AN INTEGRATED MONITORING AND ANALYSIS SYSTEM FOR PERFORMANCE DATA OF INDOOR SPORT ACTIVITIES

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Abstract

The wish of many sports scientists and trainers is accessing performance diagnoses data of athletes during training or competition. This data concerns the external conditions (e.g. speed and distance) as well as the internal (physical) strain of the players. For collecting this performance data, we have developed an analysis system, consisting of a high resolution video-system together with a wireless sensor network.
In order to record the physiological data (heart rate) of the athlete, a custom-built sensor module has been developed and integrated into a sports shirt. The integrated sensors collect the physiological data. Following the data collection some signal processing is optionally performed and the data is transmitted via a wireless communication technology to a central computer.
We use an adopted Suunto Oy Foot Pod to measure online the current speed of an athlete and compute its overall distance through integration.
In physical and tactical analysis of indoor sport games path information of the players is of great importance. In order to acquire players' path information, a training session or game is captured by a video-system consisting of two cameras which are mounted in the ceiling of a sports hall. The video data is post-processed in order to identify positions of the players and to track all players on the field.
The recorded data of the mobile devices can be processed and visualised online. For example during the sports event, the heart rate can be monitored and the trainer can decide on substituting a player based on his heart rate profile. Another application of our system is the substantial evaluation of the covered distance of basketball players per quarter. The results of this study will be presented in this paper.

Keywords: Performance analysis, video tracking, wireless sensor network

1. INTRODUCTION

For individual sports, mainly endurance disciplines, products are already available for data recording and analysis in various forms. However, a gap exists in the area of performance diagnoses in different types of sports, especially team sports, in which complex movement patterns are common and where contacts between sportsmen occur.
Video-based analysis is a common tool for analysing sport games in technical and tactical aspects. In recent years, video analysis also became an instrument for measuring performance parameters such as the overall covered distance per athlete. Individual performance analysis of players and team strategy investigations require information about the athletes' positions during the games. Hence, many European soccer clubs have equipped their sport grounds with multi camera-systems for player tracking. The advantage of video-based tracking systems is that they are entirely passive; the athlete does not have to wear any kind of sensor or marker.
The most popular tracking system is Amisco Pro distributed by MasterCoach Int. GmbH (AMISCO, 2010). The game is captured with up to eight cam-

eras for a rough online and detailed offline analysis. One or two days after a game, the coach receives a complete analysis including performance data of the players. The disadvantage of Amisco Pro is that it is based on infrared cameras. Thus, the tracking results need to be visualised in a virtual environment. Moreover, many cameras including their synchronisation effort makes the system unaffordable for clubs with less financial resources.

In this paper we describe the Sports Performance Analyzer (SPA). SPA aims on providing a new platform for analysing team sports. With only two ceiling-mounted cameras it is ideally suited for indoor sport activities such as handball, volleyball, basketball, and (ice-) hockey which are the most popular sports in Germany besides soccer (DOSB, 2009).

One part of SPA is a video tracking system that reliably computes the positions of the players during a game. Based on this data we can calculate external information, e.g. overall covered distance, speed, and acceleration of single players. This information is used for further higher level analysis such as team strategy as well as performance and fitness of the players which can help the coaches to improve their training methods.

In addition to the external information, SPA also considers the internal (physical) strain of the players indicated for example by their heart rate (HR). For monitoring the HR we cannot avoid equipping the sportsmen with a sensor module. We have developed a custom-built sensor module which is integrated into a sports shirt in order to minimise the impact on the player. Instead of transmitting the processed features (e.g. HR) to a watch and store the data on this device, we transmit the data wirelessly to a central computer. One additional attribute of SPA is the online measurement of speed and distance: We adopt the commercially available Foot Pod sensors[1] to measure the current speed of an athlete which lets us compute his overall covered distance through integration. All recorded data of the mobile devices is processed and visualised online (in real time).

