attack, only to respond when they thought an attack was carried out. The type of response was not predefined, but they were instructed to respond in order to gain a point as if in a real competition.

The procedure for all participants was the same. First, they were tested for stereovision with the Stereo Fly Test (Stereo Optical Co., Inc., Chicago, USA). This test measures whether the eyes can perceive objects at different distances presented on a slide. The participants had to wear polarized spectacles and identify which objects on the slide were pointing towards them. All participants had normal spatial vision of at least 40-60 seconds of angle of stereopsis. Immediately after the test they had time for a warm-up. So as to familiarize themselves with the virtual environment and the stereovision, the participants underwent 15-30 trial attacks. The athletes then had to respond to all 16 blocks, each including 15 attacks, with 3-5 minutes breaks in between. The test in front of the two dimensional video screen was performed in the same manner.

The athlete's physical responses were recorded with two high speed cameras (Optronis GmbH, Kehl, Germany; model CR600x2; 200Hz; 900x900 px) simultaneously. One camera captured the athletes from the front, the other from behind at a left angle. The video footage was viewed by two independent raters who assessed and classified the participant's responses into two categories: *correct* and *incorrect* responses. A response was classified as correct, when the first visible physical response was within a range of 100 ms after the begin and 200 ms after the end of the visible attack.

The repeatability was verified using the Cochran's Q-Test. The Wilcoxon test was applied to analyze the differences in responses between the 2D and 3D environment statistically.

The experiment was carried out under the ethical guidelines of the academic institution and the participants' consent.

Results

The results of the Cochran's Q-Test show no significant differences (p>.05) between the first, second or third response to the same occluded sequences, proving a repeatability of the responses to the stimuli.

Table 4: Results of the Wilcoxon test in regard to the number of correct responses in the 2D and 3D environment. The spatial occlusions are hip (h), front leg (fl) and punching arm (pa). The numbers 1-3 represent the phases for the temporal occlusions.

	h 1	**h 2**	**h 3**	**fl 1**	**fl 2**	**fl 3**	**pa 1**	**pa 2**	**pa 3**
Z-value	-.816	-2.070	-.577	.000	-1.00	-.707	-.447	-.921	-1.89
p-value	.414	.038 *	.564	1.00	.317	.480	.655	.357	.059

The participant's responses differ significantly (Z=-2.325, p=.003) between the 2D environment (31% correct responses) and the 3D virtual environment (49% correct responses). A pair wise comparison of correct responses between each sequence of the 2D and 3D environment show significant differences only for *h 2* (Z=-2.07, p=.038) as well as a tendency for *pa 3* (Z=-1.89, p=.059) (Table 4). The percentage of correct responses in each environment from all participants for each occluded sequence is shown in Figure 10.

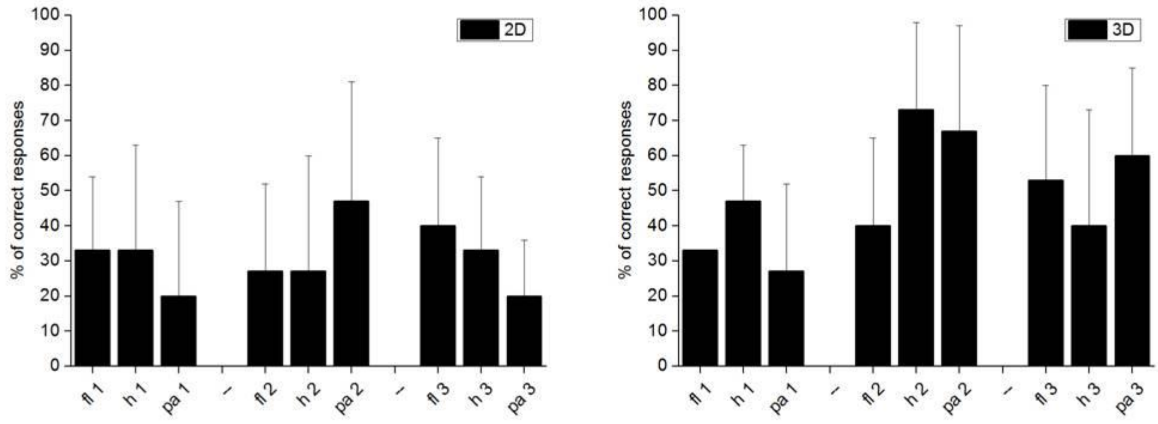

Figure 10: Left: Percentage of correct responses of all participants (n=5) to each occluded sequence in the 2D environment. Right: Percentage of correct responses of all participants (n=5) to each occluded sequence in the virtual 3D environment. The spatial occlusions are: fl: front leg, h: hip, pa: punching arm. The numbers after the spatial occlusions present the phases of the temporal occlusions (phase 1-3).

The number of correct responses to each attack presented in the 2D environment is lower than in the 3D environment. The athletes responded 33(±21)% correctly to sequences in phase 1 with occluded front leg as well as hip and only responded 20(±27)% correctly to attacks with occluded punching arm in the 2D environment. The number of correct responses to attacks presenting the first two phases are below those of phase 1 for the occluded front leg (27±25%) and hip (27±33%), but not for the punching arm, where the best results in the 2D environment are achieved (47±34%). The results for phase 3 sequences show best results for occluded front leg (40±25%) and hip (33±21%), but not for occluded punching arm (20±16%).

The athlete's responses in the 3D environment provide a more differentiated structure. The athletes responded worst to the attacks when only presenting phase 1 with occluded front leg (33±0%) and punching arm (27±25%), except with occluded hip (47±16%). The highest number of correct responses were to attacks presenting phase 1 and 2 sequences with occluded hip (73±25%) and punching arm (67±30%), except for the occluded front leg (40±25%). The percentage of correct responses decreased at the presentation of all three phases (phase 3) with the occluded hip (40±33%) and punching arm (60±25%), except for occluded front leg (53±27%) where the highest number of correct responses occurred.

Discussion

The results of the Wilcoxon test for all responses show a significantly higher number of correct responses in the virtual environment compared to those in the video based environment. This applies for each environment and all sequences. Although a detailed analyses of the results for each sequence for the 2D and 3D environment show a significant difference only for hip 2, the differences of correct reactions in each environment is apparent. The lack of more significant differences between each sequence is due to the low number of data (5 athletes with maximum three correct responses per sequence). The significantly higher number of correct responses towards all sequences is most probably due to the different environments, which differ from each other in the perception in depth, feeling of presence, immersion and the resulting possible fear of physical contact. These factors are typical for real-world environments and it may be assumed that the virtual environment offers a more realistic experimental setup than a 2D video based environment. These results confirm outcomes of previous studies from Bandow, Emmermacher, Stucke, Masik, & Witte (2013) and Bideau et al. (2010), who evaluated virtual environments in regard to realism and possible usage for studying anticipation scenarios in sports. It can be concluded that this test environment is suitable for evoking realistic responses or decisions, while cognitive processes such as anticipation are very sensitive to environmental conditions (Bideau et al., 2004).

The results of the Wilcoxon test for the responses to each sequence in the 2D and 3D environment show no significant differences. It is assumed that the failure of significance is based on the level of expertise and the presentation of the same attack with only small variations caused by the temporal and spatial occlusion. A significant difference in response is not expected, but there are tendencies which are analyzed.

The results of the 2D environment show no clear tendency in regard to the presented information and the number of correct responses. The responses to phase 1 sequences with occluded front leg and hip are more often correct compared to phase 2 sequences. The only exception showing the lowest number of correct responses in phase 1 is the occluded punching arm, which increases clearly in phase 2 and decreases again in phase 3. Contrary to responses in the 3D environment, the responses to occluded front leg and hip improve slightly in phase 3, which may be because more information is presented. The results of the 2D environment do not provide the same tendencies, as the results from the 3D environment and other studies: in 3D environments the response accuracy increases with an increase of information (Blake & Shiffrar 2013; Jones & Miles, 1978; Williams, 2004). It can be shown that the results of the 3D environment are more reliable than those of the 2D environment, as the 3D environment is able to evoke realistic responses better. The results also show that the number of correct responses in the 3D environment is lowest at the presentation of phase 1 sequences. The only exception is to the sequence with the occluded hip, which will be discussed later. In general it was expected that the participants would respond worst to phase 1 sequences, because here the least information of the attack was provided. The increase of correct responses to phase 2 sequences in comparison to phase 1 sequences was expected and confirms an improvement of correct responses with increasing information. The decrease of correct responses to phase 3 sequences with occluded hip and punching arm, which is supposed to provide most information, is therefore unexpected. It is assumed that expert athletes do not respond that often correctly to phase 3 sequences, because they know that in such situations it is normally impossible to achieve a point. This phenomenon has also been discovered in a study by Farrow and Abernethy (2001). The only improvement in response accuracy is with occluded front leg, which is discussed in relation to spatial occlusion.

In summary the results of the 3D environment show that there is a link between response accuracy and the number of presented information. The expert karate athletes are able to recognize the first visible cues in phase 1, which allows enough time for an appropriate response. Their anticipatory performance increases when receiving additional information in phase 2 and decreases in phase 3, which is supposedly based on the fact that the information experts need for anticipating and responding appropriately lie within the first two phases of an attack. These findings match the results from Blake & Shiffrar (2013), Jones & Miles (1978) and Williams (2004) that experts can perceive and use information in initial sequences of an attack for anticipation. The results of the 2D environment do not show any of the mentioned tendencies, therefore it is assumed that the lack of depth information and immersion leads to an unrealistic environment which influences the behavior.

In regard to the results to the spatially occluded sequences, the locations of the anticipatory cues change over time (or phases), especially in the 3D environment. This can be shown in Figure 10, where the difference in percentage of correct responses to one spatially occluded body part changes over each phase. Analyzing the responses to the different spatial occlusions along with the movement characteristics of each phase, the first anticipatory cues can be identified. The number of correct responses in phase 1 to occluded front leg is the same in both environments, as well as the worst response accuracy to occluded punching arm in this phase. The low number of correct responses towards the occluded punching arm and front leg of phase 1 can be explained by withholding the following information: *taking the punching arm to the body* and a *bigger step forward with the front leg.* The occlusion of the hip in phase 1 shows a low number of correct responses too, but does not cover information of high importance in the 3D environment. It seems that the occlusion of the hip in the 2D environment could be caused by the lack of depth information which covers up the *beginning lateral rotation of the torso.* It is also assumed that the exposure of the back leg contains important cues and gives enough information as supplement for the spatial occlusions. Looking at the responses to the spatial occlusion of phase 2 sequences in the 3D environment, it seems that only the occlusion of the front leg contains important cues, which is the *beginning of lifting the front leg*. This movement achieves a reduction of the distance between the attacker and the participant, which is a crucial action in karate. The occlusions of the hip and punching arm mask the movements *positioning of the punching arm* and the *lateral rotation of the torso*. While they are already in progress at the beginning of phase 2 they are predictable and expected and therefore not used as anticipatory cues. This behavior could also be seen in other studies, which observed experts ignoring redundant information (Farrow & Abernethy, 2001). In contrary the results in the 2D environment in regard to the occluded hip may underlie the same issue as in phase 1, lack of depth information with covering up the body rotation partially. Nevertheless, the response accuracy to occluded punching arm and front leg mirrors the results in the 3D environment, that the punching arm is less important than the front leg in this phase of the attack.

