Markerless Motion Tracking in Evaluation of Hurdle Clearance Parameters

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Abstract: In this study, implementation of markerless method of human body motion tracking as a tool of measurement of hurdle clearance kinematic parameters was presented. The analysis involved 5 hurdle runners at various training levels. Recording of video sequences was carried out under simulated starting conditions of a 110 m hurdle race. Kinematic parameters were determined based on the analysis of images recorded with a 100 Hz monocular camera. The suggested method does not involve using any special clothes, markers or estimation support techniques. In the study, the basic numerical characteristics of twenty estimated parameters were presented. The accuracy of determined hurdle clearance parameters was verified by comparison of estimated poses with the ground truth pose. As the quality criterion, the *MAE* (Mean Absolute Error) was adopted. In the distance parameters, the least error was obtained for the distance between the center of mass (CM) and the hurdle at the first hurdle clearance phase ($MAE = 22.0$ mm). For the angular parameters, the least error was obtained for the leg angle at the first hurdle clearance phase ($MAE = 3.1°$). The level of computed errors showed that the presented method can be used for estimation of hurdle clearance kinematic parameters.

1 INTRODUCTION

Hurdling is a group of athletic events in which technical preparation plays a significant role. The hurdle race technique involves running over 10 hurdles that are from 0.84 to 1.07 m high (depending on the particular event). In those races, the estimation of technique is focused mainly on evaluation of particular hurdles passing stages. Those stages are a complex form of dynamic motion (Iskra, 2012). The existing kinematic studies of hurdle races include mostly the analysis of selected parts of race. The most commonly analysed race element is the so called "hurdle clearance" (Čoh, 2003; Čoh et al., 2008; McDonald, 2003). Among the above-mentioned studies, the most interesting is the research conducted by Čoh (Čoh, 2003) describing the technique of running over the hurdle used by the world-record holder Colin Jackson. The kinematic 3D analysis regarded the run over the fourth and fifth hurdle. It was carried out using the ARIEL (Ariel Dynamics Inc., USA) tool. The video material was recorded with two 50 Hz cameras. The conducted research allowed for an accurate determination of the selected kinematic parameters of hurdle clearance. The same author also described a biomechanical analysis of the 100 m hurdles performed by Brigita Bukovec, the medallist of the Olympic Games in Atlanta (Čoh et al., 1998). In this paper kinematic and kinetic analysis of parameters of start, starting acceleration up to the first hurdle, the velocity dynamics between the hurdles and the technique of taking the sixth hurdle were estimated. In study a 2D video system (Ariel Performance Analysis System) was used. The all sequences were recorded with three synchronized cameras with a frequency of 50Hz. Another paper describes the study concerning 3D biomechanical analysis of sprint hurdles (Salo et al., 1997). To estimate the parameters "Kine analysis" software and two cameras (25 Hz) were used. The study involved two groups of men and two groups of women at different levels of training. The main objective of the study was to determine the level and comparison of selected kinematic parameters in the analysed groups.

In the biomechanical research of sports events, various computer vision methods play a more and more important role. Motion detection and tracking methods are used among others in analysis of athletic jumps (Ramasso et al., 2009; Panagiotakis et al.,

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2006). Chinese researchers (Xian-jie et al., 2004) suggested using computer vision for technique evaluation of athletes jumping on a trampoline. Another solution that uses computer vision techniques is system for tracking players in indoor team games e.g. handball (Perš and Kovacic, 2000). The next study (Taki et al., 1996) presented a motion analysis system of soccer games. The main goal of this paper was to evaluate the teamwork quantitatively based on movement of the players in game. Another study proposes motion tracking of a tennis racket using a monocular camera and markerless technique (Elliott et al., 2014). Whereas the work by (Sheets et al., 2011) makes use of a markerless motion capture system to test for kinematic differences at the lower back, shoulder, elbow, wrist, and racquet between the flat, kick, and slice serves. In the study seven male NCAA Division 1 players were tested on an outdoor court in daylight conditions. The next application showed that the periodic motion descriptor can successfully classify four sports types: sprint, long-distance running, hurdling and canoeing. The experimental results were performed using video material from the 1992 Barcelona Olympic Games (Cheng et al., 2004).