As shown in figure 1, the SPA system has three main modules: data acquisition (video-system (2.1.2) and wireless sensor network (2.1.1)), tracking (2.1.3) and analysis/visualisation. The acquisition module is responsible for recording video streams from two cameras and the data of the wireless sensor nodes. The recording of video and wireless sensor data streams is synchronised to make further analysis of the data easier. Because the amount of wireless sensor data is small compared to the video data, it can be processed and visualised online. For example during a sports event, the heart rate can be monitored and the coach can decide to substitute a player based on his heart rate profile.

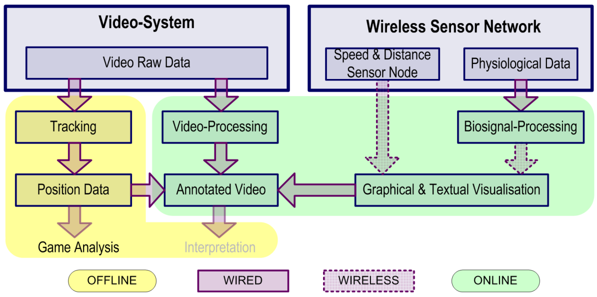

Figure 1: System structure of the Sports Performance Analyzer (SPA).

The video tracking module works offline to extract position data of the players. It utilises the two video streams to produce the positions of the players in real world coordinates (meters) which can be post-processed to gain further information. The analysis/visualisation module processes three inputs: video, wireless sensor, and position data. It produces different visualisations such as graphs and (interactive) videos with annotated information.

In section 2.2 we present a method for the identification of breaks during a basketball game: For five given player trajectories, we introduce different methods for velocity computation to define a game's state, consisting of position and velocity information for every time step. We use this data to train a Gaussian mixture model that can be used to classify the states of an unclassified basketball game as either game or break.

One application of our system is the substantial evaluation of the covered distance of basketball players per quarter. We have recorded and analysed 14 German major league basketball games of the team Paderborn Baskets with regard to the covered distance of every player of the team. Schmidt (2003) presents in a previous study a value of approximately 23km for the covered distance per team and game. Because this analysis was done manually, the statistical data base is only one game. The results of our study will be presented in 3.3.

[1]Suunto or Garmin Foot Pod based on an acceleration sensor of Dynastream Innovations.

2. METHODS

2.1. *MONITORING AND ANALYSIS SYSTEM*

A schematical representation of our system is shown in figure 2. The system consists of two data acquisition modules, namely the *video-system* and the *wireless sensor network*. Both modules are integrated in one software solution (SPA) and they can work independently or together.

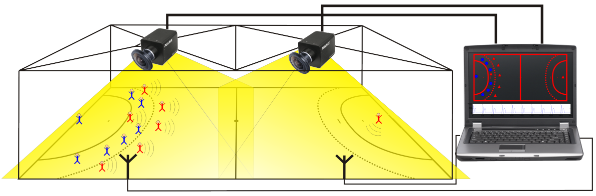

Figure 2: System for capturing match action and recording physiological data.

2.1.1. *WIRELESS SENSOR NETWORK*

One group in our sports department conducts research on skin temperature and skin conductance with the aim to better understand the interaction between physical and mental stress (Baumeister, 2008). To fulfil their request to acquire more relevant data of the athlete than the heart rate (still the most important physiological parameter for sport scientists), we have developed an advanced brest belt module. Our solution is extremely mobile (lighter than 50g) and can collect skin temperature and conductance, heart rate, and additional information from an onboard 3-axis acceleration sensor. The module itself consists of a motherboard with

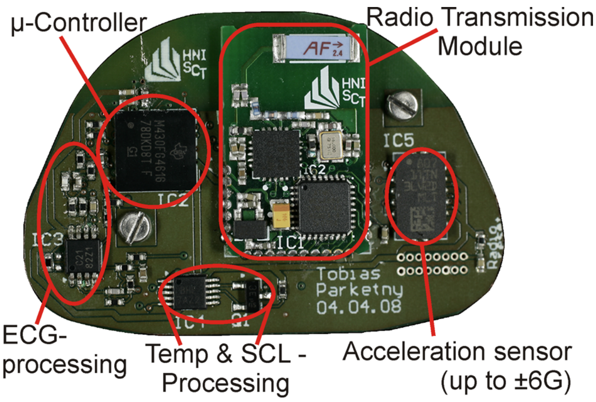

Figure 3: Breast belt module with integrated sensors, evaluation and communication unit as well as power supply.