Table 5: Marked movement characteristics which are assumed to be important cues during the attack.

	Phase 1	**Phase 2**	**Phase 3**
Movement characteristics	• exposure of the back leg • taking the punching arm to the body • beginning of lateral rotation of the torso • big step forward with the front leg	• positioning of the punching arm for attack • lateral rotation of the torso • beginning to lift the front leg	• end of lateral rotation of the torso • beginning to stretch the punching arm • moving the front leg forward

In phase 3 the number of correct responses decreases unexpectedly in the 3D environment, except for the occluded front leg, which shows the highest number of correct responses. The same is detected in the 2D environment. This occurrence can be explained through the forward movement being already in progress, since phase 2 only provides redundant information that is not taken into account for anticipation. The number of correct responses to the sequences with occluded punching arm is less, compared to those of phase 2, but the highest compared to the other spatial occlusions in phase 3. It can be concluded that the importance of the punching arm is most significant at the beginning of the attack because the movement that follows is predictable. Overall, it can be shown that the whole body movement plays an important role in anticipation and should therefore be taken into account, too, due to the occlusion of the hip masking the end of the lateral rotation of the torso, which results in a low number of correct responses, at least in the 3D environment.

It could be shown that the participants are capable in responding to all sequences, independent to how much information of the attack is given. This confirms the fact that not only isolated cues in certain body parts, but also their relation to each other provides sufficient information about an upcoming movement (Goulet, 1989; Jackson, 2007; Shim, Carlton, Chow, & Chae, 2005).

The changes of cues during the attack show the importance of parts of a movement dependent on the time or movement phases.

Conclusion

This study shows that using a virtual environment for analyzing anticipation in sports can be an appropriate option especially when compared to a video based 2D environment. The higher number of correct responses in the virtual environment is based on the advantages of a 2D to a 3D representation. It could be demonstrated that the additional information about depth and immersion has an influence on the participant’s behavior. While these aspects are important factors in real-life, it can be assumed that the virtual environment evokes more realistic responses by a person and is therefore more appropriate for studies of anticipation, especially in sports.

Furthermore, it could be shown that the combination of the temporal and spatial occlusion technique allows a more specific determination of relevant cues for an attack. The cues can be located and sorted to the defined phases as well as to their location. Based on this, the changes in cues during an attack or a movement are definable.

Analyzing the participant’s responses towards each occluded sequence certain tendencies can be discovered. The results show that there are different cues during the initial phase of an attack which can be detected by the expert karate athletes. This knowledge can be used to create a training scheme for better perception and anticipation. The success of such a training has then to be evaluated. This study could also be undertaken with novice karate athletes to analyze, whether they are able to detect the same cues. This can give further knowledge about the differences of expertise in karate and help to improve training schemes.

In order to achieve more detailed information about the cues, further studies with more isolated and also combined spatial occlusions should be implemented. The additional use of eye-tracking-systems can also foster these analyses extremely.

Acknowledgements

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Interactive Football-Training Based on Rebounders with Hit Position Sensing and Audio-Visual Feedback

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Abstract

The last decade's advancements in computer technology have facilitated a growing interest in the development of interactive sports-training equipment. This development has provided athletes and coaches with measurement and training tools, with performance analysis or skill improvement as purpose. However, most of these tools are created with a single goal, either to measure or train, and are often used and tested in very controlled settings. In this paper, we present an interactive football-training platform, called Football Lab, featuring sensor-mounted rebounders as well as audio-visual feedback. Football Lab enables the creation of novel training games, which aim to improve players' technical skills, and simultaneously function as a tool for measuring player performance and development over time. A logging of the Football Lab was conducted through 92 weeks, where the platform was available for the general public, analysis of a subset of the 20.000 games played in the period are discussed. Moreover, the paper contains a discussion covering challenges in data collection, transferability issues for interactive training equipment, as well as examples of experiments conducted with the platform. Finally, directions for future research within the area of interactive training equipment are proposed.

KEYWORDS: SERIOUS GAMES, INTERACTIVE TRAINING EQUIPMENT, TRANSFERABILITY, DATA COLLECTION, HUMAN-COMPUTER INTERACTION

Introduction

The last decade's advancements in computer technology have facilitated a growing interest in the development of interactive sport-training equipment (Baca, Dabnichki, Heller, & Kornfeind, 2009). The main part of these systems utilizes ubiquitous computing technologies to collect and process data from athletes' performances as a tool for analyzing sport-specific techniques or movement patterns. Besides using technology merely to measure athletes' performances and provide informative feedback, recently systems have emerged, which utilize technology to create dynamic interactive training environments, e.g. in (Liljedahl, Lindberg, & Berg, 2005; Ludvigsen, Fogtmann, & Grønbæk, 2010).

This paper presents an interactive football-training platform, called Football Lab, which aims to improve players' ability to pass, receive, and turn with a football (soccer ball), and simultaneously measure their game performances. The installation is based on sensor-mounted rebounders as well as audio and light feedback, which is utilized to create gamified training exercises. In close collaboration with football coaches, the authors developed Football Lab, which is part of a greater football training facility established by a Danish football club called Herning Fremad. The facility and the installation are publicly accessible night and day all year, and in this paper, we show the results of 92 weeks of Football Lab use.

Moreover, this paper opens a discussion that touch upon challenges that occur when making experiments in a public accessible platform in terms of data collection, transferability issues in interactive sport-training platforms, alternative use of the platform, and three future research questions. But first we briefly introduce state-of-the-art of existing football-training equipment to illustrate how Football Lab differs and contributes with new types of real-time feedback-based training games for football.

Existing Digital Football-Training Equipment

For several years it has been possible to use radar techniques to measure ball speeds (e.g. provided by http://www.sportssensors.com), which have been used to measure the speed of kicks to a football from a stationary position providing immediate feedback. This enables a quick evaluation of kick speeds as part of training sessions, but this is a very limited aspect of football training, omitting precision and other tactical techniques.

In recent years precise position tracking and camera-based training systems such as InMotio (http://www.inmotio.eu) and ZXY (http://www.zxy.no) have been installed in a number of training facilities around Europe to improve training. These systems features precise tracking and recording of player activities on the field during a match or during training. However, these systems only supports post-hoc analysis for coaches and players to discuss, aiming at improvements for the next training/match, thus, there is no real-time support for the training activities with these systems.

In contrast, the Footbonaut is an interactive football-training platform created by Christian Güttler, and it consists of an artificial grass field surrounded by a wall with 64 grids and 8 ball-feeding machines (Bell, 2013; Horncastle, 2012). The player then stands in the middle of the field and receive a ball from one of the machines, whereupon one of the 64 grids illuminate, indicating a designated target, which the player has to hit as fast as possible. After a session, performance data is available to the player and coach.

Footbonaut and the Football Lab platform, discussed in this paper, have several elements in common, such as the layout of the playing field, the use of immediate feedback, and the aim of improving players' ability to receive, pass and turn with the ball. However, the two systems differ in their approach to the training of passes, where Footbonaut focus solely on pass precision by having 64 targets that capture the ball. In contrary, Football Lab's four rebounders, stimulate a more controlled passing, where the perfect ball speed is essential, due to the feature that the player has to receive and handle his own pass, instead of having a target that consumes the ball and a ball-feeding machine that provide the player with a new ball. Furthermore, Football Lab is based on a gamification of training exercises, supported by hit position detection, a scoreboard, and an online high-score list, which is used as a motivational and social tool, whereas the Footbonaut primarily focus on skill improvement and measurement.

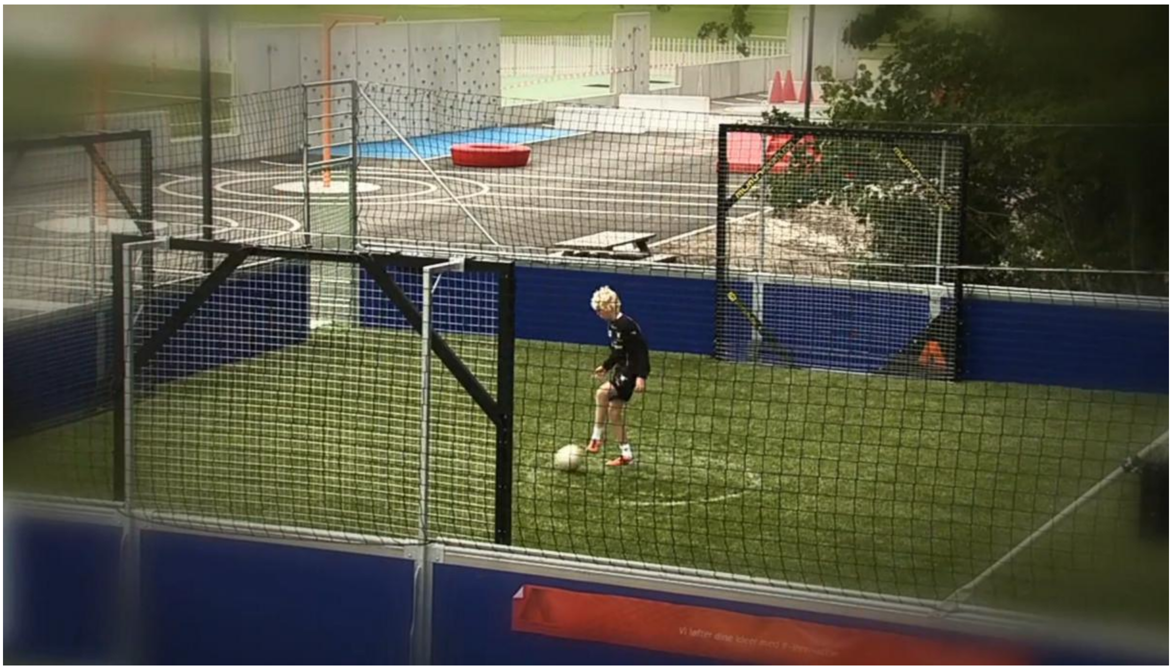

Figure 1. The Football Lab platform

The Football Lab Concept

Football Lab is an interactive football-training platform that enables players to train the ability to pass, receive and turn with a ball. In this section, we describe Football Lab in detail, explaining the physical setup of the installation, the sensing and actuation abilities available and the game platform that is facilitated. The entire Football Lab concept have been developed and created by Munin Sports, Alexandra Institue and Aarhus University in close collaboration with coaches from the football clubs Herning Fremad and F.C. Midtjylland.