In this study, the markerless method of human body motion tracking was used; it makes it possible to obtain kinematic parameters for hurdle clearance analysis. The above-mentioned parameters are determined based on the analysis of the sequence of images captured with a monocular camera. An important aspect is the fact, that the suggested method does not involve using any special clothes, markers or other estimation support techniques. To the best of our knowledge, this is the first attempt to measurement of hurdle clearance kinematic parameters with markerless motion tracking algorithm.

2 ARTICULATED HUMAN MOTION TRACKING

The purpose of tracking is to determine the current pose of a human body which reflects as closely as possible to the real pose. It should be noted that capturing the three-dimensional position of a human body is a very difficult task that requires complicated computations (John et al., 2010; Kwolek et al., 2012). The main problems include: high dimensional search space that in issues involving motion tracking can comprise of up to some dozen dimensions; noise occurring in the image and a large variability in appearance of the tracked humans and environment. A significant problem is also the complexity of human motion and the fact that particular parts of the body often are obscured. The situation gets even more complicated when images from only a monocular camera are available. In such case, problems concerning the depth estimation cause additional difficulty. Research teams solve the above-mentioned issues in many different ways. The most common method is making use of simplified human body models (Deutscher and Reid, 2005; John et al., 2010; Krzeszowski et al., 2012), 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, the particle filter algorithm (Sidenbladh et al., 2000) or its modified versions are often used (Deutscher and Reid, 2005). Those algorithms require, however, a significant number of particles in order to find the correct solution, what directly impacts the time needed for computations. Therefore, in the human body motion tracking process, particle swarm optimization algorithms (Kennedy and Eberhart, 1995; John et al., 2010; Kwolek et al., 2012), are more and more often used, because they enable a more effective exploration of the search space.

2.1 3D Human Body Model

The 3D model is used for simulation of human body motion and determination of its current pose, i.e. position and orientation in space as well as the angles between the joints. The model used in this research is based on the kinematic tree structure consisting of 11 segments; each of them is represented using a truncated cone (Krzeszowski et al., 2012; Deutscher and Reid, 2005), Fig. 1. The space, in that the model operates, is determined by the number of degrees of freedom (DoF). Each segment can include up to three DoFs that define its orientation; an exception is the pelvis that can contain three additional segments defining the model translation. For tracking the human body motion, models for which the number of DoFs ranges from 26 (Krzeszowski et al., 2012; Kwolek et al., 2012) to over 30 (Deutscher and Reid, 2005) are usually used; the model suggested in this paper includes 17 DoFs. Restriction of the search space is possible, since a concrete problem is considered, i.e. application of tracking system in order to obtain data for hurdle clearance over the distance of 110 m. If you know how the tracked human body would move, you will be able to make some additional assumptions. For example, you can assume that the hurdle runner will move perpendicularly to the camera and will not change its direction. The use of similar assumptions allowed for a significant reduction of the search space, which has a great impact on

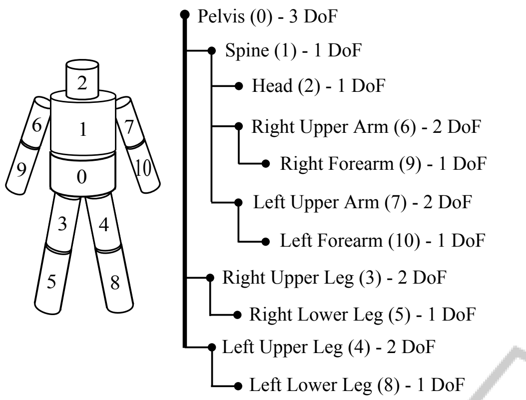

Figure 1: 3D human body model (left), hierarchical structure (right).

the complexity of the problem under consideration.

