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Observation and analysis of large-scale human motion

Janez Perš [a,*,1,2], Marta Bon [b,2], Stanislav Kovačič [a,1,2], Marko Šibila [b,2] and Branko Dežman [b,2]

[a] *Faculty of Electrical Engineering, University of Ljubljana, Tržaška 25, SI-1000 Ljubljana, Slovenia*

[b] *Faculty of Sport, University of Ljubljana, Gortanova 22, SI-1000 Ljubljana, Slovenia*

Abstract

Many team sports include complex human movement, which can be observed at different levels of detail. Some aspects of the athlete's motion can be studied in detail using commercially available high-speed, high-accuracy biomechanical measurement systems. However, due to their limitations, these devices are not appropriate for studying large-scale motion during a game (for example, the motion of a player running across the entire playing field). We describe an alternative approach to studying such large scale motion, and present a

* Corresponding author. Tel.: +386-1-4768-876; fax: +386-1-4768-279; email: janez.pers@fe.uni-lj.si

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video-based, computer-aided system, developed specifically for the purpose of acquiring large-scale motion data. The baseline of our approach consists of sacrificing much of the spatial accuracy and temporal resolution of widely used biomechanical measurement systems, to obtain data on human movement that span large areas and long intervals of time. Data can be obtained for each of the observed athletes with reasonable amount of operator work. The system was developed using the recordings of a handball match. Several field tests were performed to assess measurement error, including comparison to one of the widely available biomechanical measurement systems. With the help of the system presented, we could obtain position data for all 14 handball players on a 40 × 20 meter large court with RMS error better than 0.6 meter, covering one hour of action. Several results, obtained during the handball match study are presented, in order to highlight the importance of large-scale motion acquisition.

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1 Introduction and motivation

Most sports include complex motion, which can be studied at different levels of detail. This is especially true for team sports (e.g. soccer, handball, basketball). Some aspects of an athlete's movement can be studied in detail using commercially available high-speed, high-accuracy biomechanical measurement systems. A detailed comparison of these systems was made by Richards (1999), and the basic principles behind such measurements were presented by Gruen (1997). These systems provide high-quality, high-resolution data on human movement, however, they also impose severe limitations, which make them inappropriate for studying motion covering large areas for long intervals of time.

In team sports, action is often spread across the whole playing field (which, for example in European handball, measures 40×20 meters), and matches can last for an hour or more. Most of the biomechanical measurement systems provide extremely accurate data on human movement, but cannot effectively cover such a large area. These systems provide high temporal resolution (100 Hz or more), but over relatively short intervals of time, when the duration of a typical match is considered. Many of these systems require some kind of markers to be attached to the body of the athlete, which are distracting and not acceptable during regular league or championship matches.

For the purpose of tactical match analysis, information about movement of the athletes (players) participating in the match is needed. The accuracy requirements for such data are far lower than for the purpose of biomechanical analysis. Ten years ago, researchers used self-made, video-based systems with resolution of 1 meter for successful analysis of a soccer match (Erdmann, 1992), however, no error analysis was performed. On the other hand, it is desirable that the acquired data covers both the whole playing field and the whole duration of the match. Application of player motion analysis using conventional biomechanical motion analysis systems would therefore be extremely difficult, costly, and would result in an unacceptable amount of over-accurate data.

The development and use of a video-based, computer-assisted motion acquisition system, which can deliver the data about player position and velocity, that conforms to the requirements of team sport analysis, is in the center of our research. We observe the motion of the players on the playing field on a large scale, both temporally and spatially; we therefore refer to it as *large-scale motion*. Large-scale motion represents an "envelope" component of full-scale motion. For example, as a player runs across the playing field, his center of gravity accelerates and decelerates as he makes each step. However, we can present this motion on a large scale, in which case it is comprised of one acceleration at the start of the motion, an interval of nearly constant velocity and the final deceleration at the end of the run.

There is a strong motivation for our research. Physical training in team sports is extremely important for top performance during the matches, and training should be based on the knowledge of the specific requirements of a particular sport. Player motion data can reveal many aspects of team play that are not directly visible: for example, it can highlight the reasons why some athletes perform better than others, and it can suggest the methods of training to make good athletes perform even better. Large-scale motion data can also be compared to other variables we can monitor and record during the game, such as heart rate or expert observations about the course of the play. These variables are often recorded at markedly lower sampling rates (0.2 Hz for heart rate, for example) than motion data provided by biomechanical motion analysis systems.

The baseline of our approach consists of *sacrificing* most of the spatial accuracy and temporal resolution of conventional motion analysis systems, to obtain coverage of large areas during long intervals of time. Specific techniques of video acquisition, camera calibration and human position acquisition were used in achieving this goal. This resulted in a moderate amount of data, which can be analyzed using various methods, including popular spreadsheet and statistical packages.

The structure of this paper is as follows: first we take a quick look at related research, both in the sport science and computer vision domain. Then we present the methods we used for data acquisition: video acquisition, camera calibration, player position acquisition (tracking) and data post-processing. Our system was field tested, and the next section is devoted to error analysis, including a comparison to one of the commercially available motion analysis systems. Finally we present some results of handball match analysis to emphasize the importance of large-scale motion acquisition, and discuss the results.

