Monocular Tracking of Human Motion in Evaluation of Hurdle Clearance

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Abstract. In this paper, markerless method of human motion tracking for measurement of hurdle clearance kinematic parameters was presented. The analysis involved 5 hurdlers at various training levels. Acquisition 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 accuracy of determined hurdle clearance parameters was verified by comparison of estimated poses with the ground truth poses. As the quality criterion, the mean absolute error was adopted. The level of computed errors showed that the presented method can be used for estimation of hurdle clearance kinematic parameters.

Keywords: Hurdle clearance · Markerless human motion tracking · Particle swarm optimization · Monocular camera

1 Introduction

Hurdling is a group of athletic events in which technical preparation plays a significant role. The most prominent hurdles events are 100 meters hurdles (women), 110 meters hurdles (men) and 400 meters hurdles (both sexes). These three distances are all contested at the Summer Olympics and the World Championships in Athletics. 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 [7]. 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" [2,3,12]. Among the above-mentioned studies, the most interesting is

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the research conducted by Čoh [2] 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 meters hurdles performed by Brigita Bukovec, the medallist of the Olympic Games in Atlanta [4]. 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 50 Hz. In paper [12] McDonald performed a detailed analysis of the angular momentum of hurdle clearance and presented the assumptions that can help in obtaining minimal loss of forward velocity during hurdle clearance. Another paper describes the study concerning 3D biomechanical analysis of sprint hurdles [16]. To estimate the parameters "Kine analysis" software and two cameras with frame rate of 25 fps 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 [13,15]. Chinese researchers [21] 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 [14]. The next study [20] 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. In [19] Sim and Sundaraj proposed the use of optical flow and template matching in markerless human motion analysis. They focused on tracking major body parts of professional golfer directly from a sports broadcast video. Another study proposes motion tracking of a tennis racket using a monocular camera and markerless technique [6]. Whereas the work by [17] 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 [1].

In this paper, the markerless method of human motion tracking was used; it makes it possible to obtain kinematic parameters for hurdle clearance analysis. These parameters are crucial in the evaluation of hurdlers technique. Correct technique to overcome hurdle is a basic element of motor potential hurdler and does not expose athlete to frequent injuries (frequent in this competition). Properly selected exercises can be also use as a part of physioprevention in this

complex athletics competition. 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 measure 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 [8,11]. 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 [5,8,10], uniform background [5], 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 [18] or its modified versions are often used [5]. 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 [8,9,11], 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 [5,10], see 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 [10,11] to over 30 [5] are usually used; the model suggested in this paper includes 17 DoFs. Restriction of the search space is possible, since a specific problem is considered, i.e. application of tracking system in order to obtain data for hurdle clearance

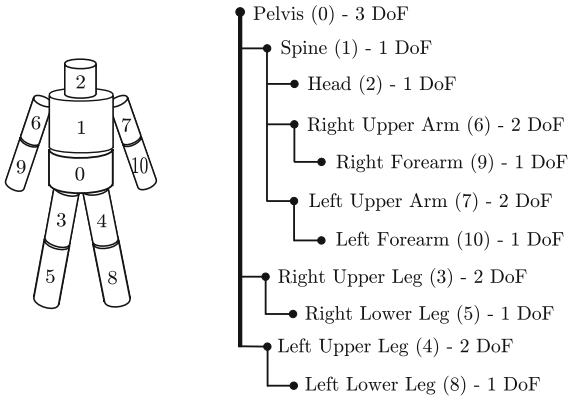

Fig. 1. 3D human body model (left), hierarchical structure (right).

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 influence on 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) [9], was used; its usefulness in solving problems related to the estimation of human pose has been repeatedly confirmed [8,10,11]. 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 **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:

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

$$x_{i,d}^{k+1} = x_{i,d}^{k} + v_{i,d}^{k+1}, \tag{2}$$

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 to the selected phases that are characteristic for the hurdle clearance analysis (see P_2, P_3, P_4 and 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 components of the sum. The first of them is determined based on the extracted human silhouette, whereas the other one was based on the edge distance map [8,10]. The value of the function is determined based on the following equation:

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

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 [22] 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)).

