Multiview Human Body Tracking of Hurdle Clearance: A Case Study

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Abstract: This initial research is a case study that uses a multiview human body tracking method as a tool to measure hurdle clearance kinematic parameters. This study is conducted on a hurdler representing a high sport level, who is a participant in the European and World Championships and the Olympic Games. The video recordings were made under simulated starting conditions of a 110 m hurdle race. Kinematic parameters are estimated based on the analysis of images from a multicamera system. The images were recorded with a resolution of 1920x1080 and with a frequency of 100 Hz. The proposed method does not use any special clothes, markers or other estimation support techniques. The parameters of the hurdle clearance were compared with the parameters obtained from ground truth poses. Mean Absolute Error and Mean Relative Error were used as the quality criteria.

1 INTRODUCTION

Hurdling is a group of athletic events in which technical preparation is very important. The hurdle race technique involves running over 10 hurdles that are from 0.84 to 1.07 m high, depending on the event. In these races, the technique evaluation is mainly focused on certain phases of human motion (Iskra, 2012). The existing studies are devoted to the kinematic analysis of the so called "hurdle clearance" (Čoh, 2003; Čoh et al., 2008). For example, the paper by Čoh (Čoh, 2003) analyses selected kinematic parameters (e.g., height of center of mass, angle of placement of a leg) that describe the Colin Jackson's hurdle clearance technique. Meanwhile, the paper by (Salo et al., 1997) contains a three-dimensional (3D) biomechanical analysis of sprint hurdles. To estimate the parameters (e.g., take-off distance, horizontal velocity), two cameras (25 Hz) with "Kine analysis" software were used. The main objective here was to determine and compare selected biomechanical parameters in two groups of men and two groups of women at different competitive levels.

There are a number of computer vision methods that play an increasingly important role in supporting sports training. For example, (Reyes et al., 2016) developed an algorithm that processes underwater video sequences for swimmer detection and tracking based on light absorbance in conjunction with compressive sensing concepts. The developed algorithm was tested on two video sequences. Meanwhile, motion detection and tracking methods have been used to analyse athletics videos (Ramasso et al., 2009; Panagiotakis et al., 2006). Another solution that uses computer vision techniques is a system for tracking players in indoor team games, such as in handball (Perš and Kovacic, 2000). Indoor sports have also been analysed by (Kim and Cho, 2016), who proposed a robust multi-object tracking algorithm for acquiring object oriented multi-angle videos. In this algorithm, multiple camera images are integrated using homography based transformation in order to cover large areas of interest. A motion tracking of a tennis racket using a markerless system with a monocular camera has been presented by (Elliott et al., 2014). Furthermore, (Sheets et al., 2011) used a markerless motion capture system to evaluate kinematic differences at the lower back, shoulder, elbow, wrist, and racquet between the flat, kick, and slice serves. In this study, seven male players were tested on an outdoor court in daylight conditions. A method to identify sports players in videos has been proposed by (Hamatani et al., 2016), where the identification was achieved by motion feature matching between (unknown) players in videos (the features were obtained from estimated postures in the videos) and wearable sensors whose

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IDs were already known. The experimental results showed that the proposed method successfully identified 10 players with 72% accuracy. Cheng et al. (Cheng et al., 2004) have shown that the proposed motion descriptor can successfully classify the following four sports types: sprint, long-distance running, hurdling and canoeing. Their experimental results were obtained using video material from the 1992 Barcelona Olympic Games. Finally, Zhang et al. (Zhang et al., 2017) proposed an algorithm to track player actions from a sports video sequence. Their method combines a particle filtering and mean shift in order to effectively trace a fast-moving target.

This study proposes a multiview markerless method of human body motion tracking to estimate hurdle clearance parameters. In our analysis, nine distance parameters and eight angle parameters are taken into account. These parameters are estimated based on the analysis of image sequences captured with a multicamera system. The tracking system that we have developed does not use any special clothes, markers or other techniques supporting estimation. This study is a continuation of research presented in our previous paper (Krzeszowski et al., 2016). To the best of our knowledge, the method of multiview markerless tracking is used for the first time for measurement of hurdle clearance kinematic parameters.