2 Related work

A lot of research related to large-scale human motion has been done in the last ten years. This area attracts, among others, sport and computer vision scientists. However, very little interdisciplinary work has been done so far. Researches in the field of sports have focused predominantly on the final application of their systems, sometimes using antiquated equipment. On the other hand, computer vision researchers have been unwilling to address some of the problems that are not of immediate importance to the computer vision theory, but are of crucial importance if these systems are to be applied in practice.

2.1 Sport science

For years, analysis of team sports consisted mainly of "observation sheets", filled in by human observers during the matches. With the advent of widely available and low-cost computers, data manipulation and analysis were modernized, although the principles remained the same (Ali and Farrally, 1991). On the other hand, video-based motion acquisition was used to obtain player positions as far back as ten years ago, using somewhat primitive, yet effective techniques of camera calibration and position acquisition (Erdmann, 1992). The latest contributions to this field consist of commercially available wearable microwave transmitters, produced by Trakus, Inc., which can be fitted inside helmets, if this is allowed by rules of the particular sport. Another contribution is a commercial video- and service-based product, AMISCO, by Sports Universal (formerly Videosports). Due to its commercial nature, little is known about the mechanism it uses to obtain player positions.

2.2 Computer vision science

Acquisition and analysis of human movement represents an interesting challenge to computer vision researchers, due to the complex structure of the human body. Overviews of the more important achievements in this field of computer vision were made by Aggarwal and Cai (1999) and Gavrila (1999). Large-scale motion acquisition and analysis were studied by Intille and Bobick (1995), with the ultimate goal of realizing a fully automated tracking of American football players. However, many important aspects of motion acquisition were neglected: for example, a single, handheld, non-stationary camera was used, which unnecessary complicated the camera calibration process. Player tracking was further aggravated by heavy perspective, due to inadequate elevation of the camera. Error analysis was not performed. Unfortunately, many of these problems are still ignored by computer vision researchers: a quick review of several articles, related to people tracking, which were presented at the recent major computer vision conference ICPR 2000 (held in September 2000 in Barcelona, Spain), reveals that most authors did not even consider error analysis or camera calibration. While excellent papers on camera calibration and error analysis exist, many application-oriented papers in the field of computer vision based human motion analysis lack these two important components.

3 Method

The process of player position and motion acquisition (tracking) consisted of several steps: camera positioning and calibration, video recording, video digitalization, digital video processing and post-processing of obtained motion data.

3.1 Camera placement

To cover the whole field, we mounted two 1/2" PAL CCD cameras (JVC TK-1281EG, 6.4×4.8 mm^2 CCD sensor size) to the ceiling of a sports hall, which was regularly used for handball and basketball matches. This arrangement of cameras provided a bird's-eye view of the players, as is needed to accurately measure player motion across the court plane. Each camera covered its half of the playing field, with some overlapping at the middle. Due to the limited height of the ceiling, wide-angle lenses with a focal length of 1.4 mm were used to ensure whole field coverage. Camera placement and combined image from both cameras are shown in Fig. 1.

[Figure 1 about here.]

3.2 Camera calibration

Detailed studies of camera calibration problem using non-metric equipment were done years ago (Tsai, 1987). Calibration methods, which map 3D object space to 2D sensor space, such as DLT, are typically used in motion acquisition tasks (Gruen, 1997). However, our goal of large-scale motion acquisition does not require extremely high accuracy. By placing cameras above the field, we knowingly omitted the vertical dimension of player motion. To obtain player position in the planar coordinate system of the handball court, we do not need optical triangulation. Without any radial distortion, it would be possible to map the objects on the court plane to their coordinates on the camera sensor simply by scaling and translation of origin between court and sensor coordinate systems. However, significant radial distortion represents a major obstacle to this simple solution. Fig. 2 shows the sequence of transformations, which define the relations between player position in the court coordinate system, which originates at the upper top corner of the court boundary rectangle, and the image coordinate system.

[Figure 2 about here.]

Generally, the image, acquired by one of our cameras, is rotated, translated, scaled, and radially distorted with respect to the court coordinate system. Translation (d_{1x}, d_{1y}) and rotation (β) can be taken into the account using the transformation T_1:

$$T1: \begin{cases} x'_1 = x_1 + d_{1x}, \quad y'_1 = -y_1 + d_{1y}, \\ x_2 = x'_1 \cos(\beta) - y'_1 \sin(\beta), \quad y_2 = x'_1 \sin(\beta) + y'_1 \cos(\beta). \end{cases} \tag{1}$$

This equation leaves us with three unknown parameters that need to be estimated during the camera calibration phase: the translation along both axes, d_{1x} and d_{1y}, and image rotation, β. This step leaves us with a radially distorted, but centered and aligned image of the playing court. Radial distortion is a non-linear function of camera radius, and we assume it is rotationally symmetric. The correction is obtained using the following sequence of calculations, T_2:

$$T2: \begin{cases} r_2 = \sqrt{x_2^2 + y_2^2}, \quad \varphi = \arctan\left(\frac{y_2}{x_2}\right), \quad r_3 = f_c(r_2), \\ x_3 = r_3 \cos\varphi, \quad y_3 = r_3 \sin\varphi \end{cases} \tag{2}$$

f_c denotes the non-linear correction function. The form and complexity of f_c depends on the severity of the radial distortion, and it can be modeled by polynomial approximation (Tsai, 1987) or, as in our case, by the following exponential function (Perš and Kovačič, 2002):

$$f_c(r_2) = \frac{H}{2} \frac{(e^{-\frac{2r_2}{H}}) - 1}{e^{-\frac{r_2}{H}}}. \tag{3}$$

For illustrative purposes only, the result of radial distortion correction is shown in Fig. 3. Nevertheless, the tracking is performed on raw, uncorrected images, and player positions in the court coordinate system are calculated after the tracking.