The Football Lab consists of a 12*12 meter square field covered with artificial grass and surrounded by boards and net to constitute a limited play field. In the 144 square meter field, four M-Station Pro rebounders from Munin Sports are placed two and two opposite to each other on the boards (see Figure 1). These rebounders are augmented with sensors and actuators connected to a training game computer and an outdoor display.

Football Lab – Sensing and Actuation Platform

Each M-station rebounder is equipped with four piezo electric sensors, detecting the vibrations of the net when hit by a ball (see Figure 2A). Signal processing based on the sensor signals enables Football Lab to detect positions of ball hits.

The platform architecture is depicted in Figure 3, and it includes an execution software engine that is implemented directly on a controller board on each rebounder in order to ensure immediate reactions to sensor activation. The software and hardware is tuned to have a reaction time between sensor activation and actuator reaction of less than 25 milliseconds, in order to ensure that players can get in flow in the training programs without delayed or lacking sensing and actuation. All detailed measurements are stored in a database and the individual game results are shown on low resolution, but powerful outdoor display (Figure 2B).

Figure 2. A (left): The mounting of the piezo electric sensor on the M-Station net and the LED-light incorporated in the M-Station frame. B (right): The Football Lab scoreboard.

Furthermore each rebounder is equipped with weather resistant RGB LED lights for sending visual cues to the players and waterproof loudspeakers to make audio cues to the players. The typical cues to players during training are combined audio-visual cues, where the rebounder loudspeaker says: “play me”, “I’m free” etc. combined with blinking LEDs.

Besides using the sensor and actuation setup merely as a part of training, Football Lab also allows players to login using their mobile phones, enabling both players and coaches to track and analyze performances and development through an online website, where all results are available. Moreover, the website contains a high score list, were top 20 players are shown, and a Facebook interface allows players to post their results to their timeline from the high score list.

Football Lab – Game Space

The sensing and actuation possibilities together with the physical setup constitute a unique game space for development of interactive football-training games. Currently, Football Lab contains three available games, all developed in close collaboration with football coaches, who coach young prospect players.

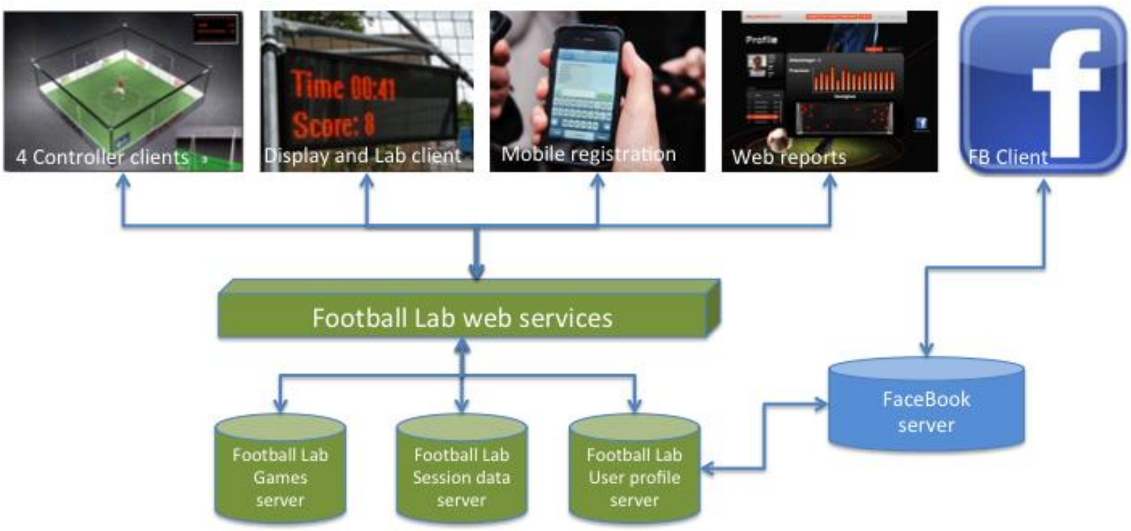

Figure 3. The Football Lab architecture. There are four controller boards and one central Lab PC for each installation Football Lab. The Lab PC is connected to a Web service that is responsible for handling of games, sessions, user profiles, and high scores etc. among multiple Labs.

Pass and Turn

In Pass and Turn, the player starts in the middle of the field with the ball. After a countdown the game starts, and an arbitrary rebounder will be marked with light and sound signals. When the marked rebounder is hit, the player is awarded points depending on how fast the rebounder was hit, and a new arbitrary rebounder is marked as the next target etc. The game measures how fast the player receives, turns and passes the ball. The game lasts a minute, and the goal for the player is to get as many points as possible. Points are calculated using the formula:

$$points = 100 * targetCount - totalHitTime$$

where *targetCount* is the number of rebounders hit, and *totalTime* refers to the time used to hit them. The calculation entail that in case of a scenario, where two players hit the same amount of rebounders, time functions as a tiebreaker, where the fastest player is awarded more points than the slower.

Dribble

Before starting a game of Dribble, the playing field of Football Lab is augmented with cones placed on marked spots. Like in Pass and Turn, the game starts after a countdown, and an arbitrary rebounder is marked. The player then has to dribble between the cones to reach the rebounder and hit it with the ball. When the rebounder is hit, a new arbitrary rebounder is marked, and the player has to dribble between the cones to return to the middle of the field and then out to the newly marked rebounder etc. Dribble lasts 30 seconds, where the player aims to maximize the achieved number of points, which are calculated the same way as in Pass and Turn.

3vs2

Contrary to Pass and Turn and Dribble, 3vs2 is a multiplayer game, where five players divided in two teams are present in the Football Lab. The team with three players tries to control the ball, and score by hitting a marked rebounder. The team with two players tries to get the ball and oppose the other team from scoring. The game lasts for two minutes and there is only one rebounder active for ten seconds every fifteen seconds. The goal for the attacking team is to

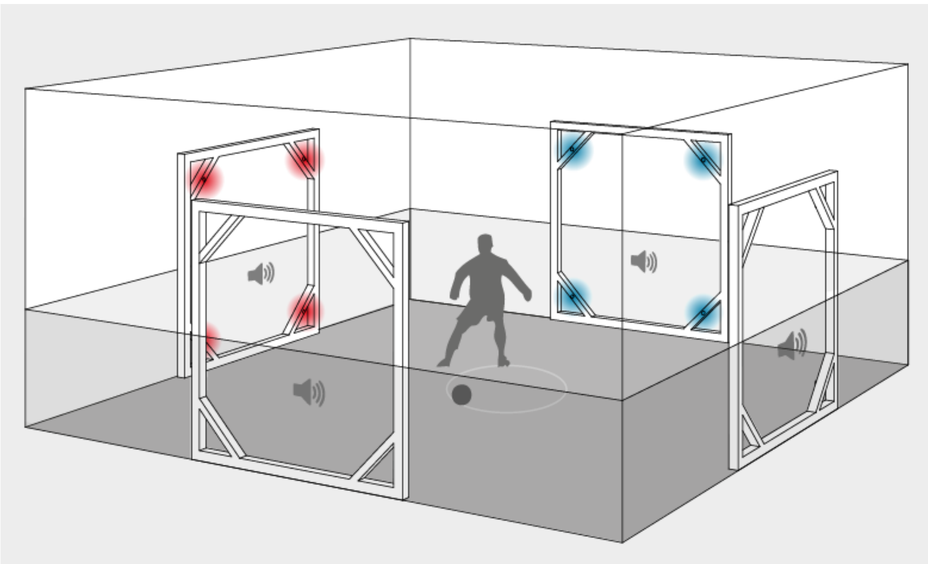

Figure 4. The Football Lab game space.

score as many goals as possible, whereas, the defending team should minimize the number of goals scored by the other team. From a training perspective, the attacking team should be able to control the ball and at all times direct their game towards the active rebounder.

Result and Analysis of Long-Term Usage

During a period of 92 weeks, we have logged every rebound hit of every game of Pass and Turn and Dribble played at Football Lab. Here, we have registered 8978 Pass and Turn games, where the main part of games is expected to originate from junior player training sessions. The distribution of the 8978 games over the 92 weeks (22 months) is depicted in Figure 5. In peak seasons days up to 180 games (including all three games) have been registered, but even in winter season months 5-10 games are played a day.

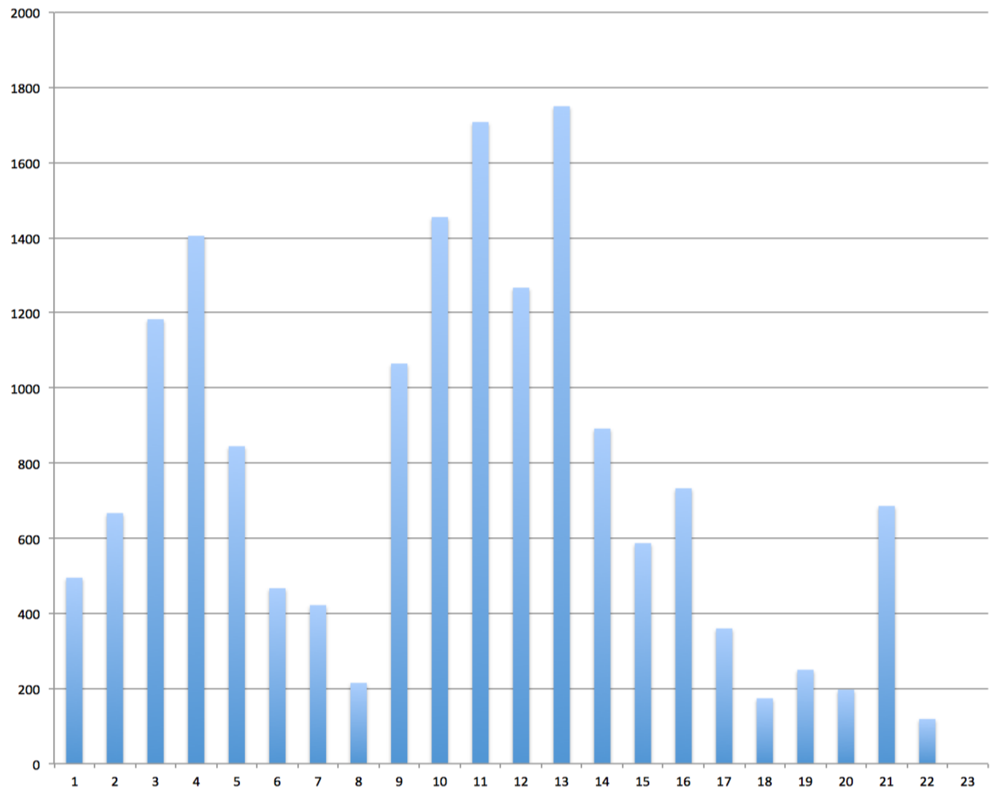

Figure 5. Football Lab usage statistics over Pass and Turn Games in 92 weeks (22 months) starting June 2011, low counts corresponds to winter months.