The discussed model is fully customizable, and its parametrisation includes a hierarchical structure as well as the length and width of the individual segments. At the moment, both the model configuration and pose of the human body in the first frame of a sequence of images are selected manually.

2.2 Tracking Algorithm

In the motion tracking process, the particle swarm optimization algorithm (PSO) (Kennedy and Eberhart, 1995), was used; its usefulness in solving problems related to the estimation of human pose has been repeatedly confirmed (John et al., 2010; Krzeszowski et al., 2012; Kwolek et al., 2012). In that algorithm, particle swarm is used in order to find the best solution; each of the particles represents a hypothetical solution of the problem. During the estimation, particles explore the search space and exchange information. In the ordinary PSO algorithm each i-th particle contains the current position $\mathbf{x}_i$, velocity $\mathbf{v}_i$, and its best position $\mathbf{pbest}_i$. Moreover, the particles have access to the best global position $\mathbf{gbest}$, which has been found by any particle in the swarm. The d-th component of velocity and position of each particle are updated based on the following equations:

$$v_{i,d}^{k+1} = \omega[v_{i,d}^{k} + c_1 r_{1,d}(pbest_{i,d} - x_{i,d}^{k}) + c_2 r_{2,d}(gbest_d - x_{i,d}^{k})] \quad (1)$$

$$x_{i,d}^{k+1} = x_{i,d}^{k} + v_{i,d}^{k+1} \quad (2)$$

where ω is constriction factor, c_1, c_2 are positive constants and $r_{1,d}$, $r_{2,d}$ are uniformly distributed random numbers. Selection of the best position for i-th particle ($\mathbf{pbest}_i$) and best global position ($\mathbf{gbest}$) are based on the fitness function value, which will be discussed in the next subsection. In our application the position of i-th particle represents the hypothetical state (pose) of an athlete.

In the standard PSO algorithm, initialization of particles in the swarm takes place based on the state (pose) estimated within the period of time $t-1$. In the suggested implementation, apart from the pose from the period of time $t-1$ there are also used four predefined poses, which correspond with the selected phases that are characteristic for the hurdle clearance analysis (see P_2, P_3, P_4 i P_5 on Fig. 3). The introduced modification enables a more precise estimation in case of the above mentioned characteristic phases and increases the probability of a correct pose estimation when one of the human body parts gets lost.

2.3 Fitness Function

The fitness function formulate the degree of similarity between the real and the estimated human pose. The fitness function used in this study is based on two sum components. The first of them is determined based on the extracted human silhouette, whereas the other one was based on the edge distance map (John et al., 2010; Krzeszowski et al., 2012). The value of the function is determined based on the following equation:

$$f(\mathbf{x}) = 1 - (af_1(\mathbf{x}) + bf_2(\mathbf{x})) \quad (3)$$

where $\mathbf{x}$ is the human body pose and a, b are experimentally chosen weighting factors. The $f_1(\mathbf{x})$ function defines the degree of overlap of the rendered 3D model with the extracted silhouette, whereas $f_2(\mathbf{x})$ is determined by comparison of the 3D model edges with the image, including the map with pixel distances from the nearest edge. Figure 2 presents exemplary images with the extracted person.

For human silhouette extraction (Fig. 2(b)) the background subtraction algorithm (Zivkovic and van der Heijden, 2006) was used. The second image used in the fitness function, i.e. the edge distance map (Fig. 2(e)), is determined based on the image with extracted edges (Fig. 2(c)), from which edges not belonging to the tracked human body were removed (Fig. 2(d)).