After the radial distortion correction, we perform the scaling and final translation, which moves the origin of the coordinate system into the upper-left court corner. Scaling is needed to obtain positions of the players in the desired measurement units.

$$T3: \quad \begin{cases} x_4 = k_x x_3 + d_{2x} \\ \\ y_4 = -k_y y_3 + d_{2y}, \end{cases} \tag{4}$$

where k_x and k_y represent unknown scaling coefficients, and d_{2x} and d_{2y} represent unknown translation components.

Transformation parameters d_{1x}, d_{1y}, β, k_x,k_y, d_{2x}, d_{2y}, and radial distortion parameter H were obtained for each camera separately, using a non-linear optimization (simplex) method with 17 different points on the court plane as references. These points were obtained at the positions of various court marks, as their positions in court coordinates are well defined by the rigid sport rules.

[Figure 3 about here.]

This method of camera calibration relies on a planar surface of the playing court. To measure the positions of humans, moving across the surface, the expected elevation of their center of gravity is taken into account, by slightly expanding equation (2) with the following correction:

$$r_3 = f_c(r_2) - f_c(r_2) \cdot \frac{h_g}{h_c}, \tag{5}$$

Where h_g and h_c denote the approximate elevation of the player gravity center and the camera, and were in our case estimated as 1.5 and 10 meters, respectively.

3.3 Video recording and digitalization

Both cameras were AC line locked to ensure proper synchronization and connected to two PAL S-VHS videorecorders (Panasonic NV-HS950), which were used to record the whole handball match, which lasted about an hour. Video recordings were taken to the lab, where they were transferred to computer disk using a S-VHS videorecorder (Grundig VS680 VPT) and Motion-JPEG video acquisition hardware (Pinnacle Miro DC30+ real-time video capture card) at 25 frames per second and 384×288 pixel image resolution. Such settings result in more than 180.000 images, which need to be stored to the digital media. Although M-JPEG compression significantly reduces the amount of storage space required, the recordings were split to 15 minute chunks. One hour of video data from both cameras required approximately 12 gigabytes of hard-disk storage space. Digital recordings from both cameras were synchronized to 1/25 second precision by observing the first throw by the player in the middle area of the field, which was visible by both cameras at the same time.

3.4 Computer-assisted motion acquisition (tracking)

Two approaches to player tracking were tested, that is, manual and automatic. Our custom developed software (SAGIT), which runs under Microsoft Windows operating system, allows either manual or automatic recovery of player positions for each and all of the players on each of the frames from the digital video sequence. The operator may switch between manual and automatic mode at any time, as desired. For example, automatic tracking can quickly provide motion data for well illuminated areas of the court, whereas manual tracking can be used to track players when they enter the areas with inadequate lighting or become involved in crowded situations.

3.4.1 Manual tracking

Manual tracking is performed by an operator using a computer mouse. Only one click per player per frame is needed. If circumstances allow, players can wear differently coloured garments during the match, to make the tracking problem easier. The process relies on the graphical interface of the tracking program, which is shown in Fig. 4. To speed up the process, the operator may instruct the program to skip several frames between subsequent clicks, and the software uses linear interpolation to obtain player position on skipped frames.

[Figure 4 about here.]

3.4.2 Automatic tracking

Although relaxed requirements considering the system accuracy reduce the manual work by several orders of magnitude as compared to biomechanic motion analysis systems, manual tracking remains a time-consuming and tedious task. Assuming favourable lightning conditions, positions of most players can be recovered by the computer itself, even without the use of distracting markers. To obtain their positions, separation of players from the background is needed. To achieve this separation, the following properties of the players can be used:

- **Presence.** Players are the only objects that are present during the game, and absent when the court is empty. Commonly used computer vision technique, called "background subtraction" takes advantage of this property. However, this technique is subject to strong distractions, caused by shadows, light reflections and similar nuisances.
- **Colour**. Players of each of the teams usually wear identically coloured garments, using different colours or colour combinations to distinguish between the teams. Provided that the chosen team colour does not match the colour of the court, colour tracking techniques can provide us with the estimates of player positions.
- **Shape**. The human body in motion, especially when observed from the bird's-eye perspective, has a distinctive shape that is different from other marks on the court. By using the "template tracking" technique, estimates of player positions can be refined to achieve desired accuracy.

The combination of colour- and shape-based tracking is used in our automatic tracker, as described by Perš and Kovačič (2001). However, this method is not completely reliable; a human operator is still needed to initialize the tracker (e.g. to mark the starting positions of the players) and supervise the tracking process. In the case of a tracking error, one is able to stop and re-initialize the process. In our test, the automatic tracking speed averaged 4.5 frames per second, using full temporal resolution (25 Hz) video, and process needed approximately one operator intervention per player during the processing of 30 second (750 frame) sequence of the handball match, during which all 14 players were tracked simultaneously.