(a) (b) (c) (d) (e)

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

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 meters 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 [2], 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 [2,3,7]. 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.

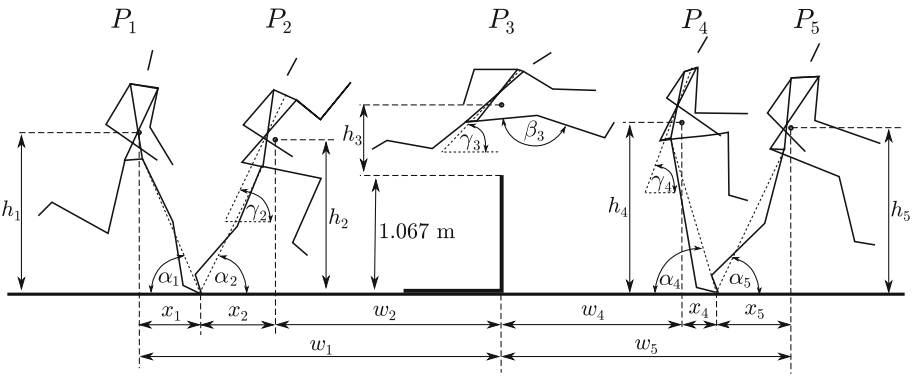

Fig. 3. Hurdle clearance: P_1 - take-off phase (braking), P_2 - take-off phase (propulsion), P_3 - flight phase, P_4 - landing phase (braking), P_5 - landing phase (propulsion).

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 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,

Table 1. Description of parameters.

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

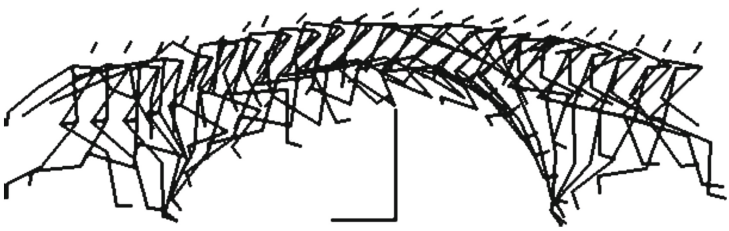

Fig. 4. Motion history for athlete 1, number of frames: 92 (for better readability, only every fourth frame is shown), duration of video sequence: 0.911 s.

which corresponds to the 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

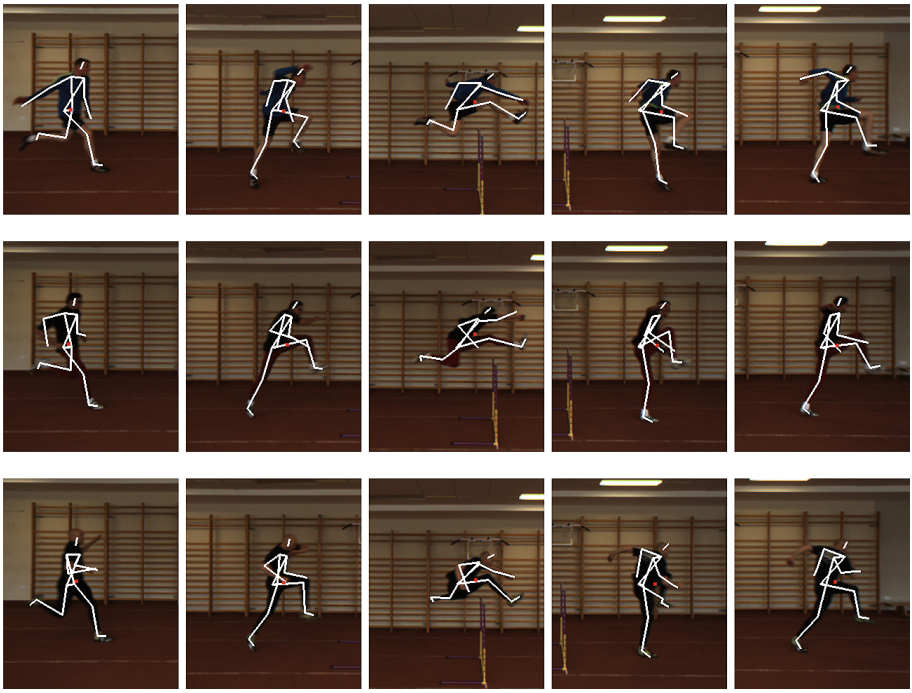

Fig. 5. Tracking results on the three video sequences: first row - athlete 1 in frames #6, 21, 44, 70, 76, second row - athlete 3 in frames #6, 21, 39, 64, 69, third row - athlete 5 in frames #5, 20, 38, 61, 68.