an additional radio transmission module (daughterboard). For online processing we have equipped the motherboard with a 16bit low-power RISC microcontroller, containing 12bit A/D converters and three operational amplifiers. The microcontroller is powerful enough for processing algorithms, e.g. heart rate detection. Together with the communication stick (daughterboard), the battery lifetime for the complete module is more than 24 hours in operation (general cell coin - 220mAh).

<u>Technical Data Radio Transmission Module:</u>

- Topology: multipoint-to-point (star)
- Frequency band: 2.4GHz
- Range: 30m
- Max. number of sensor nodes: 30
- Less than 10% packet loss
- Power consumption:
  - 35mW in operation (TX mode)
  - 21μW in sleep (power down mode)
  - 70.5μW average[2]

For rough online results of the covered distance ($\pm$10%), we adopt the commercially available Foot Pod products. For a detailed later (offline) analysis, motion capturing (video tracking) methods are used.

2.1.2. *VIDEO-SYSTEM*

The afore mentioned indoor team sports are played on field sizes up to 40m $\times$ 20m. Assuming a minimum hall height of 7m, a field of vision of more than 150 degrees is required. No commercially available lens is able to map this range of vision without distortion. Even using one single fisheye lens will lead to too much information loss close to the back lines. To solve this problem, we have installed two video cameras. They are placed at the hall ceiling, one over the middle of each half of the field, recording the game from a bird's eye view. A fisheye lens is used in order to capture the required view. The selected megapixel cameras are equipped with a Bayer CCD sensor and a Gigabit-Ethernet interface. Each camera is capable of delivering up to 30 frames per second (fps) which causes a data rate of more than 30MB/s. With an up-to-date desktop processor a live preview can only be done with a reduced resolution and/or reduced frame rate. For a preview in high definition with full frame rate a hardware support by graphic accelerators or FPGAs is necessary.

[2] Provided that each packet requires 300μs to be transmitted (32Bytes@1 Mbit/s) and the packet rate is 5Hz.

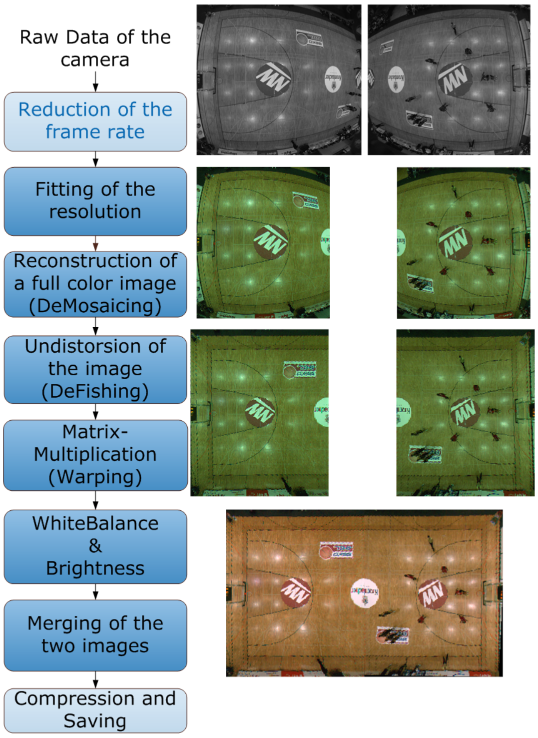

Figure 4: Image pre-processing steps.

As input data for the image pre-processing serve the full raw images of the camera. First, a region of interest (ROI) is selected and a colour reconstruction (DeMosaicing) is done for this part of the image. Then geometrical transformations are executed for producing undistorted images (DeFishing by Look-Up-Table, Warping by Matrix-Multiplication). Finally, a white balancing is performed, the two images are merged together for an online preview, and the video can be saved in a file (avi-container with MPEG4 codec). For later (offline) tracking the raw data is saved with a lossless compression algorithm (lagarith codec).