3.4.3 Trajectory Post-processing

The trajectories obtained using automatic tracking methods contain a certain amount of noise, which makes player velocity calculation extremely difficult. On the other hand, manually obtained trajectories usually consist of alternating linear intervals and rapid direction changes, due to linear interpolation between successive clicks. To obtain smooth trajectories, which describe physically plausible motion, trajectory smoothing is needed.

An obvious way of trajectory smoothing is by use of the Gaussian smoothing kernel, as shown in (6). We process x and y components of the trajectory separately, treating them as one-dimensional time-dependent signals

$$\begin{aligned} x'(t) &= \frac{1}{2N_F+1}\sum_{i=-N_F}^{N_F} x(t+i)\cdot G(i), \\ y'(t) &= \frac{1}{2N_F+1}\sum_{i=-N_F}^{N_F} y(t+i)\cdot G(i), \end{aligned} \tag{6}$$

where $2N_F+1$ denotes the width of the kernel, x' and y' are the smoothed components of the trajectory, and x and y are the components of the raw trajectory. G is the set of Gaussian coefficients which define the shape of the kernel. The precalculated set of $2N_F+1$ coefficients in the range of Gaussian function $(-3\sigma, 3\sigma)$ was used. Kernel width $2N_F+1$ is directly related to the intensity of the smoothing. Larger N_F yields smoother trajectories.

Part of the post-processing stage is also the calculation of player velocity and distance covered. Velocity is simply calculated by differentiating the trajectory over time, and the distance covered is obtained by scaling and adding up the absolute velocities over the successive intervals of time.

4 Error analysis

There are several sources of errors that can influence the overall uncertainty of tracking. Analytical derivation of system accuracy and precision is difficult, as many factors, including operator decisions, influence the results. Therefore, field tests were conducted to evaluate the system. To simulate real-world conditions, we conducted our experiments by employing automatic tracking procedures, complemented with manual corrections when automatic tracking failed.

4.1 Types of errors

Errors that affect measurements of large-scale motion can be grouped into the following categories:

- **Movement of player extremities.** We track motion of humans across the plane. Ideally, their acquired positions would not change, unless they walk or run from one point to another. However, due to the limitations of our setup (we are observing a large 3D space and assuming 2D motion) their acquired positions change due to movement of their extremities and their vertical movement. This effect is categorized as an error of our tracking system.
- **VCR tape noise and compression artifacts** degrade image quality. There are several thresholds built into the automatic tracking algorithms, and in some cases the "decision" taken by the automatic system can be influenced by such artifacts.

- **Quantization error.** Due to severe radial distortion, the quantization error becomes significant at locations near the court boundaries. Assuming the input image resolution of 384-by-288 pixels, one pixel near the optical axis of the camera covers the area of 4-by-4 centimeters in our setup, while at the court corners, one pixel covers the area of 20-by-20 centimeters.
- **Imperfect camera calibration.** The assumptions on which our camera calibration method is based are not always true. For example, optical axes of cameras are not exactly perpendicular to the court plane, which results in inaccurate radial distortion correction in some parts of the court (since the assumption of rotational symmetry is violated). In most cases, these errors can be ruled insignificant, especially as they influence limited areas of the court and affect only player position, and not velocity or distance covered.
- **Operator mistakes.** As the system is operated and supervised by humans, there always remains a possibility of human mistakes, which is impossible to evaluate. In the rest of this paper we will assume that results of the tracking were acquired *without* operator mistakes.

Following an established categorization of measuring errors to random and systematic (Taylor, 1982), the movements of player extremities, tape noise, compression artifacts and the quantization error can be classified as *random* errors. On the other hand, imperfect camera calibration is *systematic* in its nature (and could be measured and compensated for, provided there would be a strong need for such compensation).

Influences of above described errors can be combined in certain situations (for example, movement of player extremities near the court boundaries will be more significant due to a larger quantization error than similar movement near the court center).

4.2 Ground truth

Use of mechanical test devices would surely overrate our system in terms of accuracy and precision, as such devices (for example, mobile robots) cannot re-create the complexity of human movement, which contributes to the measurement errors. Instead, several handball players were asked to move under the camera, following the predefined paths. Ground truth was therefore obtained simply by drawing a pattern of lines near the middle of one of the halves of the handball court. The pattern, shown in Fig. 5 was created and measured using a measuring tape.

[Figure 5 about here.]

4.3 Experiments

Errors in motion acquisition depend on several factors. Player position plays an important role due to radial distortion – position measurements of the players near the court boundary are less accurate. The same assumption can be made for the players who are involved in different activities (jumping, throwing, ball passing), when compared to players who are standing still. The intensity of trajectory smoothing is also an important factor, especially in velocity measurements. To address the effects of these factors, several experiments were designed:

Experiment I. In the first part of the experiment, players were instructed to stand still at the predefined places. In the second part of the experiment, they were instructed to perform various activities (passing the ball, jumping on the spot, etc.) but they were not allowed to move *across* the court plane. The reference position was obtained from the drawn pattern. Reference velocity and distance covered were exactly zero, since the players never left their designated positions.