2 METHODS

2.1 Multiview Human Motion Tracking

The purpose of human body tracking is to estimate a pose that reflects as closely as possible a real pose. It should be noted that capturing the 3D position of a human body is a very difficult task (John et al., 2010; Kwolek et al., 2012). The main problems include: high dimensional search space, image noise, the large variability in the appearance of the tracked humans and environment, the complexity of human motion and the fact that particular parts of the body are often obscured. Although these issues can be solved in many different ways, the most common methods use simplified human body models (Deutscher and Reid, 2005; John et al., 2010; Kwolek et al., 2012; Krzeszowski et al., 2016), uniform background (Deutscher and Reid, 2005), and also properly selected clothes of the tracked human body in order to facilitate the determination of distinctive features. In the process of tracking, a particle filter algorithm (Sidenbladh et al., 2000) or its modified versions are frequently used (Deutscher and Reid, 2005). However, these algorithms require a significant number of particles in

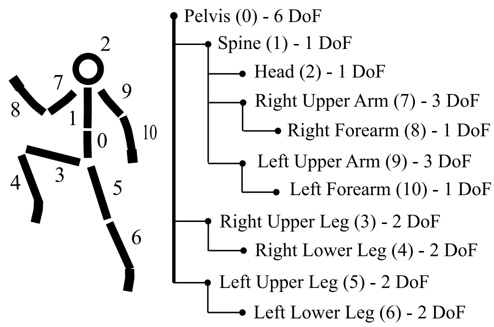

Figure 1: 3D human body model (left), hierarchical structure (right).

order to find the correct solution, which directly impacts on the time needed for computations. Therefore, in the human body motion tracking process, particle swarm optimisation algorithms (Kennedy and Eberhart, 1995; John et al., 2010; Kwolek et al., 2012; Krzeszowski et al., 2016) are mostly used because they enable a more effective exploration of the search space.

A 3D model is used to determine the human body pose; that is, the position and orientation in space as well as the angles between the joints. The model that is used in this research is based on the kinematic tree structure consisting of 11 segments, each of which is represented by a truncated cone (Kwolek et al., 2012; Deutscher and Reid, 2005), see Figure 1. The space in which the model operates is determined by the number of degrees of freedom (DoF). Each segment includes up to three DoFs that define its orientation; the only exception is the pelvis, which contains three additional segments defining the model translation. The model used in this paper includes 24 DoFs. In our method both the model configuration and the pose of a human body in the first frame of a sequence of images are selected manually.

The particle swarm optimisation algorithm (PSO) (Kennedy and Eberhart, 1995; Krzeszowski et al., 2016) is used in the motion tracking process. In our method, the position of a particle represents the hypothetical state (pose) of an athlete. The best solution is selected based on a fitness function value. The fitness function determines the degree of similarity between the real and the estimated human pose. In this study, the fitness function consists of two components. The first is determined on the extracted human silhouette, whereas the second is based on the edge distance map (John et al., 2010; Krzeszowski et al., 2016). The value of the function for the cth camera is calculated using the following equation:

$$f^c(\mathbf{x}) = 1 - (af_1^c(\mathbf{x}) + bf_2^c(\mathbf{x})) \quad (1)$$

where $\mathbf{x}$ is the human body pose (the position of a particle) and a, b are experimentally chosen weighting factors. The $f_1^c(\mathbf{x})$ function describes the degree of overlap of the rendered 3D model with the extracted silhouette, and $f_2^c(\mathbf{x})$ is determined by comparing the 3D model edges with the image, including the map with pixel distances from the nearest edge. The fitness function for all cameras is determined according to the following equation:

$$f(\mathbf{x}) = \frac{1}{C}\sum_{c=1}^{C} f^c(\mathbf{x}) \tag{2}$$

where $C = 3$ is the number of cameras.

2.2 Data Acquisition

The proposed method was applied for two image sequences. The recorded athlete was a participant in the European and World Championships and the Olympic Games. The data were registered in the athletics hall with a tartan track. Throughout the research, the sequence of passing the third hurdle in the regulation conditions of 110 m race (hurdle height: 1.067 m, distance between the hurdles: 9.14 m) was captured. The sequences, in the form of color images of size 1920x1080, were captured with three Basler Ace acA1920-150uc cameras with the frequency of 100 Hz. Figure 2 illustrates how the cameras were arranged in the athletics hall. The parameters of the cameras have been estimated using the TSAI calibration method (Tsai, 1987).