2.1.3. VIDEO TRACKING

The tracking algorithm used in our system is Template Matching (Lewis, 1995). This method is used to find the parts of an image which match with a reference image (template). A template of the upper part of the body (head and shoulders) is used to search for the player in the next frame. The player's shape changes slightly between two consecutive frames so the template is adapted. The template image is compared to all parts of the searched image and a measure of similarity is computed in each comparison step. The position with the highest value of similarity is the possible position of the template in the searched image.

A strategy based on partitioning of the search space is used to handle the tracking of multiple players. The tracking is done under human supervision to correct the errors that cannot be handled automatically. A detailed description of our tracking algorithm can be found in Monier (2009). The tracking itself is performed on the distorted raw images because no benefit can be achieved by pre-processing the images. As mentioned above, the images are recorded using a fisheye lens. For the purposes of creating distortion-free images and converting the tracked image-positions to real-world positions, a number of transformations have to be applied. The series of steps is presented in figure 5, steps 1-4:

The first step is the undistortion of the points in the fisheye image (**DeFishing**). Because of small variations in the camera position and viewing-angle, a software calibration (**Warping**) has to follow. The corrected world coordinates are mapped from the players **head to** his **foot** position. The final position describes the foot position of the player on the field. All further steps of transformation (5-8) are needed during tracking if a player changes between the two field sides, because the tracking will be continued with the other camera. On the opposite side of the field, the transformations have to be inverted to map the real-world coordinates to the distorted image. As a final step, we smooth the calculated foot coordinates in the world coordinate space using a moderate zero-phase low pass filter[3].

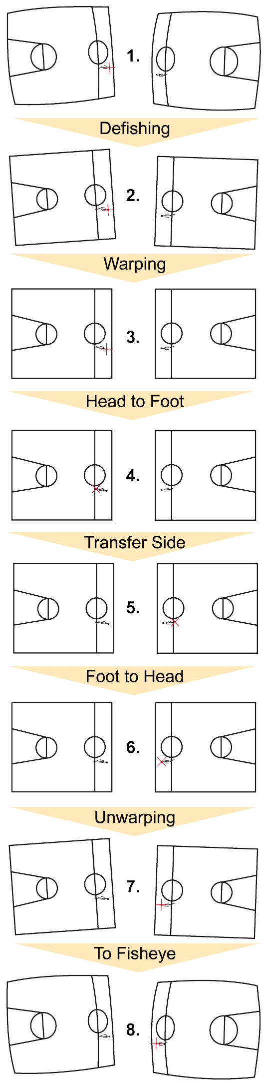

Figure 5: Coordinate Transformations.

[3] Digital FIR-filter, order = 16, $\omega_n = 0.1$.

2.2. NET-TIME COMPUTATIONS

In this section we present a method to divide each quarter of a basketball game into *action* and *break* parts. These results can be used for post-game analysis, for example to calculate the distances covered by the players or their average velocities. A similar application can be found in (Perse, 2009).
Although the parameters in the presented method are fine tuned for basketball games, this method could be adapted to other team sport games.

2.2.1. DATA

We have tracking data from a number of basketball games available. This data consists of the positions of all active players over each quarter. It is used to construct a state $(position, velocity)$ of the game for every timestep t_i, $i = 1, \dots, N$.
For the position information we use the five player positions $(x_{i,1}, y_{i,1}) \dots (x_{i,5}, y_{i,5})$ of the five active players in each timestep t_i and calculate the average position of the players via

$$\begin{pmatrix} x_i \\ y_i \end{pmatrix} = \frac{1}{5} \sum_{p=1}^{5} \begin{pmatrix} x_{i,p} \\ y_{i,p} \end{pmatrix} . \qquad (1)$$