Experiment II. Players were instructed to run and follow the square trajectory. The influence of trajectory smoothing was observed.

Experiment III. Players were instructed to run and follow the circular trajectory with constant velocity. Error in velocity measurements was assessed.

Experiment IV. We compared our system to a widely used, video-based biomechanical measurement system, APAS-99 (Ariel Performance Analysis System), manufactured by Ariel Dynamics Inc., which was used as a ground truth this time.

4.4 Results

All position measurements were done at 25 Hz framerate, and various amounts of smoothing, controlled by the smoothing kernel width $2N_F + 1$ were applied to the trajectories before the velocity, distance and acceleration calculations were performed.

Five players participated in Experiment I, three of them near the court center, two near the court boundary. Players were standing still for 60 seconds in the first part of the experiment and performed various activities for 180 seconds in the second part. RMS errors in player position (E_p), velocity (E_v) and error in distance covered per player per minute (E_{dc}) were measured. Results are shown in Table 1. It can be seen that trajectory smoothing radically reduces the errors in player velocity and distance covered, but has only marginal influence on the error in player position.

[Table 1 about here.]

Experiment II has been designed to evaluate the adverse effects of the trajectory smoothing, using square trajectory as a reference. Trajectories of the five players who participated in the experiment were concatenated and the RMS distance between measured and reference trajectory, shown in Fig. 6 was calculated as

$$D_r = \sqrt{\frac{1}{n}\sum_{i=1}^{n} |d_i|^2} \tag{7}$$

The results show that heavy smoothing hides rapid changes in the player trajectory. Kernel widths of 11 and 25 samples represent the compromise which yields the most accurate results.

[Figure 6 about here.]

During Experiment III, errors in velocity measurements during player movement were assessed. The RMS error in player velocity was observed, and the reference velocity was simply calculated from the length of the circular path and the time each player needed for one round. Five players took part in the experiment, and their average velocities ranged from 2.69 to 3.22 m/s. RMS errors in measured velocities ranged from 0.21 to 0.35 m/s (6.4% to 12%) when an 11 samples wide smoothing kernel was used, and from 0.07 to 0.20 m/s (2.4% to 6.8%) when a 25 samples wide kernel was used.

Part of velocity variation can be contributed to the players themselves, as humans are not able to control their velocity to the extent required in this experiment. It is therefore most likely that our tracker was performing even better than the actual measurements have shown.

Experiment IV was designed to gain insight into the relation between the full-scale motion of the human body center, which is best captured using biomechanical motion acquisition technology, and the large-scale motion, which is captured by our system. A single player was instructed to run around three markers in one of the corners of the court, as shown in Fig. 5. To capture the full-scale motion of the player, we used APAS-99 system to manually track 16 distinctive points of the human body. APAS "digital 7" filter was employed to smooth the trajectories. The center of gravity was calculated by means of the Dempster equations using APAS software. The components of the motion of the gravity center which are parallel to the court plane were used as a ground truth.

The whole video sequence lasted approximately 3.4 seconds (86 frames at 25 Hz). The results are consistent with previous experiments, with the RMS error in position being 0.36 m. However, the velocity measurement error of 0.5 m RMS illustrates the important difference between both systems - the level of detail that they capture. This difference can be further observed in Fig. 7. Velocity and acceleration graphs, obtained with APAS show accelerations and deccelerations of the center of gravity, which are associated with each of the player's steps. However, our system recorded only those accelerations which correspond to the turning points in player trajectory. Acceleration was calculated by simple differentiation $a = \triangle v / \triangle t$.

[Figure 7 about here.]

4.5 Conclusions

The results of our experiments can be compiled to define the overall error of our system as shown in Table 2. To ensure the validity of specified results, this table is based on the worst case scenario.

[Table 2 about here.]

5 Handball match analysis

The presented method for large-scale motion acquisition is especially useful in team sport analysis. Information on the intensity of player activity is of crucial importance in studies that aim to define and improve the methods of player training, which would further increase their efficiency.

Several parameters of long-term motion are important in this context, with total distance covered by a particular player being the main focus of most of the related research. However, reported results vary wildly; researches reported values that ranged from as low as *two* to as high as *seven* kilometers per match (Kotzamanidis et al., 1999). These variations can be largely attributed to the different methods that were used, as some of the researchers had no possibility of *measuring* the distance during the *whole* match and relied on extrapolation of the data as obtained during a particular interval of the match. Large variations between the results obtained by different researchers and incomplete or missing documentation about *how* the measurements were obtained, rendered this data highly inappropriate for systematic scientific analysis.

5.1 *Experiment*

The subject of the study was the evaluation of the intensity of the activity (effort) of players during a handball match. The measured sample consisted of six players of a Slovene First Division male team (20-28 years of age), who played a model match. Positions of the players for the whole match were obtained at 25 Hz using the previously described system for large-scale motion acquisition. To distinguish between different intensities of player movement, we defined boundaries in player velocity as follows: walking if $v < 1.4$ m/s, slow running if 1.4 m/s $\leq v <$ 3.0 m/s, fast running if 3.0 m/s $\leq v <$ 5.2 m/s and sprint if $v \geq$ 5.2 m/s.