For the analysis, we have omitted games, which were found to be incomplete or implausible, from the statistics to avoid disruptions in the result and analysis, and expect the rest of the games to be accomplished according to the rules. We have summarized the statistics collected from the 8978 games in Table 1.

As expected, the result shows that the average player is fastest hitting the same rebounder twice, and slowest in turning 180 degrees. However, the result also shows that the average player is slower turning left than turning right. The significance of the difference in time between average right turns and left turns, where supported by a t-test ($p = 0.001$).

Table 1. Statistics of 8978 Pass and Turn games played on the Football Lab platform. The table shows the median, average, minimum, and maximum time (in milliseconds) players used for turning right, left, 180 degrees, and no-turn. Furthermore, the table shows the median, average, minimum and maximum number of rebounders hit per game. Additionally, the standard deviation is stated for both turn times and hits.

Turn	Median	Average	Minimum	Maximum	STD
Right	2964ms	3407ms	78ms	25685ms	1545ms
Left	3031ms	3485ms	375ms	26282ms	1640ms
Same	2887ms	3354ms	422ms	22390ms	1643ms
Behind	3228ms	3603ms	484ms	21578ms	1504ms
Hits	17	17	11	49	5

Furthermore, the standard deviation (STD) reveals that players potentially can improve 45% in terms of speed in receiving, passing and turning with the ball. The gap between quicker and slower players suggests that some players could benefit from training directed towards these specific skills. In collaboration with trainers and coaches, the result and findings were evaluated, and ideas for new tailored training games emerged.

Table 1 also shows that an average player makes 17 passes during a one minute game of Pass and Turn. For comparison the top passers of Premier League average 78 passes per 90 minutes of play (Coverdale, 2013). Hence, an average player playing five one-minute games of Pass and Turn would make more passes than a professional player would in a 90-minutes football game.

Moreover, observations of 12 males players (4 aged 11-13, and 8 aged 13-15) playing three Pass and Turn games each, showed that the elder players in general scored higher per game (μ=27.1; σ=1.64; n=24) than the younger ones (μ=23.1; σ=3.0; n=12). A t-test confirmed the difference between the scores to be significant ($p = 0.0001$). Furthermore, the player, who the participants agreed to be the best technician, also made the highest score (30 targets hit), suggesting that players, who posses proper ball-handling skills, perform better in Football Lab. All players participating in the observation was considered to be among the best of their classes, explaining why their number of hits where higher than the average number of hits presented in Table 1.

The players and coaches at Herning Fremad have shown great general interest in Football Lab. The game and competitive elements make the players challenge each other and create small competitions, and the extensive number of games played witness of a popular platform. Football Lab is widely used, both as a training tool utilized by coaches in regular training sessions, especially with younger players, as well as by players and schoolchildren outside practice sessions.

Discussion of Experiences with Football Lab

Challenges in Data Collection

By making Football Lab an open-for-all platform with high availability, we encountered two significant challenges in the data collection process: Anonymity and improbable games.

Anonymity

With the creation of Football Lab and the appertaining login system, players were given a unique opportunity to log their games, high scores and development. As an evaluation means of the Football Lab platform for future development, and as player evaluation tool for coaches, a database of individual player results and development would have been desired and ultimately a powerful instrument. However, almost every player, who has used Football Lab, has chosen to play anonymously, which makes it impossible to identify the development of individual players. We believe that the players' choice of being anonymous is primarily caused by the mobile login system, provided by Football Lab. Most players do not bring mobile phones to the football field, making the login system unavailable. Thus, development of a new on-location available login system has been initiated to utilize the full potential of Football Lab as a player analysis tool.

Improbable games

During the data analysis, we encountered a number of improbable results, where scores seemed impossibly high or suspiciously low. Through an investigation of the use of Football Lab, we found two reasons for the improbable results. Firstly, unexpected use of the platform was observed, were four players played the game together without a ball, but simply hitting the rebounders using their hands immediately after activation. This phenomenon has created a number of games with impossible scores. Secondly, a vast amount of games was found to be incomplete and had very low scores. The low-scoring games are partly a result of various demonstrations of the platform, coaches introducing the platform to new players and test of the platform hardware. Despite the knowledge of these extremities, a complete elimination of all improper results has not been possible, since the obtained result database contains gradual transitions from demonstrations to low-scoring performances, and from high-scoring performances to scores obtained by not conforming the rules of the game. However, in our data analysis we have removed results with a score lower than 11 and higher than 49, and classify results outside these limits to be improbable. Nevertheless, the minimum and maximum values, seen in Table 1, reveals that more fine-grained sorting is desirable, e.g. indicated by an improbable minimum right turn of 78 milliseconds, and a suspicious maximum left turn of 26 seconds. Games with measurements close to the minimum and maximum values, however, only represent an insignificant part of the sorted results.

Transferability in Training Games

Transferability relates to how skills, which are achieved by training with an interactive training system, transfer to the targeted sport, and is found to be the single most important criteria for design of sport-training equipment and exercises in general by Fogtmann et al. (Fogtmann, Grønbæk, & Ludvigsen, 2011). Transferability between lab training and field performance has been investigated in many papers, e.g. (Williams, Ward, & Chapman, 2003) and (Farrow & Abernethy, 2002), where studies are used to determine if perceptual skill training in the lab can improve athletes ability to anticipate situations in a field test. We assert that Football Lab facilitates a transfer of technical motor skills such as receiving the ball, rapid turning with the ball, and controlled passing of the ball, from a lab environment to the field. The transferability of Football Lab training is ensured by the use of similar equipment (ball and shoes) and surface as in real football, which makes the basic movements identical. However, Football Lab does not cover the entire skillset required to play football, e.g. run patterns or reading and anticipating other players' actions. The static setting of Football Lab makes it favorable for players solely to focus on technical ball handling, rather than applying intensive run patterns or creating an overview of the playing field. Furthermore, passing the ball to static rebounders is dissimilar from passing to dynamic moving co-players. Nevertheless, we claim that Football Lab is an excellent training tool, especially for younger players. By using a competitive element in a gamified setup, Football Lab encourages players to repetitive training of fundamental ball-handling skills: Receiving, turning and passing, which are motor skills particularly transferable to football.

Platform for Advanced Experimentation

Besides being used for football training, the Football Lab platform has been applied in advanced experimentation with interactive physical games. Jensen et al. (Jensen, Rasmussen, & Grønbæk, 2013) explores opponent formats in computer-supported physical games, and investigate how different ways of competing have different influence on games. Jensen et al. propose a framework, describing various opponent formats, and consecutively present two new games for Football Lab. The new games are created without changing the original Football Lab setup, and merely utilize the multi-colored LEDs as a means for distinguishing marked targets to enable development of multi-player games, where both sides can score, within the same platform. The possibility of rapid development of new games within the framework of the Football Lab setup provides a unique platform for doing idea generation and research with a reliable, easy-to-test and already deployed platform.

Future Research Questions for Interactive Training Systems

In the process of creating and testing the Football Lab platform, we have encountered numerous challenges and obstacles. In this section, we present three questions for future research that focus on improving data collection in public accessible platforms, creating intelligent and adapted training systems, and evaluating skill assessment of athletes using novel training equipment.

How do we create login systems that improve data quality in public accessible platforms?

In order to exploit the full potential of the Football Lab platform there is a need to address the challenge posed by identifying user profiles, which was insufficient in the current SMS based login system. The deployment and long-term testing showed that players do not bring their mobile phones to the football field in order to login. However, we still believe that players and coaches have interest in tracking personal performances over time. Thus, we are currently in the process of developing a login system that allows players to login on the spot, and we are considering making login mandatory in order to play a game, to ensure improved quality of future data collections and analysis. The question is: How do we create an unobtrusive and easily accessible login system and encourage players to use it? Such a login system would be desired within any open interactive training platform to increase the quality of data collected. At the moment, a temporary login system has been deployed, which allows a fixed number of players to log in without using a mobile phone, which enables tracking of a predetermined group of players in on-going testing of new games for the platform. However, this is not a sustainable solution for the future, and players in the test are obliged to use the login system, not persuaded by the system. In future installations, we will allow players to enter their phone number on a touch display, identifying them before a game, and use the SMS gateway to ask for a confirmation from the player that it was his/her game that was registered. However, typing a phone number before each game is not optimal, and other methods have to be investigated, e.g. using RFID keys for login may be an alternative option. When we get a new simple on-entry login system for the players, it will furthermore allow us to make controlled experiments over various time periods to analyze and determine the exact effects of both long and short-term usage of Football Lab as a training tool.

Can we utilize Dynamic Difficulty Adjustment in interactive training equipment?

If a login system for Football Lab is successfully deployed, not merely does it enable performance tracking, but it also creates the possibility for developing new games for the platform that is tailored to the individual player. The concept of Dynamic Difficulty Adjustment (DDA) has emerged as a way to dynamically match the difficulty of a game to the player's capabilities, both in design of computer games (Hunicke & Chapman, 2004) and exergames (Sinclair, Hingston, Masek, & Nosaka, 2010). DDA collects performance data from a game, processes the data and adjusts the game difficulty accordingly. In interactive training equipment, a similar approach is possible, where applying an algorithm to analyze collected performance data, could lead to a tailored game for the individual player. As a result, training sessions would focus on the player's deficiencies and shortcomings based on an objective evaluation by the system, and coerce a concentrated training of these weaknesses. In Football Lab, a DDA approach could for example be used to increase the number of left turns in games for players, who are significantly faster to turn right than left. We suggest future research in the area of applying DDA to interactive training systems and the effects it has on players' skill improvement.