We propose a total of five different methods to compute the velocity data. Two of these methods generate a scalar value whereas the other three methods yield a two dimensional vector as a result. We will compare these methods in section 3.2. For all methods we need a time interval of $t_{s,i} = t_i - t_{i-1}$ to scale velocities to m/s. In our case the length of all time intervals is constant and equal to the frame rate of about $1/30$th of a second, thus $t_{s,i} = t_s = const.$

I. The first method is to calculate the vector from one average trajectory point (as introduced in (1)) to the next:

$$v_i = \frac{1}{5\, t_s} \sum_{p=1}^{5} \left(\begin{pmatrix} x_{i,p} \\ y_{i,p} \end{pmatrix} - \begin{pmatrix} x_{i-1,p} \\ y_{i-1,p} \end{pmatrix} \right) .$$

II. For the second method, we simply compute the norm of velocity I.

$$v_i = \frac{1}{5\, t_s} \left\| \sum_{p=1}^{5} \left(\begin{pmatrix} x_{i,p} \\ y_{i,p} \end{pmatrix} - \begin{pmatrix} x_{i-1,p} \\ y_{i-1,p} \end{pmatrix} \right) \right\|_2 ,$$

thus reducing the dimension of the velocity information to one.

III. The third method is a variation of II.:

$$v_i = \frac{1}{5\, t_s} \sum_{p=1}^{5} \left\| \begin{pmatrix} x_{i,p} \\ y_{i,p} \end{pmatrix} - \begin{pmatrix} x_{i-1,p} \\ y_{i-1,p} \end{pmatrix} \right\|_2 .$$

This value will always be greater or equal than method II. It represents the varying velocities of the players better, because the velocities of two players moving in opposite directions do not cancel each other out.

The last two methods represent the velocity information in polar coordinates. Both utilise the angle φ between the x-axis and the velocity vector (see I.), which is defined[4] as

$$\varphi = \operatorname{atan2}\left(\sum_{p=1}^{5} \left(x_{i,p} - x_{i-1,p} \right), \sum_{p=1}^{5} \left(y_{i,p} - y_{i-1,p} \right) \right) .$$

IV. The fourth method is a combination of the angle φ and method II.:

$$\begin{pmatrix} v_{i,1} \\ v_{i,2} \end{pmatrix} = \left(\frac{1}{5\, t_s} \left\| \sum_{p=1}^{5} \left(\begin{pmatrix} x_{i,p} \\ y_{i,p} \end{pmatrix} - \begin{pmatrix} x_{i-1,p} \\ y_{i-1,p} \end{pmatrix} \right) \right\|_2 , \varphi \right)^T .$$

V. Finally, the fifth version is a combination of φ and method III.:

$$\begin{pmatrix} v_{i,1} \\ v_{i,2} \end{pmatrix} = \left(\frac{1}{5\, t_s} \sum_{p=1}^{5} \left\| \begin{pmatrix} x_{i,p} \\ y_{i,p} \end{pmatrix} - \begin{pmatrix} x_{i-1,p} \\ y_{i-1,p} \end{pmatrix} \right\|_2 , \varphi \right)^T .$$

For each timestep we get a three or four component vector X_i that characterises the current state of the game:

$$X_i = (x_i, y_i, v_i) \in \mathbb{R}^3 \text{ or } \quad X_i = (x_i, y_i, v_{i,1}, v_{i,2}) \in \mathbb{R}^4 .$$

Additionally to the data described above, we divided 23 quarters manually into action and break sections. This knowledge can be used to train an appropriate model for the labelling of new quarters.