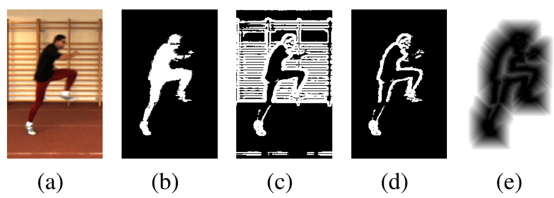

Figure 2: Person extraction. (a)-input image, (b)-foreground, (c)-edges, (d)-masked edges, (e)-edge distance map.

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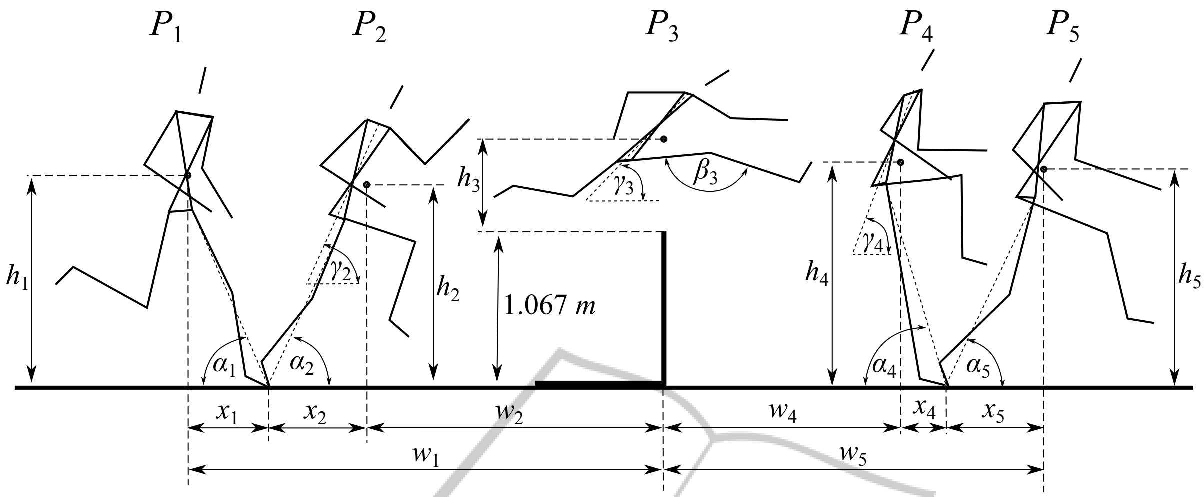

Figure 3: Hurdle clearance. P_1 - take-off phase (braking), P_2 - take-off phase (propulsion), P_3 - flight phase, P_4 - landing phase (braking), P_5 - landing phase (propulsion).

2.4 Data Collection

The analysis involved five hurdlers at different training levels. Among recorded contestants there was a four times Polish runner-up and twice Polish Youth Champion at 400 m hurdles. The study was carried out at sports facilities at Opole University of Technology. Registration was made in the athletics hall with four tartan tracks. Throughout the research, the sequence of passing the fourth hurdle in the regulation conditions of 110 m race (height: 1.067 m, distance between the hurdles: 9.14 m) was captured. As shown in the previous studies (Čoh, 2003), according to the race speed curve, the speed between the third and fifth hurdle is the greatest and the technique of passing the hurdles is independent of the low start difficulty and increasing fatigue. The analysis included 21 parameters that are presented in Fig. 3. The parameters were selected based on the literature review (Iskra, 2012; Čoh, 2003; Čoh et al., 2008). In the analysis, 13 distance parameters and eight angle parameters were taken into account. The description of the specified parameters is shown in Table 1. The sequences were captured with industrial 100 Hz Basler Ace acA645-100gc camera.

Table 1: Description of parameters; units: h, w, x [mm], α, γ, β [°].