2.3 Evaluation of the Parameters

Five key points (P_1–P_5) were analysed in three phases of hurdle clearance. The analysis included 17 parameters, which are presented in Figure 3. The parameters were selected based on the literature review (Iskra, 2012; Čoh, 2003). The quality of the tracking was evaluated based on the estimated pose and the ground truth pose. The ground truth pose was obtained by manually matching the 3D model to the athletes on

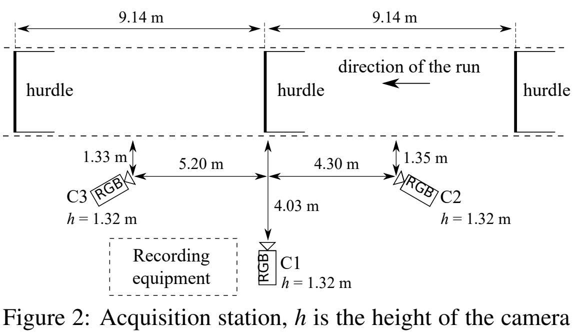

Figure 2: Acquisition station, h is the height of the camera from the ground.

those images that contained the five key poses characteristic for hurdle clearance (Figure 3). The error level was determined for each parameter. The parameters were estimated by the implemented algorithm and they were then compared with the values of the ground truth reference model (the model was manually adjusted to the analysed images). The quality criterion was defined for each parameter as:

$$e_n = |\hat{X}_n - X| \tag{3}$$

$$MAE = \frac{1}{N}\sum_{n=1}^{N} e_n \tag{4}$$

where e_n is the absolute error, N is the number of algorithm repetitions, $\hat{X}_n$ is the estimated value (determined by the algorithm), X is the ground truth value, and MAE is the mean absolute error. Moreover, the mean relative error was calculated from the following formula:

$$MRE = \frac{1}{N}\sum_{n=1}^{N} \frac{e_n}{X} \cdot 100 \tag{5}$$

3 EXPERIMENTAL RESULTS

An example of the tracking results for the selected sequence for three views is shown in Figure 4. The basic statistics for the analysed parameters, the ground truth value X, and the errors MAE and MRE are presented in Table 1. These results were obtained for $N = 10$ repetitions of the tracking algorithm. The error analysis shows that among all of the distance parameters, the estimation of CM height over hurdle in P_3 (h_3) for sequence 1 is determined with the greatest MRE error. This error is equal to 13.3% ($MAE = 37.3$ mm). In the case of sequence 2, this error is smaller and equal to 7.9% ($MAE = 23.6$ mm). Krzeszowski et al. (Krzeszowski et al., 2016) used a monocular motion tracking system, and this parameter was determined with $MAE = 30.5$ mm and $MRE = 8.3\%$. The smallest MRE error for both sequences is obtained for the CM distance from the hurdle in P_1 (w_1). This error is equal to 0.5% ($MAE = 13.5$ mm) in sequence 1 and it is equal to 0.7% ($MAE = 17.3$ mm) in sequence 2. In the work by (Krzeszowski et al., 2016), the errors for w_1 were $MAE = 25.8$ mm and $MRE = 1.0\%$.

By analysing the angular errors it can be seen that the smallest MRE error was obtained for the angle of the trial leg in P_2 (α_2) and it is equal to 2.4% ($MAE = 1.6°$) in sequence 1 and 4.1% ($MAE = 2.9°$) in sequence 2, whereas the angle of inclination of the torso in P_3 (γ_3) is determined with the greatest error $MRE = 40.1\%$ ($MAE = 16.4°$) in sequence 1 and $MRE = 32.9\%$ ($MAE = 13.4°$) in sequence 2. In the