2.2.2. GAUSSIAN MIXTURE MODEL

We use two Gaussian mixture models (see (Rasmussen, 2006)), one to characterise the action states and one for the break states. These models are trained using the data from section 2.2.1 and

[4] atan2 is a variation of the inverse tangent function and places angles correctly in all four quadrants.

used for the classification of unclassified data. In a Gaussian mixture model a sum over k Gaussian distributions is used to approximate the state of a system

$$P(X_i|m_l) = \sum_{j=1}^{k} \alpha_j P(X_i|\mu_j, \Sigma_j)\,,$$
$$\text{and} \sum_{j=1}^{k} \alpha_j = 1\,,$$

with $m_l \in \{action, break\}$. We separate our data into two sets: those states when the game's time was running, and those states when the clock was stopped. With these sets, two Gaussian mixture models are trained using the EM-Algorithm (see section 3.2 for details). The training returns two sets of parameters, $(\alpha_j^{(a)}, \mu_j^{(a)}, \Sigma_j^{(a)})$, $j = 1, \ldots, k$, for the points belonging to the action set and $(\alpha_j^{(b)}, \mu_j^{(b)}, \Sigma_j^{(b)})$, $j = 1, \ldots, k$, for the points belonging to the break set.

Our goal is to divide a new quarter into two sets action and break. This can now be done by classifying each state using the models explained above. We use Bayes's rule to compute the probability of a given state X_i of the game to belong to either action or break:

$$P(m_l|X_i) = \frac{P(X_i|m_l)P(m_l)}{P(X_i)}\,. \tag{2}$$

Because the length of one quarter is fixed to 10 minutes, $P(action)$ equals 600s divided by the total length of the quarter in seconds, and $P(break) = 1 - P(action)$. We say, a state belongs to the action phase, if $P(action|X_i) \geq P(break|X_i)$ and it belongs to the break phase, if $P(action|X_i) < P(break|X_i)$. Thus it is not neccessary to know $P(X_i)$ in equation (2) to classify a state.

Results of this method will be presented in 3.2.

3. RESULTS

In this section we are going to present evaluation results of the different modules of our SPA system. Our developed heart rate sensor node is capable of transmitting every single heart beat so that a beat-to-beat analysis becomes possible. Moreover, all wireless sensor data can be visualised online in our SPA software. Unfortunately, the use of these breast belt modules is not allowed in official basketball games, so that we do not have any physiological data to augment our tracking data.

3.1. VIDEO TRACKING RESULTS

Regarding the video-system, the processing rate without correction (f_{auto}) for tracking five players (NoP) is 10fps. The average number of corrections (cR) is 0.004 corrections per frame and player. The average correction time (cT) for one error is 3.3 seconds. Finally, the frame rate for tracking including correction (f_{corr}) is 6fps (Monier, 2009).

$$f_{corr} = \frac{1}{1/f_{auto} + cT \cdot cR \cdot NoP}$$

Compared to the source frame rate of the video (30fps), the processing time is five times longer than the gross playing time. Considering the accuracy of the tracking system, we ran several test cycles which resulted in an accuracy of above 94% (Paier, 2009).

One main application of our system is the evaluation of the covered distance to generate an individual profile for each player in basketball games. The primary output of the video tracking is the filtered position data which is used to calculate the covered distance of the players in the game. For the gross covered distance, we consider all players of the host team for the complete game including breaks[5]. To extract the net covered distance from the position data, we have tested automated methods. Before we present our results in section 3.3 we are going to validate the methods introduced in section 2.2.

3.2. NET-TIME COMPUTATION RESULTS

The numerical computations are carried out using Matlab and its Statistics Toolbox. The `gmdistribution.fit` function, which is part of this toolbox, estimates the parameters for the two Gaussian mixture models using the expectation maximization (EM) algorithm.

To judge the effectiveness of our algorithms, we compare the automatic labelling using the Gaussian mixture model with the manual labelling. We compute the number of correctly classified trajectory points (those points, where automatic and manual labelling yield the same result) and divide it by the total number of points. This correctly classified ratio measures the performance of our algorithm.

[5]Except for official team timeouts.

k	I	II	III	IV	V
	velocity computation method				
3	0.7888	0.7724	0.8279	0.7725	0.8409
4	0.8076	0.8088	0.8587	0.8092	0.8603

Table 1: Ratio of correctly classified points using the five different velocity computation methods for $k = 3$ and $k = 4$.