5.2 *Results*

The players covered on average a distance of 4800 m during the analyzed match. Variations for different players in the distance covered are from -7% to +6%. Sprints amounted to 7% of the playing time, 25% of playing time was spent in fast running, 31% in slow running and 37% in walking or standing still.

6 Discussion

The most reliable way of obtaining player motion data is the observation of players during the top league or championship matches. The measurements, that have been published in literature so far are either unreliable or too poorly documented to be used in training planning, as they are based mainly on extrapolation of short intervals of time in which the motion was observed. Biomechanical motion analysis devices can be used to gain insight into the player motion details, however, their specific nature does not allow continuous and cost-effective motion acquisition on large areas, for example playing courts, for long intervals of time.

Our system, as presented, solves several of these problems. Relaxed accuracy requirements enabled us to significantly simplify the camera setup and accelerate the motion acquisition process. These modifications allow the capture of large-scale motion of players. System error was measured and the structure of the system is documented, which is important for scientific use of obtained motion data.

The importance of large-scale motion acquisition was illustrated on the example of a handball match, but it goes far beyond studying physiological demands of a particular sport. Such data can be used in tactical match analysis and can be compared to other parameters that are captured during gameplay, thus increasing our knowledge of sport.

Authors' note

The experimental research, presented in this paper, has been performed in accordance with the ethical guidelines, laid down by the Faculty of Sport at the University of Ljubljana. Written permissions were obtained from all participants involved in the study.

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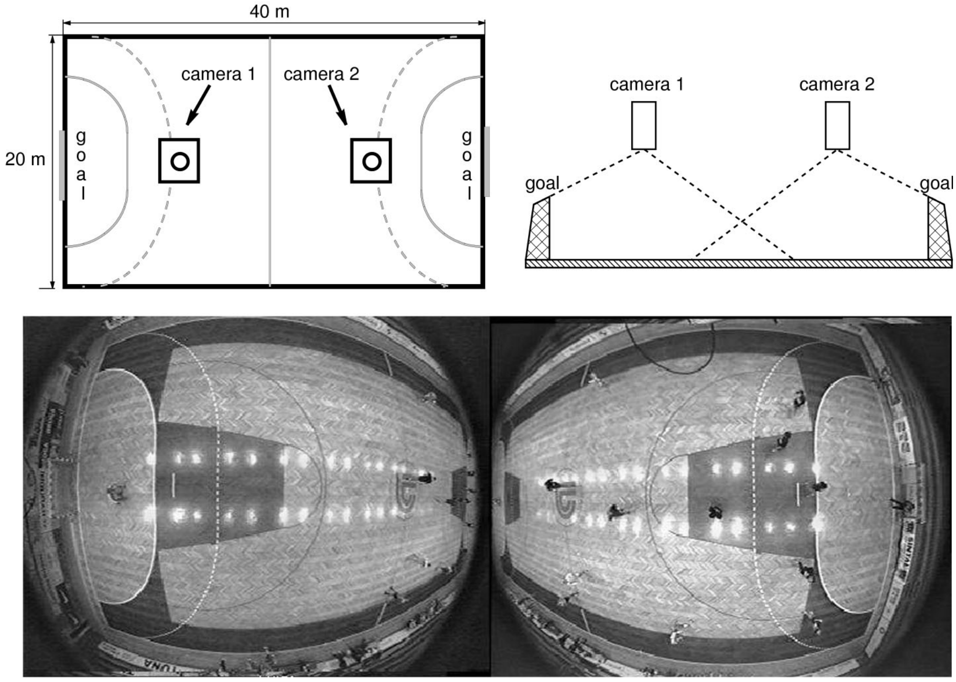

Figure 1. Handball playing court and camera placement (top). Example of combined images from two cameras, taken at the same instant of time (bottom).