How do we evaluate transferability from exercise to the field?

As previously mentioned, transferability is widely discussed, e.g. by (Fogtmann, Grønbæk, & Ludvigsen, 2011), (Williams, Ward, & Chapman, 2003) and (Farrow & Abernethy, 2002), in relation to development of training equipment and exercise, and how the training new systems and tools affects the actual performance of athletes. The challenge of determining the level of transferability from training equipment to field performance is present in both perceptual and motor skill training. In addition to the conduction of tests, showing that a training method improves the skill of a player compared to control and placebo groups in controlled settings, there is a need to objectively measure the potential improvement of players' skills in real game context. The recent advancements in sensor technology promise a future, where every single movement of an athlete is measureable, and this could be utilized to develop a tool and a standard for evaluating training equipment based on in-game performances. However, we are aware that such an evaluation method induces certain challenges, e.g. in team sports, such as football, where no two games are alike, making it troublesome to create a standard evaluation method based merely on movements. Nevertheless, we believe that it is possible to approach an unbiased evaluation of training equipment based on wearable sensors in future research.

Conclusion

In this paper, we presented the novel interactive real-time football-training platform called Football Lab, which is based on large ball rebounders with a sensor-actuator based game engine. We reported on the experiences from one installation of the Football Lab in Herning, Denmark, where the log files indicated that junior players find the Football Lab training games exciting, illustrated by up to 180 games/day in high season and 5-10 games/day in the most low season winter month. The data collection from the games showed potential for design of new Pass and Turn games tailored to individuals such as left foot and right foot players to try to improve their performance. Moreover, we described challenges encountered in the creation and deployment a public accessible football-training platform, where players chose to be anonymous and comprise the rules of the game, which ultimately lowered the quality of data collected. Additionally, we reported on transferability issues found in novel sport-training systems and referred to alternate use of the platform for more advanced experiments with multi-player training games, exploring different opponent formats. Finally we have outlined a few central issues for future research in the area of interactive sport-training games covering improvement of data quality, utilization of dynamic difficulty adjustment, and evaluation of interactive sport-training systems.

Acknowledgements

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A novel method for the analysis of sequential actions in team handball

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Abstract

Performance in team sports crucially depends on the knowledge about the own and the opponents strengths and weaknesses. Since the analysis of single actions only provides restricted information on the game process, the analysis of sequential actions is from great importance to understand team tactics. In this paper, we introduce a novel method to analyze tactical behavior in team sports based on action sequences of positional data which are subsequently analyzed with artificial neural networks.

We present custom-made software which allows annotating single actions with accurate manual position information. The process of building action sequences with the notational information of single actions in team handball is described step by step and the accuracy of the position determination is evaluated. The evaluation revealed a mean error of 0.16m (± 0.17m) for field positions on a handball field. Inter- and intra-rater reliability for identical camera setups are excellent (ICC=0.92 and 0.95 resp.). However, tests revealed that position accuracy is depending on camera setup (ICC=0.36).

The results of the study demonstrate the applicability of the described method to gain action sequence data with accurate position information. The combination with neural networks gives an alternative approach to T-patterns for the analysis of sport games.

KEYWORDS: SPORT GAMES, NOTATIONAL ANALYSIS, ACTION SEQUENCES, GROUND POSITION DATA, NEURAL NETWORK

Introduction

Success in competitive team sports depends on athletes' performance as well as on tactical behavior and strategy. Knowledge of the opponent's strategy can make an important difference in competition. Furthermore, knowledge of strength and weakness of the own team is necessary to improve performance. Therefore, the accurate analysis of game situations is a key factor to success.

To handle the large amount of data necessary in notational analysis the use of computers is well established (Hughes & Franks, 2008). In complex team sports, statistics about the frequency of single events are a common and appropriate tool to get quantitative information about single player and team performance (Meletakos & Bayios, 2010; Meletakos, Vagenas & Bayios, 2011). However, it has some important limitations. Since a single action happens in the context of the game flow, its preceding actions have to be considered to fully understand tactical behavior. Therefore, analyzing action sequences, i.e. chains of single actions, instead of single actions is suggested by Carling et al. (2008). Besides the determination of key actions (e.g. shots in team sports), it is important to understand how they emerge. This can be done by observing their history in the game. In team handball this can be done by observing the passes preceding a shot.

One approach to get deeper insight into the complexity of sport games is the analysis of temporal patterns (T-patterns). Such T-pattern analyses are able to detect events which occur in the same order and with the consecutive time distance, thus typical tactical behavior of a team. The temporal relationship between events is the main idea of the pattern detection (Borrie, Jonsson & Magnusson, 2002; Magnusson, 1996; Magnusson 2000, Magnusson 2005). Summarized in a review by Jonsson et al. (2010), it is shown that a high number of complex temporal patterns are detectable in several different types of sport games like soccer, boxing, basketball, or swimming. One disadvantage in existing analysis by means of T-patterns is the precision of the athlete's position. While some works did not consider the position, others only used a classification according to field zones. Such rough position information might be insufficient in high level sport games where accurate position data is of great importance. Another drawback, which may explain why areas instead of accurate position data are used, is that T-pattern analyses only detect patterns if they coincide exactly. Patterns which differ slightly are not determined although they might be quite important in sports practice.

An alternative approach is to analyze exact position data of action sequences. Lately, Link & Ahmann (2013) used position data to analyze different game situations in beach volleyball. They filter their data with reference to Hansen (2003) who describes that game situations are classified by a trained observer relating to several actions within the whole game situation. After this rough classification they use position data to get deeper insight in the variations of game situations.

A method to automatically identify tactical strategies is to classify action sequences by reference to their position data. Patterns with similar position data can be determined by means of artificial neural networks (Perl et al, 2013). Such approaches have been successfully applied in soccer (Memmert et al., 2011; Memmert & Perl, 2009). In these studies, action sequences described by position data are limited by time windows and patterns are identified by an artificial neural network. Compared to these studies, the presented approach uses action sequences which are limited by the number of actions allowing analyzing the origin of a key action. In this paper, we present a novel method which allows obtaining accurate position data and analyzing sequential data in sport games by means of neural networks. Besides the methodological description we present evaluation data for inter- and intra-rater reliability of the annotation system. Furthermore, we present the analysis of offensive patterns as an example for possible applications. Specifically, we investigate the relationship between the variation of offensive tactics and the overall team success.

Methods

For the generation of sequential position data, a custom built software system, "Movement and Action Sequence Analysis" (MASA) was developed. The process of data acquisition and processing is realized in three general steps: the recording of videos, the annotation of single actions, and the processing and analysis of the retrieved data, as shown in Figure 11.

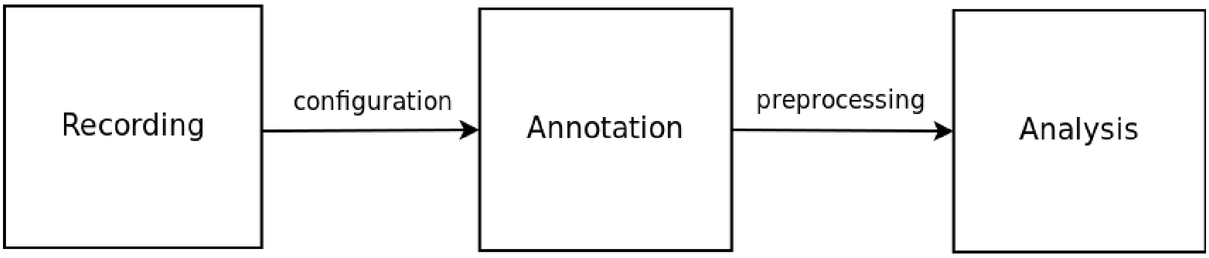

Figure 11: General process of data acquisition and processing

Recording

In order to cover the entire area of a team handball field of size 40x20 m with sufficient resolution, we deploy a multiple camera system as shown in Figure 12. We choose network cameras (Axis P1346 and P1347) which provide live-streams with a resolution of 1024x768 pixels at 20 frames per second. The streams of up to 8 cameras are sent to a central processing server which synchronizes the incoming video data based on the time stamp information provided by each camera sensor. Depending on the recording environment, the camera sensors are either directly connected to the recording server over a wired local area network (LAN) or using high performance wireless access points, e.g. if Ethernet cables may not be placed due to location-specific restrictions. The synchronization via the sensor time stamps allows to detect network communication errors, e.g. if data packets are lost during transport. In such cases, the corresponding camera image is marked as unreliable and replaced by the preceding frame to ensure synchronized processing of all video streams.

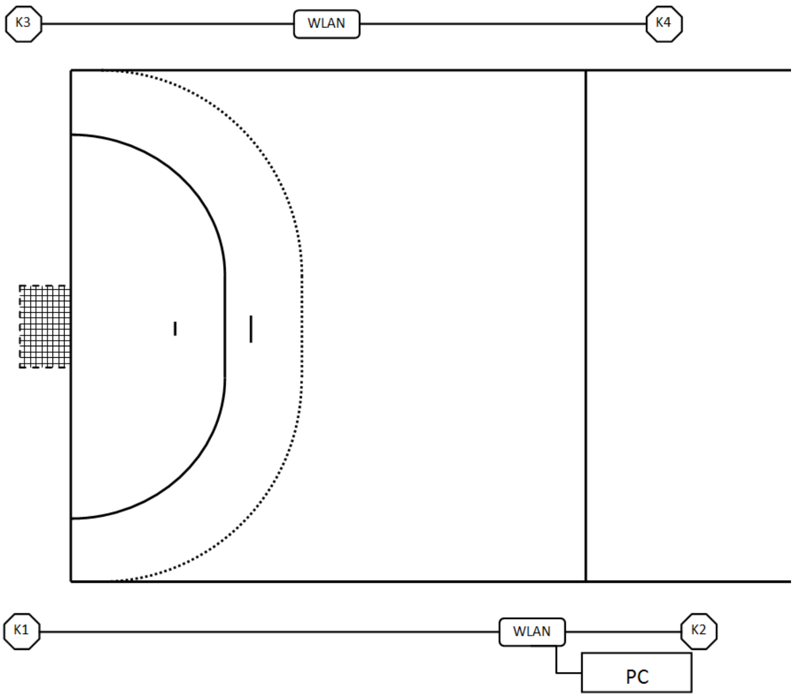

Figure 12: General setup of the test environment for the system evaluation (K... camera, PC...personal computer, WLAN...wireless network router)

Furthermore, the incoming video data must be pre-processed in order to obtain correct measurements for the analysis. In particular, this is done using a two-step procedure consisting of rectification - to account for lens distortion effects - and registration - to obtain metric coordinates from pixel measurements, - as follows.