Several parameters have to be adjusted in order to maximise the performance of the classification algorithm. The first parameter is the number of Gaussian distributions for the mixture model. We tested $k = 3, 4, 5$ distributions, whereas for $k = 5$ the EM-Algorithm did not converge. The second parameter is the velocity computation method. We carried out all computations using the five proposed methods. The results for $k = 3, 4$ and for the five velocity computation methods are shown in table 1.

Since the best results could be achieved for $k = 4$ and velocity computation method 5, we use these values throughout the rest of the computations.

As a result of the process described in section 2.2.2 we receive a classification of a quarter into action and break parts, that still contains unrealistically many switches between the two. To overcome this problem, we perform a two step post-processing. First, we filter the resulting data using a zero phase digital lowpass filter. Secondly, we remove break sequences, that are less than 5s long. Our analysis of the manually labeled quarters shows us, that only 3 of 407 or 0.74% of all breaks are less than 5 seconds long. Hense, to cut off below 5s seems reasonable.

Using the above described post-processing steps, the correctly classified value improves to an average of 90.42% correctly classified points.

In table 2 our final testing results are shown. We computed the sum of the net distances the five players cover in each quarter using the manual and the automatically computed action and break division. On average the automatically computed value differs from the manually extracted values by 7.75%.

Game	Qtr	d_{man} [km]	d_{auto} [km]	Dev. [%]
1	1	5.702	5.664	0.67
	2	6.112	5.471	11.73
	3	5.513	5.308	3.86
	4	5.388	5.406	0.33
2	1	5.693	5.428	4.87
	2	6.205	5.675	9.34
	3	5.361	5.098	5.16
	4	5.659	5.327	6.24
	5	2.992	2.600	15.09
3	1	6.063	5.416	11.93
	2	5.900	5.455	8.15
	3	5.751	5.496	4.64
	4	6.095	6.609	7.78
4	1	6.219	5.533	12.40
5	1	5.556	5.182	7.22
	2	5.238	4.991	4.95
	3	5.522	4.986	10.76
	4	5.291	4.988	6.09
6	1	6.367	5.425	17.36
7	1	5.910	5.435	8.73
	2	5.400	5.299	1.90
	3	5.995	5.344	12.18
	4	6.290	5.889	6.80
avg.		**5.662**	**5.306**	**7.75**

Table 2: Comparison of the covered net distances of the basketball players. We have manually divided a total of 23 quarters of 7 games into action and break parts. We used this data to calculate the cumulative net distances d_{man} covered by the five players in each quarter (see column three). In column four we present the net distances d_{auto}, that were calculated using the algorithms presented in section 2.2. In column five the deviation of d_{auto} from d_{man} is shown. The last row shows the average of all distances and deviations.

3.3. COVERED DISTANCES

We have analysed a total of 56 quarters from 14 randomly chosen games over two and a half years. Table 3 and figure 6 present the results in textual and graphical form respectively.

	Q1	Q2	Q3	Q4	SUM
GROSS	6996.3	7386.6	7243.0	7901.0	29524.0
NET	5867.0	5545.0	5648.6	5580.6	22641.2

Table 3: Mean gross and net covered distance of a basketball team per quarter.

We can confirm the results of Schmidt (2003), who calculated 23185.6m in average for one team per game.

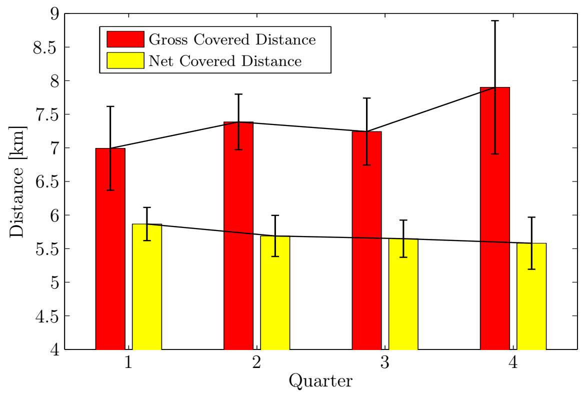

Figure 6: Mean gross and net covered distance of a basketball team per quarter and the standard deviation.