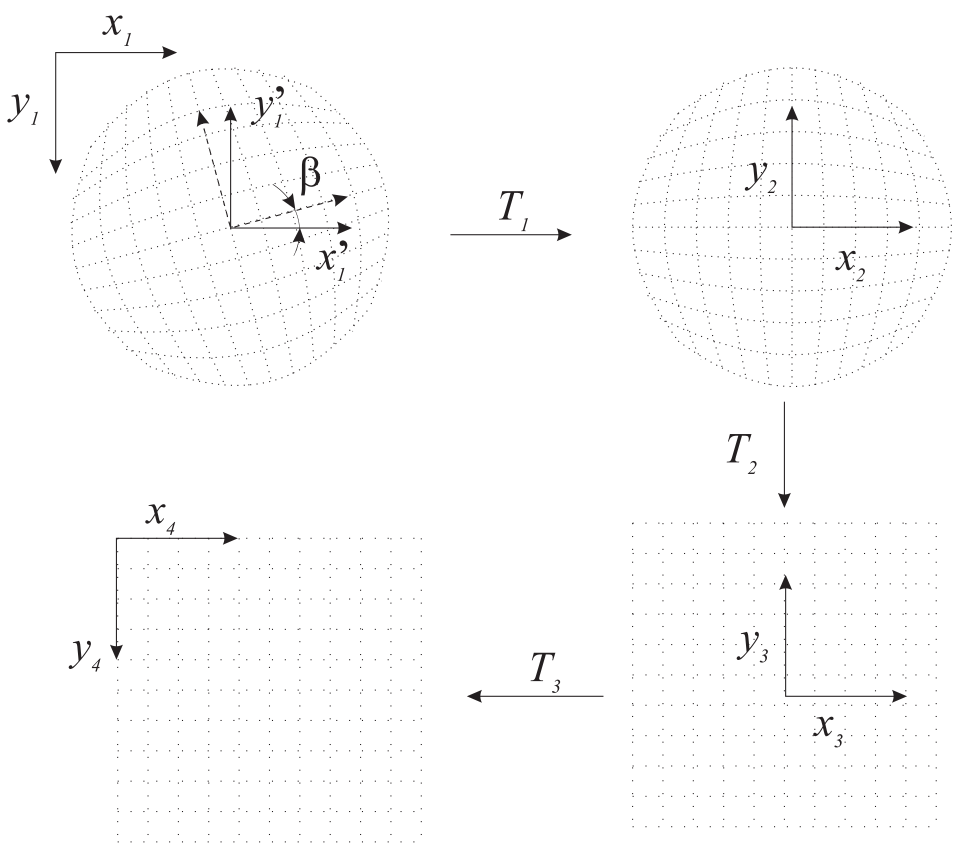

Figure 2. Sequence of transformations, which define relations between pixels on the camera sensor and an object on the court plane.

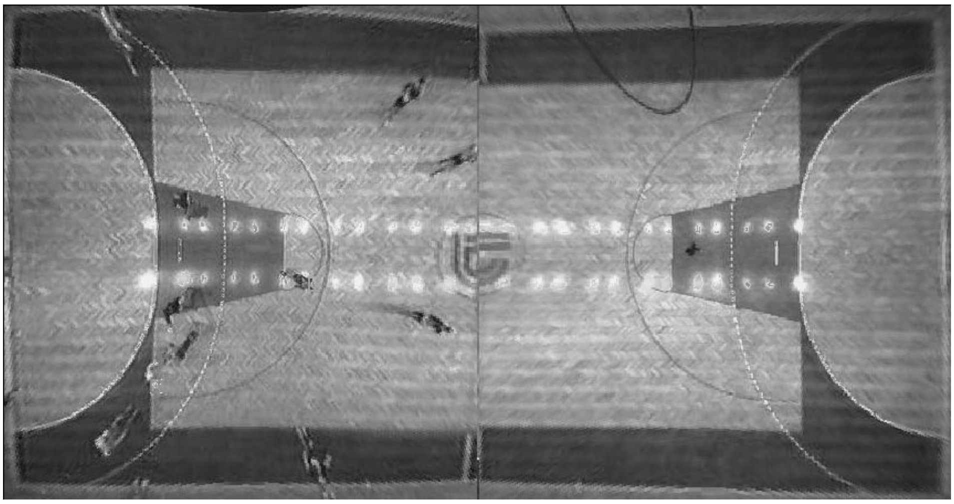

Figure 3. A combined image from both cameras after the radial distortion correction.

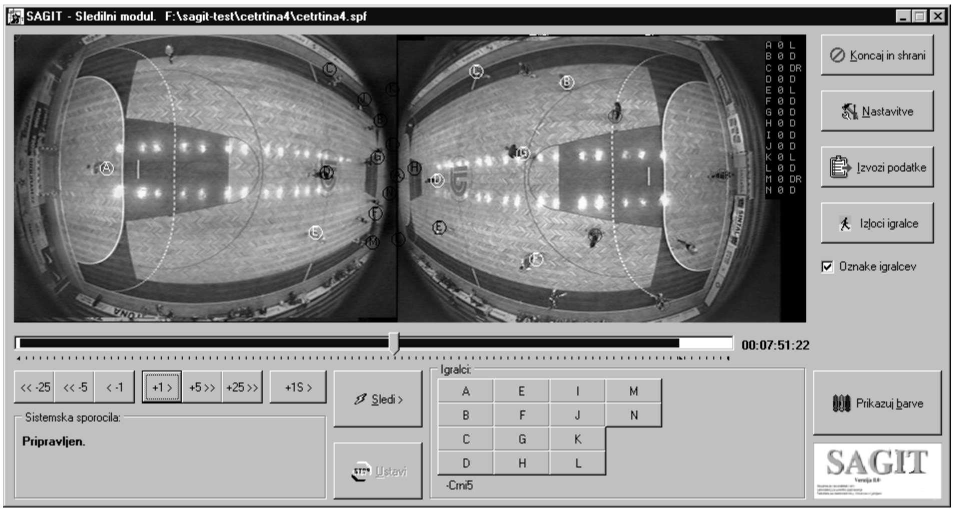

Figure 4. A graphical user interface to the tracking program.