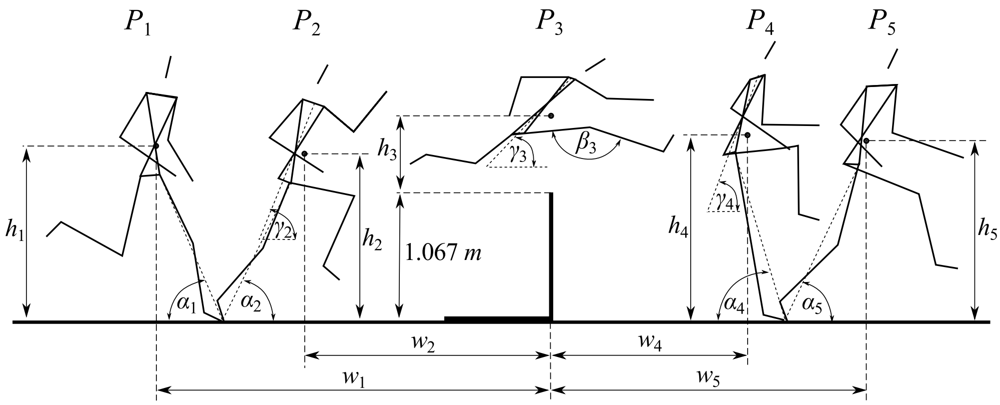

Figure 3: Key points and parameters of hurdle clearance: P_1 is the braking point in take-off phase, P_2 is the propulsion point in take-off phase, P_3 is the center of mass (CM) over the hurdle in flight phase, P_4 is the braking point in landing phase, P_5 is the propulsion point in landing phase, h_1 is the height of CM, w_1 is the CM to hurdle distance, α_1 is the angle of the trial leg, h_2 is the height of CM, w_2 is the CM to hurdle distance, α_2 is the angle of the trial leg, γ_2 is the angle of inclination of the torso, h_3 is the height of CM (over the hurdle), β_3 is the angle of the lead leg, γ_3 is the angle of inclination of the torso, h_4 is the height of CM, w_4 is the CM to hurdle distance, α_4 is the angle of the lead leg, γ_4 is the angle of inclination of the torso, h_5 is the height of CM, w_5 is the CM to hurdle distance, and α_5 is the angle of the lead leg.