Camera Calibration

Since the projection of 3D real world points onto a 2D image plane discards information, the camera network must be calibrated prior to obtaining meaningful measurements. This calibration allows for computing metric measurements from the recorded image data using the widespread *central perspective projection* model, also known as *standard pinhole camera*, which assumes that no lenses are used, i.e. the camera aperture is a single point, the pinhole (Hartley & Zisserman, 2004). This model follows the principle of col-linearity, i.e. each real-world point is projected by a straight line through the projection center (optical center) onto the image plane, as illustrated in Figure 13.This means that all three points, i.e. the real-world point P, the center of projection C, and the imaged point $(x, y)^T$, are located on the same line. Projecting a real-world point onto the image plane can now be done as follows.

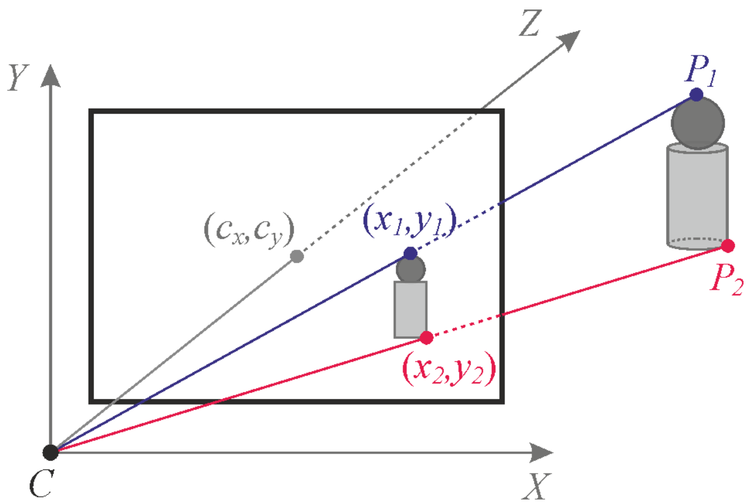

Figure 13: Image formation using the pinhole camera model, assuming that the camera coordinate axes are aligned with the world coordinate system. Following the col-linearity principle, 3D real-world points Pi=(Xi,Yi,Zi)T are projected by a straight line through the optical center C onto the image plane coordinates (xi,yi)T

First, the point's coordinates $P=(X,Y,Z)^T$ are transformed from the world coordinate system to the camera coordinate system, i.e. $\tilde{P}=(\tilde{X},\tilde{Y},\tilde{Z})^T$. Therefore, the point needs to be translated and rotated with respect to the camera pose. This transformation is defined as $\tilde{P} = \mathbf{R}P - \mathbf{R}C$, where **R** denotes the rotation matrix of the camera. In a subsequent step, the point is projected onto the image plane of the camera. The corresponding transformation is defined by the camera's intrinsic parameters, namely:

- the focal lengths for the x and y dimensions, i.e. f_x and f_y, which define the magnification in the corresponding direction,
- the factor γ to account for a possible skew between the sensor axes - in case the sensor is not mounted perpendicular to the optical axis,
- the location of the optical center, also called principal point, i.e. the pixel coordinates $(c_x, c_y)^{\mathrm{T}}$ where the optical axis intersects the image plane - this position is used as a translation vector, since in general, the origin of coordinates in the image plane (mostly top-left) is not at the principal point.

Using the intrinsic camera parameters, $\tilde{P}$ can now be projected onto the image plane to obtain the pixel coordinates $(x, y)^T$ as:

$$x = \frac{f_x \tilde{X} + \gamma \tilde{Y}}{\tilde{Z}} + c_x, \quad y = \frac{f_y \tilde{Y}}{\tilde{Z}} + c_y$$

The pinhole model assumes a linear projection, i.e. straight lines in the world project to straight lines in the image. Therefore, it is only an approximation of the real camera projection, since in general, standard lenses usually suffer from distortion and thus, image coordinates are displaced. Most frequently, camera lenses suffer from radial distortion, which manifests itself as a visible curvature in the projection of straight lines, specifically near the image borders. Hence, in order to apply the pinhole model, the distortion needs to be corrected in a pre-processing step, i.e. the images need to be rectified.

According to Szeliski (2010), lens distortion occurs during the initial projection of $\tilde{P}$ onto the image plane. Hence, image correction needs to be applied at this place. Therefore, let $(\hat{x}, \hat{y})^T = (\tilde{X}/\tilde{Z}, \tilde{Y}/\tilde{Z})^T$ denote the normalized image coordinates, obtained after the perspective division, and before scaling by the focal length and shifting by the optical center. Following Hartley and Zisserman (2004), the correction can now be applied by using a Taylor expansion to approximate the true radial distortion. Thus, we obtain the normalized image coordinates $(\hat{x}_d, \hat{y}_d)^T$ after accounting for the distortion as

$$\hat{x}_d = \hat{x}\left(1 + \kappa_1 r + \kappa_2 r^2 + \kappa_3 r^3\right), \quad \hat{y}_d = \hat{y}\left(1 + \kappa_1 r + \kappa_2 r^2 + \kappa_3 r^3\right)$$

where $r = \sqrt{\hat{x}^2 + \hat{y}^2}$ is the radial distance from the image center and κ_i are the radial distortion coefficients. After this correction, the rectified pixel coordinates can be computed as:

$$x = f_x \hat{x}_d + \gamma \hat{y}_d + c_x, \quad y = f_y \hat{y}_d + c_y$$

Note that the choice of the order of the polynomial actually depends on the camera optics, i.e. distortion models for wide-angle lenses as used in our experiments require higher-order polynomials to provide an accurate correction, in contrast to distortion models for standard consumer camera lenses. Specifically, we assume a third order radial distortion model and use a publicly available MATLAB toolbox (Bouquet, 2013) to estimate both, the intrinsic camera parameters, as well as the distortion coefficients by recording a known checkerboard pattern. This so-called intrinsic calibration allows for pre-computing a mapping from recorded image pixels to pixels of a rectified image and thus, the computational effort to correct for lens distortion required at runtime decreases to a simple lookup of corresponding image coordinates.

Annotation of actions

The MASA application is a prototype tool where the gathered video data is annotated. It connects video data with user input and stores it in a database. The user input consists of the type of action and its field position.

The graphical user interface consists of three major parts as shown in Figure 14. (1) The video area where by default two videos are displayed. (2) An action area where, depending on the predefined category system, available actions are visible, including a top view of the playing field and a game overview including the present score. (3) A list containing all annotated actions.

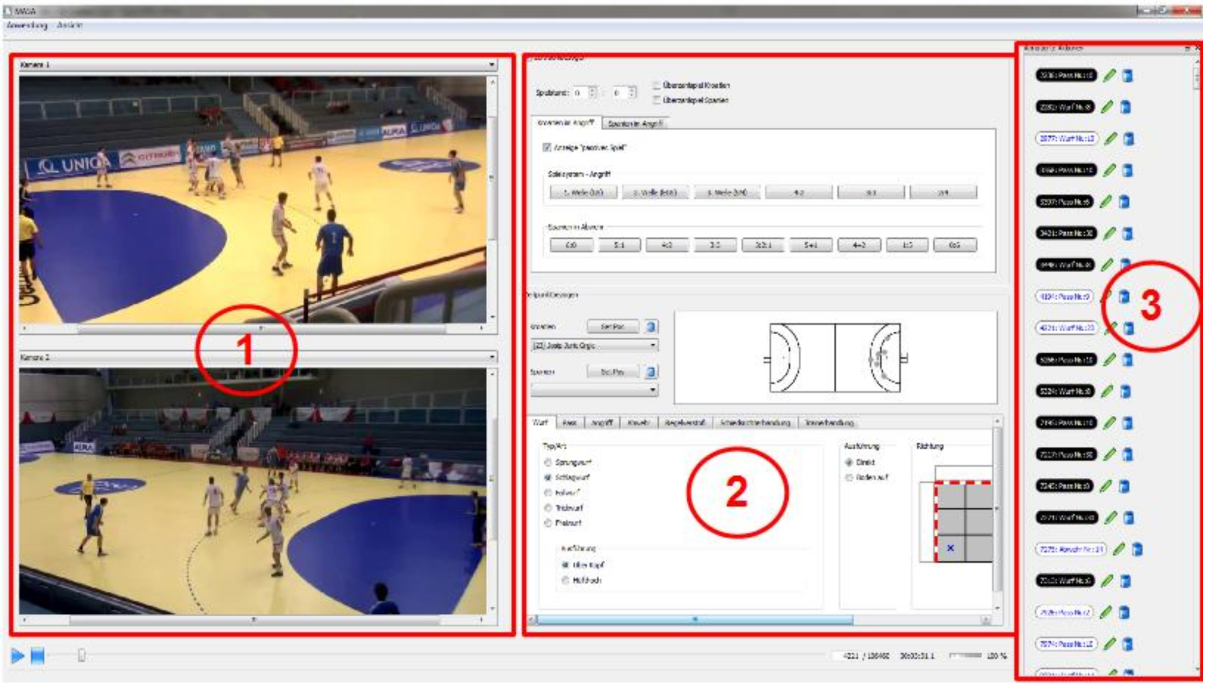

Figure 14: Overview of the MASA-GUI, parts (1)-(3) described in text

The video area in MASA is designed for a multi-camera setup. While it is possible to have only one video source, most situations require multiple views from different angles and positions to cover the area of interest. It is also possible to annotate ongoing games live in real time and link the video footage later.

A complete notation includes information about the time, the position, the type, and the protagonist of the action. The instant of time is determined by the video frame. All other information is added in the action area of the GUI with the following steps.

To specify the type of action, actions must be classified first. The action area is a graphical representation of a category system that is used to identify different types of actions. For example shots, passes, referee or coach interferences. These general categories are called root categories and are represented as tabs in the action area (see Figure 15).