Parameter	Description
P_1 - take-off phase (braking)	
h_1	height of CM
α_1	angle of the leg (ground contact)
x_1	CM to foot distance
w_1	CM to hurdle distance
P_2 - take-off phase (propulsion)	
h_2	height of CM
α_2	angle of the leg (ground contact)
x_2	CM to foot distance
w_2	CM to hurdle distance
γ_2	angle of inclination of the torso
P_3 - flight phase	
h_3	height of CM (over the hurdle)
γ_3	angle of inclination of the torso
β_3	angle of the attacking leg
P_4 - landing phase (braking)	
h_4	height of CM
α_4	angle of the leg (ground contact)
x_4	CM to foot distance
w_4	CM to hurdle distance
γ_4	angle of inclination of the torso
P_5 - landing phase (propulsion)	
h_5	height of CM
α_5	angle of the leg (ground contact)
x_5	CM to foot distance
w_5	CM to hurdle distance

3 EXPERIMENTAL RESULTS

The markerless motion tracking method was evaluated on five video sequences with hurdle runners. The quality of tracking was made by analyses carried out both through qualitative visual evaluations as well as using of ground truth data. Ground truth data were obtained by manually matching 3D model to athletes on the images containing of five phases characteristic for hurdle clearance analysis (Fig. 3). In Fig. 4

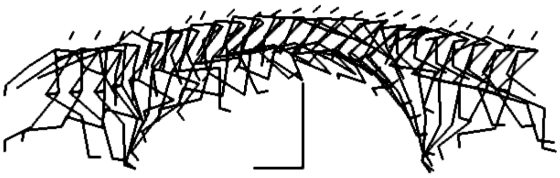

Figure 4: Motion history for athlete 1, number of frames: 92 (for better readability, only every fourth frame is shown), duration of video sequence: 0.911 s.

the motion tracking history for the selected athlete was presented. In order to increase the legibility of the generated trace, every fourth recorded frame was presented. The entire sequence was composed of 92 frames, which corresponds to a duration 0.911 s.

The precise detection of the selected hurdle clearance stages was presented for three chosen athletes (Fig. 5). As one can observe, projected 3D model matches athletes on images reasonably well. From the analysis it follows, that the algorithm provides satisfactory detection of lower limbs whereas there are some problems with estimation of the correct pose of arms. Those problems arise in consequence of the mutual covering of particular parts of body, and they are extremely difficult to eliminate while a monocular camera is used. However, it should be emphasized that in the conducted research, no parameters associated with upper limbs motion were taken into account. In consequence, incorrect arms motion tracking does not impact the measurement of analysed parameters. In the case of lower body there are difficulties in tracking between phases P3 and P4. It may happen that one of the legs is 'lost' (tracking is failed), such a situation can be observed in Figure 5 for the athlete 5, frame #61. However, due to the use in the process of initializing the particles of four predefined poses (Section 2.2), the algorithm is able to correct the error in subsequent frames and estimate the correct posture (Fig. 5, athlete 5, frame #68). Also in this case, the cause of tracking errors are difficulties in estimating the position of a human body pose on the basis of images from a monocular camera.

Numerical characteristics of 21 measured kinematic hurdle clearance parameters are presented in Table 2. This table gives an accurate description of the variables under consideration and their basic statistics, i.e. the arithmetic mean of $\bar{x}$, the minimum value *min*, the maximum value *max*, standard deviation *sd* and coefficient of variation:

$$V = \frac{sd}{\bar{x}} \cdot 100\% \tag{4}$$

The analysis shows that the average length of hurdle clearance was approximately 3525.2 mm (x_2, w_2, x_4, w_4). The taking off distance was 364.6 mm longer than the landing distance. The trunk inclination angle in landing position was at the level of 57.4°. The greatest variability was observed for distance parameters between the center of gravity and the spot where the foot touched the ground. The measured values are consistent with the sport level of the researched group.

Table 2: Characteristics of kinematic parameters; units: h, w, x [mm], α, γ, β [°].