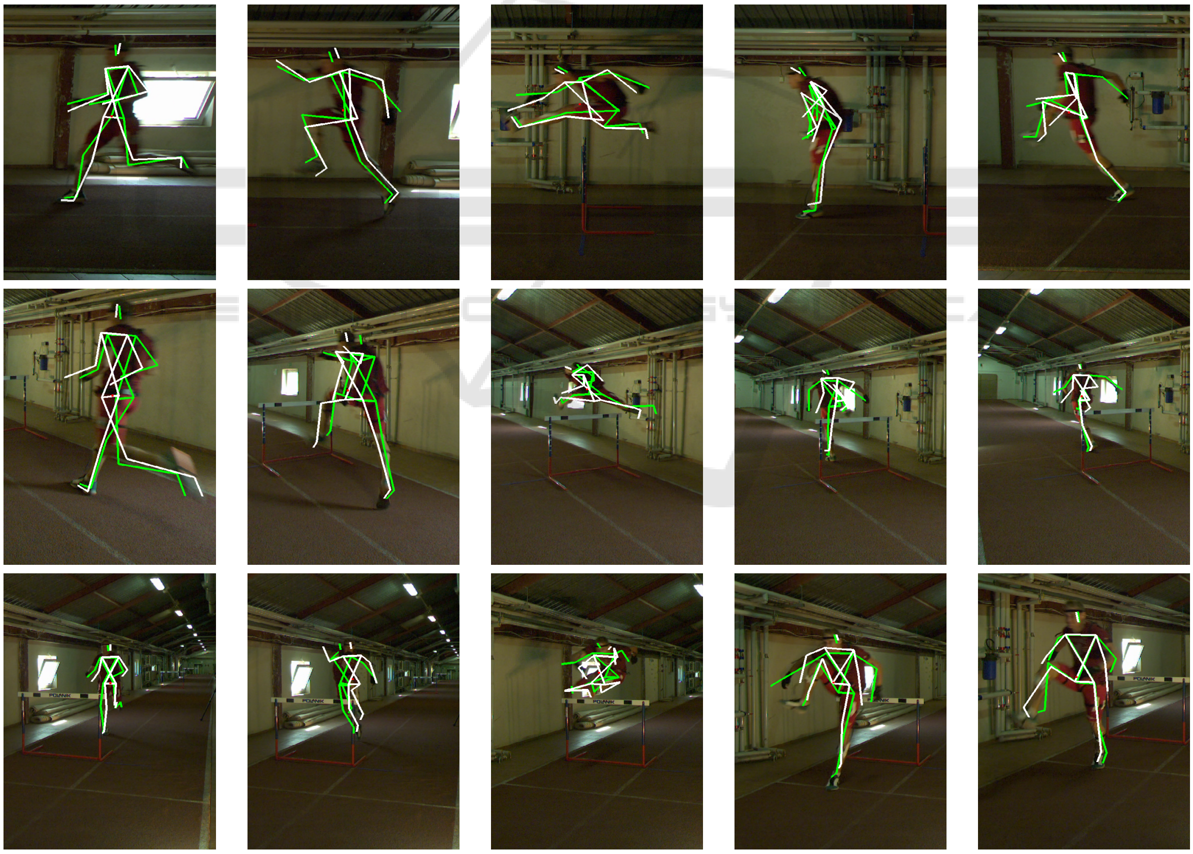

Figure 4: Example of tracking results on sequence 1, frames #5, 19, 40, 57, 65; the green skeleton is the ground truth pose and the white skeleton is the estimated pose.

work by (Krzeszowski et al., 2016), the estimation errors for the mentioned parameters were $MAE = 7.8°$ and $MRE = 10.1\%$ for α_2, and $MAE = 5.9°$ and $MRE = 12.1\%$ for γ_3.

It should be emphasised that in this paper the errors were calculated for two particular sequences,

Table 1: Measured parameters and errors; units: h, w [mm], α, γ, β [°], MRE [%].

	Sequence 1					Sequence 2				
Parameter	$\bar{x}$	sd	X	MAE	MRE	$\bar{x}$	sd	X	MAE	MRE
P_1										
h_1	961.7	8.2	953.5	9.2	1.0	966.2	20.3	959.1	14.8	1.5
w_1	2513	15.1	2502	13.5	0.5	2565	14.9	2550	17.3	0.7
α_1	66.4	2.7	62.4	4.0	6.4	64.6	3.7	61.4	4.2	6.9
P_2										
h_2	1155	10.1	1159	8.7	0.8	1123	11.4	1130	11.5	1.0
w_2	1541	11.7	1525	16.2	1.1	1623	15.3	1605	18.4	1.1
α_2	67.5	2.1	67.2	1.6	2.4	69.8	2.5	72.0	2.9	4.1
γ_2	76.3	4.2	74.9	3.8	5.0	75.9	4.3	75.9	3.1	4.1
P_3										
h_3	246.7	21.3	280.8	37.3	13.3	287.9	29.2	297.9	23.6	7.9
β_3	133.8	29.6	164.0	30.2	18.4	139.0	24.5	164.0	25.7	15.7
γ_3	57.2	5.4	40.8	16.4	40.1	53.9	8.2	40.8	13.4	32.9
P_4										
h_4	1176	45.5	1099	80.1	7.3	1144	30.5	1100	43.2	3.9
w_4	1128	26.3	1175	46.9	4.0	1235	29.3	1296	60.8	4.7
α_4	73.2	6.9	70.4	6.0	8.6	74.7	3.9	68.0	6.8	10.0
γ_4	58.9	10.8	65.8	10.5	15.9	53.0	11.4	65.8	14.4	22.0
P_5										
h_5	1118	84.9	1041	87.2	8.4	1094	40.3	1049	49.0	4.7
w_5	1670	71.1	1683	53.8	3.2	1777	52.4	1810	48.3	2.7
α_5	91.7	33.3	70.0	22.3	31.8	75.3	5.1	70.0	6.1	8.7

while in the work by (Krzeszowski et al., 2016) the mean errors were obtained for 10 sequences.

4 CONCLUSIONS

This paper has proposed a multiview markerless method to track human body motion. This method was tested by experiments that were performed on two image sequences of an athlete clearing a hurdle. The estimated parameters were compared with the parameters obtained from ground truth poses. The error analysis indicates that the preliminary results are promising but that further research is necessary. Consequently, our further work will focus on a detailed evaluation and improvement of the proposed method. We will also concentrate on its use to support the technical preparation of hurdlers.

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