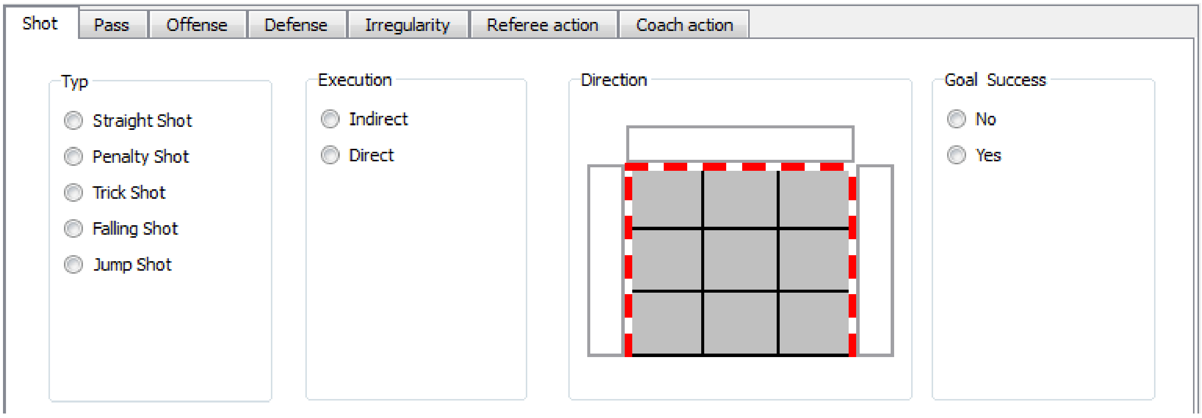

Figure 15: Action area of the MASA application

Each root category is then specialized in subcategories which can as well be specified recursively. A shot e.g. has different properties such as shot technique, quality, and shot direction. If necessary, special widgets can be assigned to the properties e.g. a frontal representation of the goal facilitates the input of the shot direction (see Figure 15).

The protagonist and timing are annotated in a widget combined with the video area. A click on the playing field in the video area calculates the actual position on the field in Cartesian coordinates. The player can then be selected from a combo box (see Figure 16). Additional position information, for example the formation of the defense team, can be set as well.

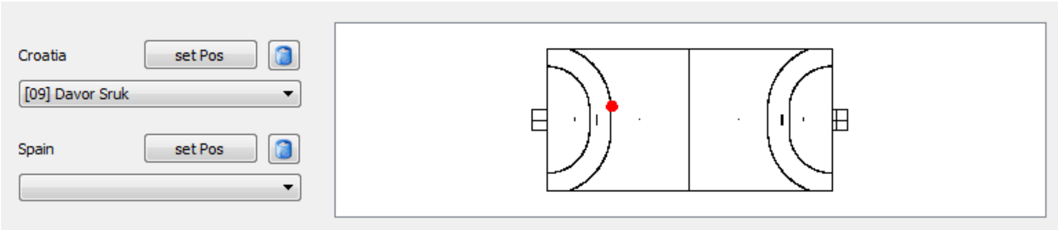

Figure 16: Position and player part of action area of the MASA application

The list area (see (3) in Figure 14) offers the opportunity to navigate through a game and alter previous inputs. A list item shows the player number in team color and the annotated action. List items are linked to the video with time stamps which allows the user to review, edit, or delete the related action.

MASA is open source software based on the Qt framework. Additional libraries are OpenCV and qwt. While qwt contains GUI components for the graphical display of data, OpenCV is a video processing library. Furthermore, MySQL is used as a database engine. All of these libraries are available on Microsoft and Linux-based operating systems. Working builds of MASA exist on both of these systems. MASA was not only created for the purpose of analyzing team handball games with neuronal networks but for a broad spectrum of tasks. The primary application area of the software is scientific. This is due to the fact that the manual position determination is a time-consuming task and the analysis with neural networks is not trivial. However, the annotation tool MASA itself is suitable for sport practice and valuable for coaching staff. The classification system is not static and can be customized to a wide area of needs with a built-in creation tool explained in the next section. The flexibility of the annotation process and the opportunity of exact position determination in addition with the mutli camera option are the main features that distinguish MASA from other software tools used in Team Handball.

Database model

The base for the flexible structure of MASA is the database model used and the dynamic GUI creation.

The data structure of a category system can be represented as a multi branch tree, with first level categories called root categories. Branches and nodes are stored in a table and have id numbers of their parents and certain properties. One of the properties determines how a branch is represented in the GUI, for example as multiple choice selection, text entry, or checkbox widget. Since the demands in different sports are varying, the structure of the category system is created by the user for his/her individual needs within the application. The user-built category system is used as an associative entity for the data in the annotation process. The advantage of a system that allows users to define their own categories is that such a tool can be used for a wide variety of tasks without overloading the GUI and making the annotation process as easy as possible.

Position determination

To accurately obtain metric positions of the team handball players, the transformation from image points to real world locations on the ground plane must be known. Therefore, we register each camera image with a known ground plane model by estimating a plane-to-plane projective coordinate transformation (*homography*). Since a homography is defined by a 3x3 projective transformation matrix, it provides 8 degrees of freedom and thus, at least 4 non-collinear corresponding point matches between image coordinates and ground plane coordinates must be available to estimate the transformation (Hartley & Zisserman, 2004). In particular, the user provides a set of corresponding points from a camera image and the ground plane model by selecting salient points such as corners of the handball field, markers on the goal, or previously placed markers within the field. If the user provides more than the minimum number of corresponding image points, we apply RANSAC (Fischler & Bolles, 1981) to robustly estimate the projective transformation matrix **H**. Given the estimated homography **H**, metric locations can be obtained from image locations using homogeneous coordinates (Bloomenthal & Rokne, 1994) as follows. First, the image pixel at location (x, y) is represented as a homogeneous coordinate by padding its coordinate vector with 1. This allows to formulate the projective transformation as the matrix multiplication $(\tilde{X}, \tilde{Y}, \tilde{W})^T = \mathbf{H}(x, y, 1)^T$. To obtain the corresponding metric coordinates $(X, Y)^T$ on the real-world ground plane, the projective coordinates must be divided by the scaling factor $\tilde{W}$, i.e. $(X, Y) = \left(\frac{\tilde{X}}{\tilde{W}}, \frac{\tilde{Y}}{\tilde{W}}\right)$.

Within the presented process of analyzing action sequences in team handball, several working steps have to be performed. Most of these steps are standard procedures in notational analysis and have been evaluated extensively in the literature (Carling, Williams & Reilly, 2005; Hughes & Franks, 2004; Tilp et al., 2006). However, the determination of position is novel and therefore will be evaluated in this paper.

Evaluation of the position determination

To evaluate the accuracy of the position determination, real world coordinates were compared with coordinates determined with the help of the MASA-software. Since camera positions are symmetrical for the handball field, only one half of the field with marked and measured lines was recorded with four cameras from typical views during game situation. Following the configuration of the camera setup, a set of predefined points were tagged by the assistance of the software system Figure **17** shows the schematic layout of the evaluated points.

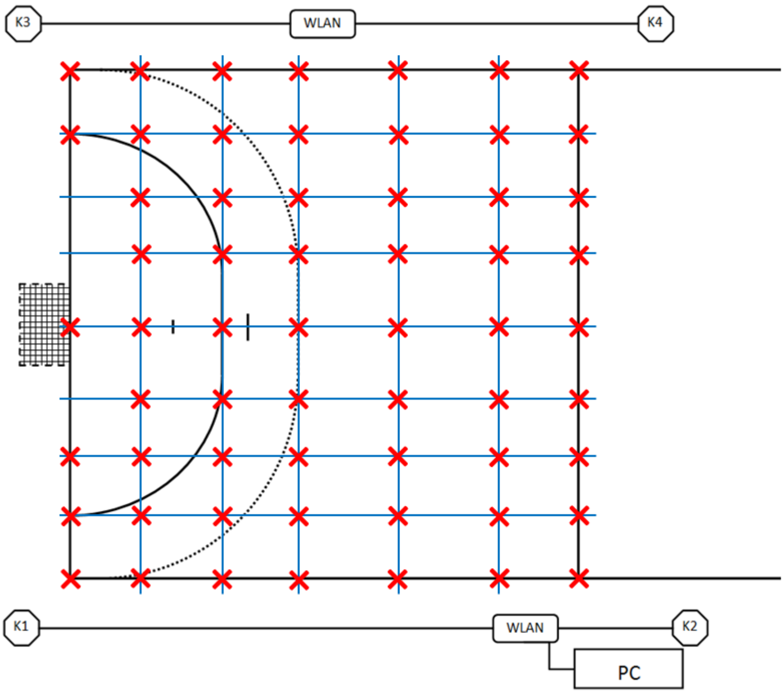

Figure 17: Schematic layout of the tagged points considered in the evaluation. In the presented camera set-up the non-marked points of the line grid close to the goal lay in the blind spot of the cameras K3 and K1 and are far away from the cameras K4 and K2. Since these areas are not relevant during a handball game, we did not evaluate accuracy.

The annotation was done separately for every camera. In total 125 points were annotated within one single test-session from the different camera views. Differences between the real world coordinates and the computed coordinates were calculated to estimate errors. Means and standard deviations of these differences were calculated per camera and for the entire test recordings.

To validate inter-rater reliability of the position determination, two different raters annotated the set of points with two different camera setups, i.e. with different homographies. To test intra-rater reliability, one tester performed a retest after one week. The statistical analysis of the measurement was performed with MS Excel 2010 and SPSS 20. Test results were assessed by the intraclass correlation coefficient (ICC) between the different raters, between the different camera configurations, and between the test and the retest, respectively.

Data processing and analysis

Generating input vectors

The database does not contain action sequences but the annotated single actions. Therefore the data of interest needs to be extracted and formatted into an input vector that can be handled by the neural network software DYCON® (Perl, 2002).

In the preparation process coordinates have to be scaled for the neural network software and transformed to account for the changeover of teams following half time.

The amount of data put into the neural network for one game situation is limited due to technical properties and game play relevance, i.e. passes before penalty shots are not relevant for the shot action. In this study the number of actions before a shot was chosen in contrast to the "sliding-window method" mentioned by Memmert et al. (2011). Consultation with experts and literature study resulted in the conclusion that five passes prior to a shot is an adequate number to properly cover important tactical information.

To study action sequences in team handball the input vector for the neural network consists of coordinates which represent the path of the ball from five passes before the shot and the shot itself. Therefore the input vector has the following format:

P R P R P R P R P R S (S= shot, R =receiver, P = passer).

Each of these points consists of an x- and a y-coordinate. The coordinates are harvested automatically from the database with an appropriate algorithm. Thus, a discrete action sequence covering the way of the ball is created. Shots with less than five actions, for example a penalty shot or a fast break play, are excluded from the input data.

Analysis of action sequences

In order to analyze playing behavior and team tactics, the action sequence data of players' positions is analyzed by means of artificial neural network using the DYCON® software (Perl, 2002). The software is able to classify the action sequences and as a result, each neuron of the network represents a playing pattern. Furthermore, similar patterns are summarized to clusters, which then represent similar playing behavior. An example of a neuronal net and some of the found patterns are shown in Figure 18.