Param.	*min*	*max*	*sd*	$\bar{x}$	*V* [%]
P_1					
h_1	764.0	1040.0	76.2	927.9	8.2
α_1	65.4	46.1	3.6	55.7	6.4
x_1	239.0	534.5	59.8	378.9	15.8
w_1	2249.0	2741.0	153.8	2551.0	6.0
P_2					
h_2	952.4	1196.0	59.0	1098.0	5.4
α_2	70.2	97.4	7.3	81.1	9.0
x_2	167.3	589.6	104.4	407.3	25.6
w_2	1304.0	1717.0	107.8	1538.0	7.0
γ_2	55.7	81.4	6.3	68.5	9.2
P_3					
h_3	228.7	437.9	61.6	319.4	19.3
γ_3	34.1	56.1	4.7	46.0	10.3
β_3	119.9	173.0	14.8	146.6	10.1
P_4					
h_4	967.2	1193.0	59.4	1093.0	5.4
α_4	99.4	15.1	13.8	81.3	14.0
x_4	18.4	433.2	88.5	236.7	37.4
w_4	1180.0	1486.0	73.1	1344.0	5.4
γ_4	44.1	74.9	7.8	57.4	13.5
P_5					
h_5	903.4	1124.0	63.9	1008.0	6.3
α_5	54.5	94.3	7.7	68.2	11.4
x_5	194.6	811.7	109.7	606.5	18.1
w_5	1663.0	1958.0	73.0	1807.0	4.0

The next step included determination of the error level of particular parameters. Values computed by using the implemented algorithm were compared with the values of the theoretical ground truth reference model (model manually adjusted to the analysed images). The quality criterion was defined for each parameter as:

$$e_j = |\hat{X}_j - X_j|, \tag{5}$$

$$MAE = \frac{1}{N} \sum_{j=1}^{N} e_j, \tag{6}$$

where e_j - absolute error, N - total number of data, $\hat{X}_j$ - estimated value (determined by the algorithm), X_j - ground truth value, MAE - mean absolute error. The

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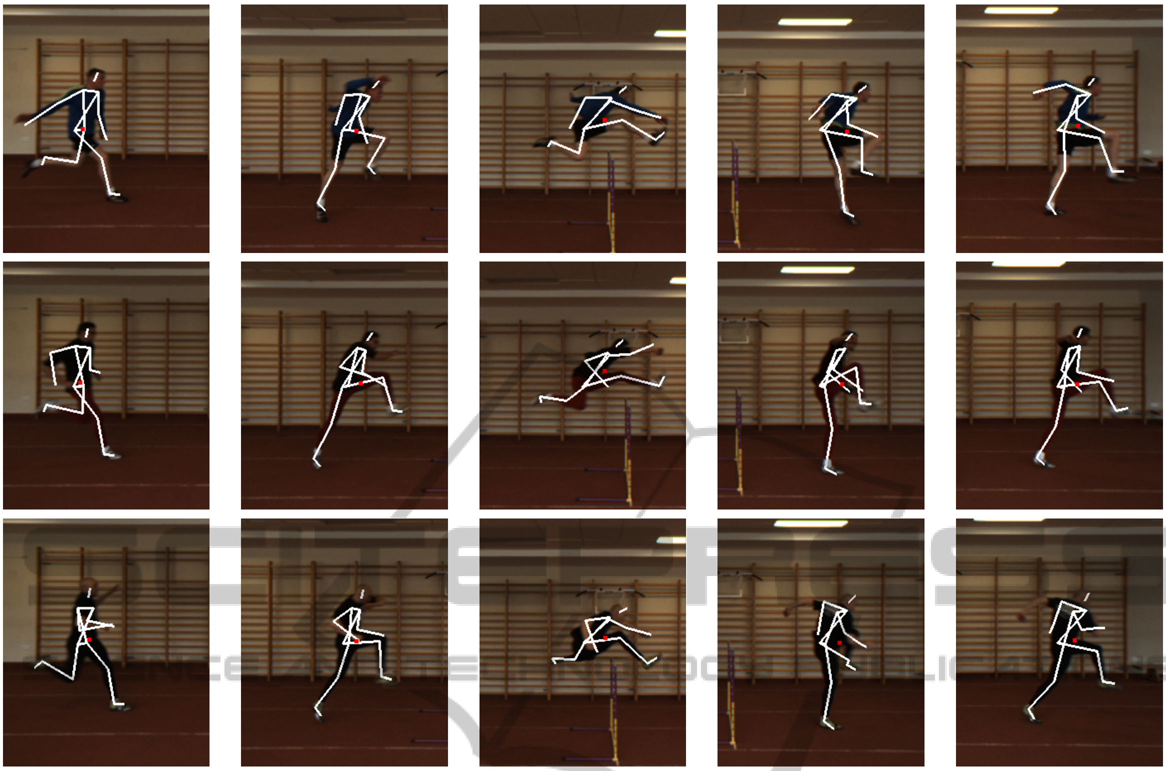