4. DISCUSSION

An application of the tracking system is the substantial evaluation of the covered distance of basketball players per quarter. Additional information, e.g. the covered distance of the players classified by their positions and into different speed ranges can be computed with little effort. Moreover, considering the players' positions, a position specific performance profile can be generated.
As an enhancement of the sensor network we apply receiver diversity technology for better energy-efficiency and communication reliability, respectively. Our system also provides large flexibility for further design improvements, e.g. the implementation of the 3-axis acceleration sensor presented in Christ (2010).
A small drift of the template out of the tracked part presents a problem in the video tracking system. To overcome this problem and to reduce the number of corrections we are going to enhance the tracking algorithm by making use of colour information in future versions. As an alternative to the existing tracking method, we actually test different tracking algorithms (e.g. Particle Filter tracking).
The net-time computation algorithm presented in 2.2 already works quite reliable, but its accuracy could be further improved by training the model with more data. Instead of using manually generated data, we are going to use statistical *play-by-play* data, provided by the Beko BBL.

5. CONCLUSIONS

In this paper we have presented our Sports Performace Analyzer (SPA) system. SPA consists of a video tracking system for indoor sport activities and a sensor network that measures physiological parameters of the players. It makes it possible to visualise the actual performance of the players during training or competition. This knowledge can be used by sport experts to optimise training patterns and game strategies.

Acknowledgements

We wish to thank Paderborn Baskets 91 e.V., Beko Basketball Bundesliga (Beko BBL), Swiss Timing Ltd., the Paderborn Center for Scientific Computations, and many students for their help and support.

AMISCO 2010. *http://213.30.139.108/sport-universal/uk/sources/PDF/sup.pdf*.

Baumeister J., Reinecke K., Schnittker R., Weiß M. (2008). Influence of cognitive stimuli during physical load on skin conductance response. *European Journal of Applied Physiology (in preparation)*.

Christ, P., Rückert, U., & Mielebacher, J. (2010). Detection of body movement and measurement of physiological stress with a mobile sensor node in obesity prevention. *The 10th Australasian Conference on Mathematics and Computers in Sport (Preprint submitted to MATHSPORT 2010)*, Darwin, Australia, 5 - 7 Jul 2010.

DOSB - Deutscher Olympischer Sportbund. (2009). Bestandserhebung 2009, *www.dosb.de/de/service/statistiken*.

Lewis, J. P. (1995). Fast normalized cross-correlation. *Vision Interface. Canadian Image Processing and Pattern Recognition Society*.

Monier, E., Wilhelm, P., & Rückert, U. (2009). Template Matching Based Tracking of Players in Indoor Team Sports. *Third ACM/IEEE International Conference on Distributed Smart Cameras (ICDSC 2009)*, Como, Italy, 30 - 2 Sep 2009.

Paier, D., Schnittker, R., Reinecke, K., Wilhelm, P., Preis, R., Weiß, M., Baumeister, J. (2009). Physiologische Spielbeobachtung - Testgüte des Videotrackings im Sports Performance Analyzer (SPA). *Deutsche Zeitschrift für Sportmedizin 60(7-8)*.

Perše M., Kristan M., Kovačič S., Vučkovič G., Perš J. (2009). A trajectory-based analysis of coordinated team activity in a basketball game. *Computer Vision and Image Understanding, Volume 113, Issue 5*, 612-621.

Rasmussen, C., Williams, C. (2006). Gaussian Processes for Machine Learning. MIT Press. Cambridge, Massachusetts.

Schmidt, G., & von Benckendorf, J. (2003). Zur Lauf- und Sprungbelastung im Basketball. *Leistungssport, 33 (2003)*, 42-48.

Wilhelm, P., Monier, E., Xu, F., & Witkowski, U. (2008). Analysis of Indoor Team Sports Using Video Tracking and Wireless Sensor Network. *Current trends in Performance Analysis: World Congress of Performance Analysis of Sport VIII*, 345-348.