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 Fig. 5 for the athlete 5, frame #61. However, due to the use in the process of initializing the particles of four predefined poses (Sect. 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:

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

Table 2. Characteristics of kinematic parameters.

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

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.

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:

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

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

Table 3. Errors of estimated parameters.

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

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 normalized mean absolute error was calculated from formula:

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

where max - maximum value of parameter, min - 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

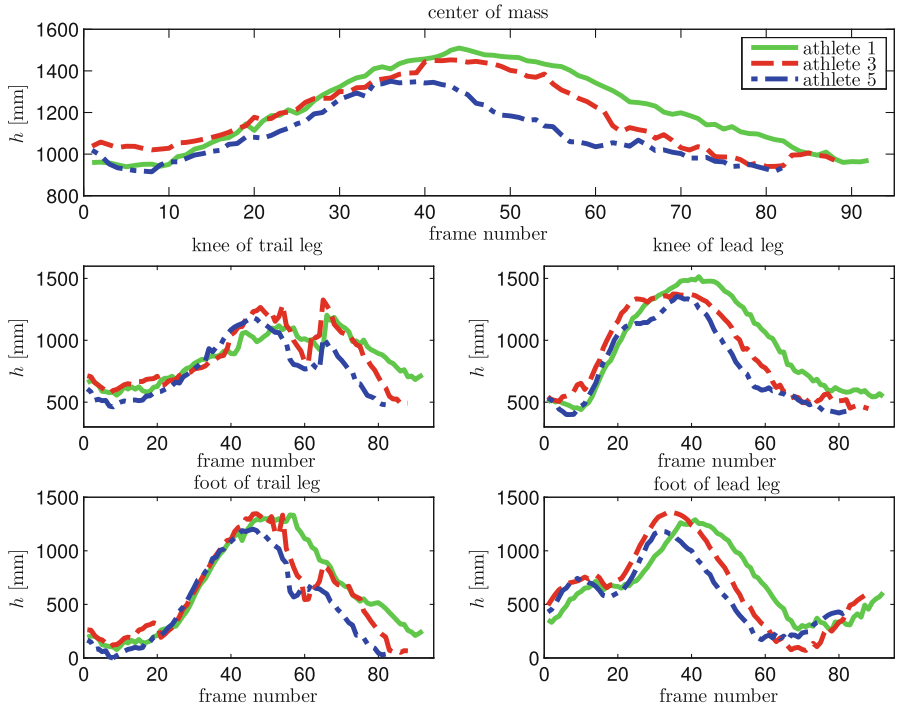

Fig. 6. Trajectory of movement of center of mass, knees and feet for three selected athletes.

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 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.

In the analysis of hurdle clearance the velocities of center of mass and swinging leg play an important role [2]. Figure 7 illustrates the velocity of CM during clearing the hurdle by athlete 3, which was characterized by the best hurdle clearance technique. The velocity of center of mass was presented for the five phases (see P_1–P_5 on Fig. 3). The analysis shows that the athlete during take-off phases (P_1 and P_2) accelerates gradually to reach the maximum velocity in the