Figure 5: Tracking results on the three video sequences. First row - athlete 1 in frames #6, 21, 44, 70, 76, second row - athlete 3 in frames #6, 21, 39, 64, 69, third row - athlete 5 in frames #5, 20, 38, 61, 68.

normalized mean absolute error was calculated from formula:

$$NMAE = \frac{MAE}{max - min} \cdot 100\%, \qquad (7)$$

where *max* - maximum value of parameter, *max* - minimum value of parameter.

Table 3 includes the minimum error $min(e_j)$, maximum error $max(e_j)$, standard deviation $sd(e_j)$ and the average error, defined as *MAE* and *NMAE*. The error analysis revealed that among all distance parameters, estimation of distance between CM and the spot where the foot is touching the ground at the moment of leaving the hurdle (landing) is determined with the greatest error (x_4). That error was $MAE = 135.5$ mm. It is however, worth noting that for that parameter, the least difference from ground truth was only 1.8 mm. The CM height parameters featured relatively small values of *MAE* ($27.1 - 66.8$ mm), the CM distance from the hurdle (w_1) at the P_1 phase was determined with the least error. The accuracy of parameters estimation was also defined by the *MAE* error. The angle of the front leg at the 1st stage (α_1) features the least error (3.1°), whereas the trunk angle during landing (γ_4) is determined with the greatest error (10.0°).

The paper focuses on the analysis of five key phases of hurdles clearance, however, the presented algorithm can also be used for the analysis of hurdler's motion during the entire sequence. Figure 6 shows the trajectory of the center of mass, knees and feet for three selected hurdlers. All of the presented trajectories are of similar nature, nevertheless, some differences arising, inter alia, from different body built and technical level of individual athletes etc. can be noticed. For example hurdler 1 shows the highest position of the center of mass for most of the flight and his flight time is the longest (about 50 frames), which can be observed by analysing the trajectory of feet. By contrast the flight time of the fifth athlete is the shortest, approximately 40 frames.

4 CONCLUSIONS

In this paper, markerless method of human body motion tracking was presented. Experimental results on five various sequences of hurdle runners demonstrate the effectiveness of the approach. The quality of tracking was made by analyses carried out both through qualitative visual evaluations as well as using of ground truth data. Ground truth data were obtained