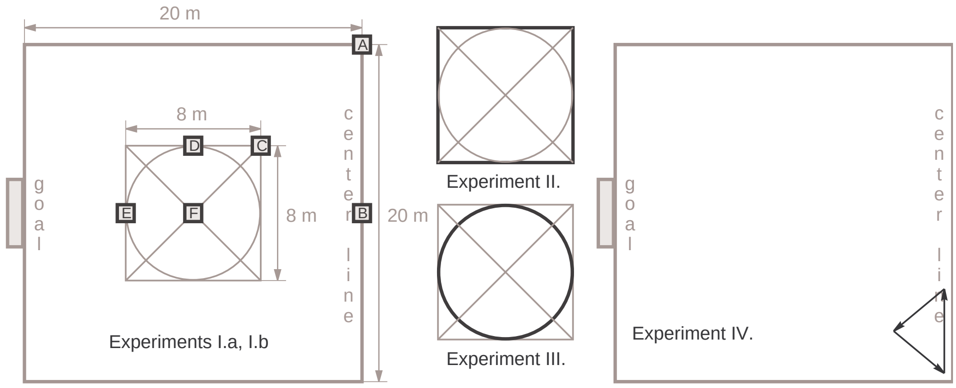

Figure 5. The setup for Experiments I-IV on one of the halves of a handball court. Left: player positions during Experiment I are marked with black boxes. Middle: Reference player trajectories for Experiments II and III shown with thick lines. Right: Approximate player trajectory for the Experiment IV.

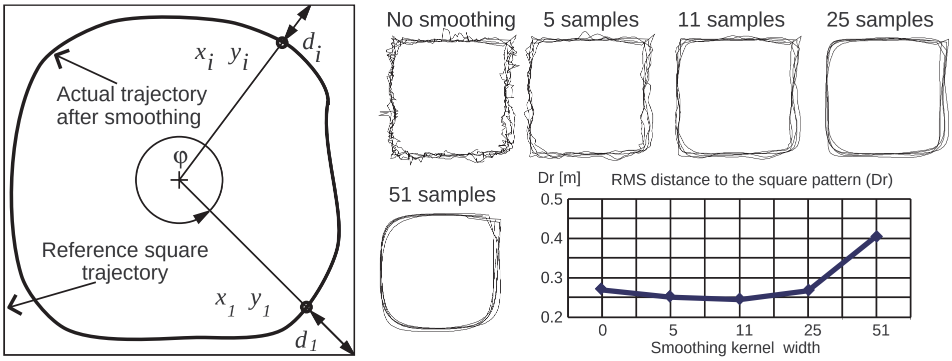

Figure 6. Left: evaluation of trajectory distortion due to smoothing. Right: Effect of different smoothing kernel widths $(2N_F + 1)$ to square trajectory and to RMS radial difference D_r.

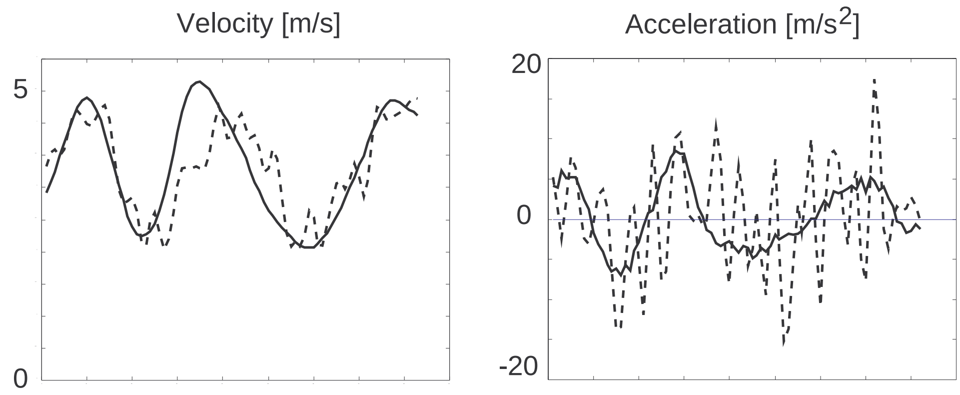

Figure 7. Velocity and acceleration graphs, provided by APAS (dashed line) and our system (solid line).

Table 1
Results of the Experiment I. Smoothing kernel width $(2N_F + 1)$ of 0 denotes no smoothing.

	Still players					Active players				
$(2N_F + 1)$	0	5	11	25	51	0	5	11	25	51
Center										
E_p (m)	0.18	0.18	0.18	0.18	0.18	0.28	0.28	0.28	0.27	0.27
E_v (m/s)	0.98	0.12	0.06	0.04	0.03	2.00	0.61	0.36	0.18	0.09
E_{dc} (m)	7.72	1.82	0.90	0.64	0.49	35.0	16.0	10.3	5.80	3.04
Boundary										
E_p (m)	0.50	0.50	0.50	0.50	0.50	0.64	0.63	0.62	0.61	0.61
E_v (m/s)	1.35	0.19	0.05	0.02	0.02	2.10	0.37	0.16	0.08	0.04
E_{dc} (m)	31.7	6.26	2.04	0.92	0.47	67.5	14.8	6.58	3.26	1.77

Table 2
Tracker error. Numbers in parentheses indicate error in player position near the court boundary. Smoothing kernel width is specified.

Error using:	11 samples wide kernel	25 samples wide kernel
Position, still player:	0.2 (0.5) m RMS	0.2 (0.5) m RMS
Position, active player:	0.3 (0.6) m RMS	0.3 (0.6) m RMS
Velocity, uniform motion at 3 m/s:	0.4 m/s RMS	0.2 m/s RMS
Velocity, uniform motion at 3 m/s (%):	12%	7%
Path length, still player:	+0.9 m/min	+0.6 m/min
Path length, active player:	+10 m/min	+6 m/min