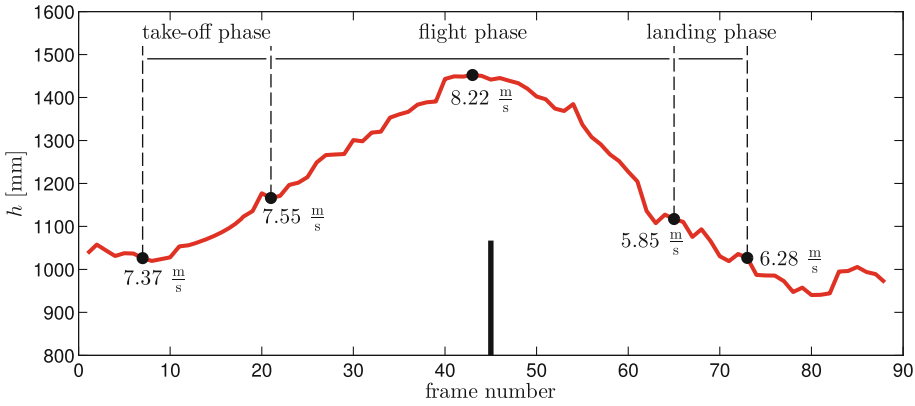

Fig. 7. Velocity of center of mass during clearing the hurdle by athlete 3.

phase of flight. In the next phase it can be observed a decrease in velocity to the value of 5.85 $\frac{\text{m}}{\text{s}}$. In the phase P_5 hurdler accelerates to achieve optimal velocity to overcome next hurdle. Average velocity of CM between phases P_1 and P_5 is equal to 6.93 $\frac{\text{m}}{\text{s}}$.

The velocity components of center of mass and the velocity of swinging leg for take-off and landing phases of athlete 3 was presented on Fig. 8. The horizontal velocity of the CM in the braking phase is 7.35 $\frac{\text{m}}{\text{s}}$ and increases to 7.39 $\frac{\text{m}}{\text{s}}$ in the next phase. In addition to the horizontal velocity of the CM, an important parameter of the P_2 phase is the vertical velocity, which is equal to 1.54 $\frac{\text{m}}{\text{s}}$. The horizontal and vertical velocity determine the elevation velocity of the CM, which is 7.55 $\frac{\text{m}}{\text{s}}$. The velocity of hurdle clearance depends also on the velocity of the swinging leg during the take-off phases [2]. The velocity of the knee of the

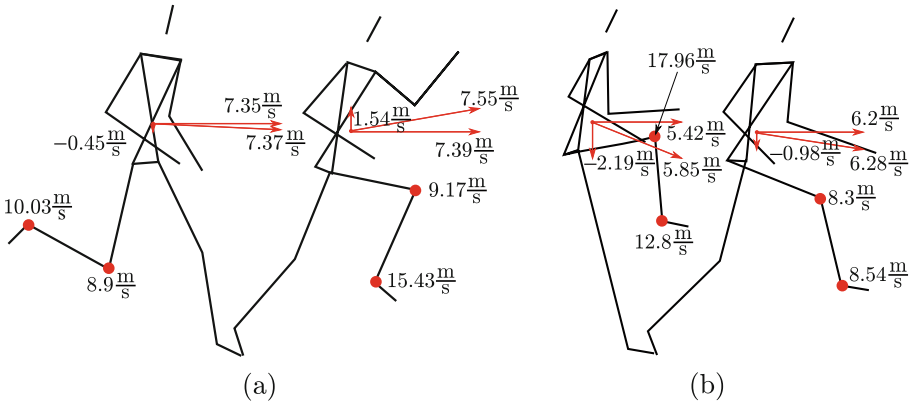

Fig. 8. Velocity components of center of mass and the velocity of swinging leg for athlete 3: (a) - take-off phases (P_1 and P_2), (b) - landing phases (P_4 and P_5).

swinging leg for analysed athlete is equal to 9.17 $\frac{\text{m}}{\text{s}}$ and the velocity of the foot is 15.43 $\frac{\text{m}}{\text{s}}$. During landing phase ($P_4$) the vertical velocity of the CM is at the level of -2.19 $\frac{\text{m}}{\text{s}}$. The horizontal velocity of the CM is 5.42 $\frac{\text{m}}{\text{s}}$ and increases to 6.2 $\frac{\text{m}}{\text{s}}$ in phase P_5.

4 Conclusions

In this paper, markerless method of human motion tracking was presented. Experimental results on five various video sequences of hurdlers demonstrate the effectiveness of the approach. The quality of tracking was made by analyses carried out both using of ground truth data as well as through qualitative visual evaluations. Ground truth data were obtained by manually matching 3D model to athletes on the images. The error analysis justifies the use of 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 hurdle runners. With a simple method of determining the parameters of hurdle clearance the progress and impact of training means on hurdlers 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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