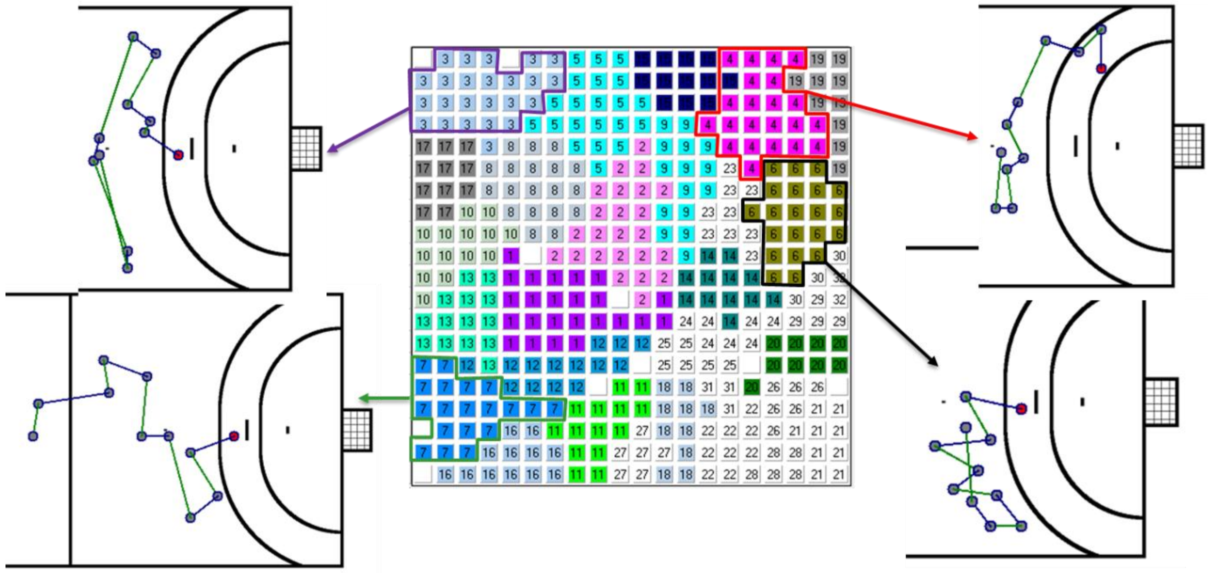

Figure **18**: Centre: Exemplary result of a neural network analysis showing different patterns. Boxes represent single neurons. Neurons in same colors represent clusters, i.e. representation of similar offensive patterns. Left and right: Exemplary offensive patterns determined by the network which show the ball path consisting of five pass positions (blue dots) and the shot position (red dot). Green lines represent ball paths and blue line represent running paths.

Schrapf & Tilp (2013) have already shown that offensive patterns can be determined with the presented method. They also have shown that some patterns are more successful than others. One could assume that the variation of offensive team tactics might be a success factor. Therefore, we analyze the relation between the variation of offensive patterns and overall team success from six games (eight teams) during the European U18 Team Handball Championship 2012 in Austria. There are several possibilities to operationalize variation in playing patterns. For this study we operationalize variation by determining the number of different patterns used by each team. The amount of different offensive patterns is determined by neural network analysis as described above and the overall team success is assessed by the final tournament ranking position. The relation is determined with Spearman's correlation coefficient.

Results

Evaluation of position estimation

The average error of the position estimation is 0.16 m (± 0.17 m). A detailed overview about the error rates per camera is shown in Table 6.

Table 6: Error rates of position estimation (values in meter)

	Minimum error	**Maximum error**	**Average error**	**Standard deviation**
Camera 1	0.03	0.53	0.14	0.10
Camera 2	0.01	0.70	0.13	0.12
Camera 3	0.01	0.98	0.22	0.22
Camera 4	0.01	1.15	0.15	0.17
Overall	0.01	1.15	0.16	0.17

An overview about the smallest and largest error rates is shown in Table 7. Error rates of test runs with best and worst average error rates are indicated for each camera view from all test runs with different camera settings and different testers.

Table 7: Error rates of single cameras from best and worst experiment based on average error (values in meter)

	Best case				**Worst case**			
	C1	**C2**	**C3**	**C4**	**C1**	**C2**	**C3**	**C4**
average error	0.13	0.09	0.16	0.11	0.16	0.17	0.27	0.21
standard deviation	0.07	0.04	0.13	0.05	0.10	0.16	0.26	0.25
minimum error	0.03	0.03	0.03	0.03	0.03	0.01	0.03	0.01
maximum error	0.28	0.24	0.61	0.22	0.44	0.62	0.98	1.15

Table 8 shows the quartiles of the single error rates. It indicates that 75 % of all errors are below 0.20 m. The 90% quantile error rate is at 0.33 m.

Table 8: Quartiles of the error rates (values in meter)

	From	To
1st quartile	0.01	0.06
2nd quartile	0.06	0.11
3rd quartile	0.11	0.20
4th quartile	0.21	1.15

The intraclass correlation coefficient (ICC) for verification of the software systems inter-rater reliability is 0.92 (significance level 0.000) regarding different test person and same camera setup. The intra-rater reliability test lead to an ICC of 0.95 (significance level 0.000). A retest with different camera setups and the same test person lead to an ICC of 0.36 (significance level 0.000).

Relationship between offensive pattern variation and overall-success

The analysis of offensive action sequence by neural networks revealed that the different teams played between 18 and 27 different offensive patterns (examples in Figure 18) per game A correlation coefficient of r_s=0.6 (Spearman) however, indicates a rather low relationship between offensive variation and success (Figure 19).

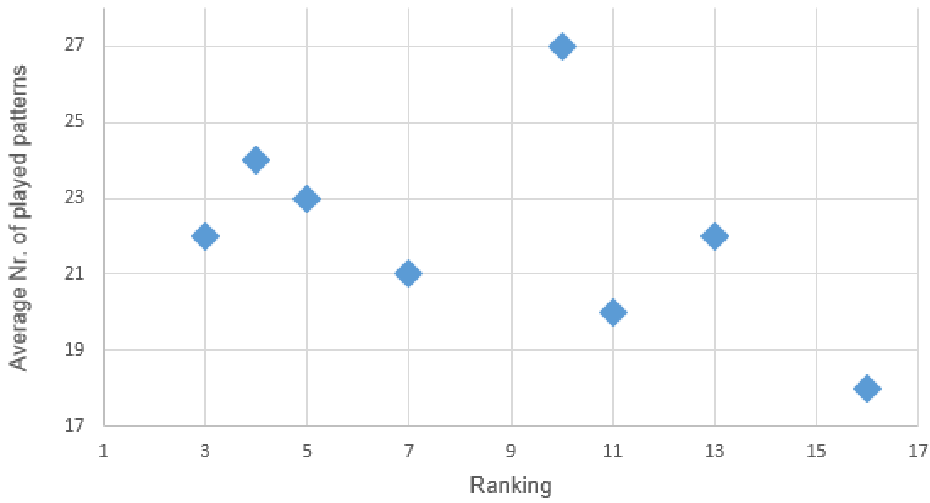

Figure 19: Number of offensive patterns played by teams and the final tournament ranking of the analyzed teams

Discussion

Evaluation results show that the presented system is able to produce action data including accurate position data to create action sequences in team handball. Due to the flexible annotation process almost any type of action with user-defined details can be captured. The independent procedure for extracting annotated data allows obtaining arbitrary data sets by combining single action data stored in the database.

Due to the open nature of the system components, it is possible to adjust the working effort to specific problems. While researchers might use the system to perform detailed but also time-consuming analyses, sport practitioners might create simple but effective category systems for their requirements. The notation process for example is not bound to a specific camera system, but can handle any form of video data. Input vectors for the neural network can also be generated from data sets of other annotation systems. Furthermore, data gathered from the notation process can be used for classical analyses like shot statistics etc.

An important aim of the study was to evaluate if the accuracy of position determination is sufficient to analyze sequential actions in team sports. An average error of 16 cm indicates that the system provides appropriate position data for this task. Considering the area taken by an athlete standing or the deviations during running movements, the error appears negligible. Statistical analyses of the error occurring the evaluation show a very well inter-rater reliability (ICC of 0.92) and also an excellent intra-rater reliability (ICC of 0.95). However, evaluation of the system's objectivity regarding different camera setups has led to a rather low ICC of 0.35. From this can be concluded that the preparation of the system's camera setup has a significant effect on the results of the position estimation. Moreover, best and worst case values of the evaluation show that the maximum error due to an improper camera setup can be above 1 m. Such an inaccuracy would definitely lead to non-satisfying analysis results. However, a closer examination of the average results of the different camera setups reveals that worst results for each single camera only leads to an average error of 27 cm. A detailed analysis of the field areas with greater error rates show that error rates increase at the bottom end of the single views, i.e. when the point of interest is in great distance from the camera (e.g. the left corner seen from camera 2 in Figure **17**). Considering the software's ability to select positions from different camera views, the user is able to minimize errors by selecting positions onto a view, where the player is in the front of the video. Moreover, the 90% quantile of all test data is at 33 cm, which shows that there are only a few positions on the field which are determined with mediocre accuracy. Overall, error rates determined in the present study are similar to other positional determination system, i.e. visual position estimation in beach volleyball with average error rates from 0.25 to 0.35 m (see Figure 12 in Mauthner et al., 2007), large scale motion acquisition in team handball with a root mean square (RMS) error of 0.18 to 0.64 m (Perš et al., 2002) or photogrammetric technique in order to determine referee position during a football match with a RMS error of 0.23 and 0.17 m for x- and y-axis, respectively (Mallo et al., 2007).

The process of classifying action sequences from position data by means of artificial neural networks was already described by Schrapf & Tilp (2013). They reported that the system is able to successfully identify offensive playing patterns by classifying action sequences in junior team handball. The obtained amount of detected patterns appears suitable for the use in sports practice. Their study revealed dominating offensive patterns as well as varying success rates of used offensive strategies in team handball.

Conclusion

Summarizing, the study revealed the applicability of the used method to gain action sequence data with accurate position information which can be used to analyze tactical behavior in complex sport games like team handball. The presented system enables annotating single actions live during matches or off-line from recorded videos. Exact position information can be added in an off-line process. Subsequently, appropriate data export algorithms are able to merge single actions into sequences of actions which are then analyzed by artificial neural networks. First analyses with position data of action sequences from team handball (Schrapf & Tilp, 2013) already indicate the applicability of the proposed method.

Future challenges will be the inclusion of defensive team behavior in the analyses and the application of the system in sports practice. Especially the interaction between the opposing teams may lead to valuable information for coaches to improve the tactical training and the tactical behavior during competitions.

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