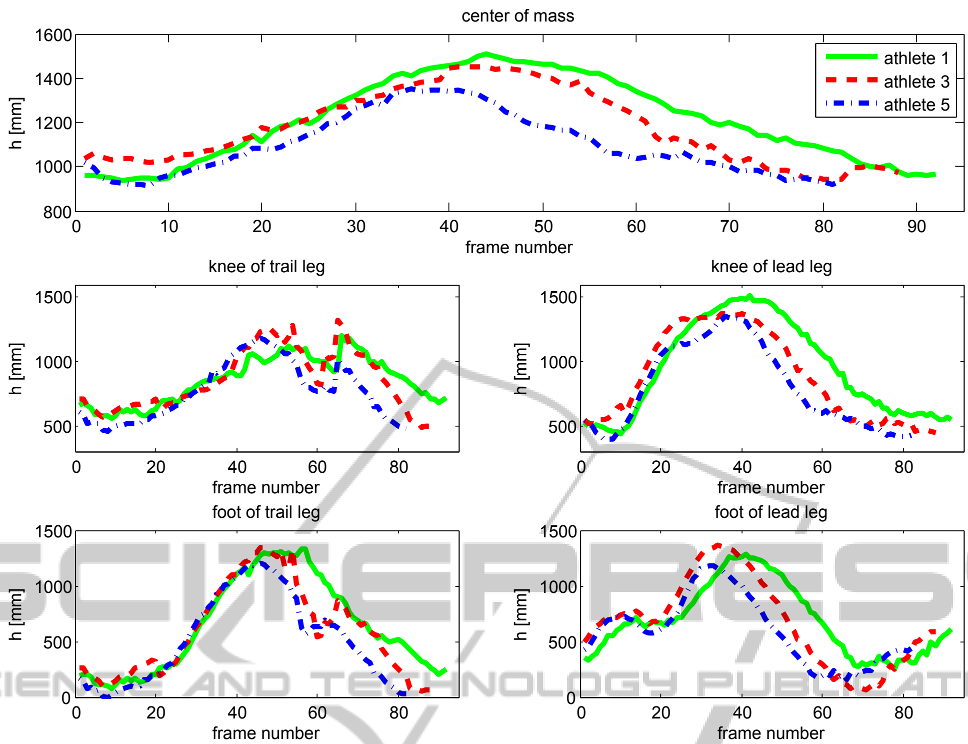

Figure 6: The trajectory of movment of center of mass, knees and foots for three selected athletes.

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Table 3: Errors; units: h, w, x [mm], α, γ, β [°].

Param.	$min(e_j)$	$max(e_j)$	$sd(e_j)$	MAE	$NMAE[\%]$
P_1					
h_1	0.5	95.9	29.0	37.0	13.4
α_1	0.1	7.1	1.8	3.1	16.1
x_1	4.2	113.3	28.3	41.3	14.0
w_1	1.8	58.7	14.6	22.0	4.5
P_2					
h_2	6.5	141.2	30.4	66.8	27.4
α_2	0.1	18.9	5.1	5.5	20.2
x_2	1.8	364.9	83.0	105.2	7.8
w_2	2.9	77.3	18.9	32.3	24.9
γ_2	0.2	9.3	2.4	3.5	13.5
P_3					
h_3	0.6	103.0	25.4	27.1	12.9
γ_3	0.0	12.1	3.4	4.5	20.5
β_3	0.4	27.2	5.6	7.0	13.2
P_4					
h_4	0.7	107.5	26.5	41.2	18.2
α_4	0.5	57.5	9.4	7.6	9.0
x_4	1.8	232.1	63.9	135.5	18.2
w_4	0.7	173.6	44.8	55.7	32.7
γ_4	0.1	25.8	6.9	10.0	32.5
P_5					
h_5	1.2	97.6	27.4	38.4	17.5
α_5	0.1	14.9	3.8	4.0	10.1
x_5	6.1	235.9	56.1	99.0	16.0
w_5	3.9	128.9	30.5	59.3	20.1

by manually matching 3D model to athletes on the images. The error analysis indicated that, there are reasons for using presented method for measurement of hurdle clearance kinematic parameters. The proposed system of estimating kinematic parameters can be used in assessing the progress of training and technical preparation of hurdlers. With a simple method of determining the parameters of hurdle clearance the progress and impact of training means of hurdle races can be monitored. Further work will focus on the use of data obtained for the analysis of more kinematic parameters as well as dynamic parameters of hurdle clearance. In further works a multi-camera system is also going to be tested.

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