Kinematic Analysis of Hurdle Clearance using a Mobile Device

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Abstract: This paper presents a human motion tracking method using a mobile device. The proposed method may be used as a tool to measure hurdle clearance kinematic parameters and help coaches to evaluate the athlete's technique. The video recordings were made under simulated starting conditions of a 100 m women hurdle race. Kinematic parameters were estimated based on an analysis of images sequence from a mobile device. The images were recorded on a HTC M8s smartphone with a resolution of 1920x1080 pixels and with a frequency of 30 Hz. The system was tested on two mobile development platforms and three image sequences. The proposed method does not use any markers, special clothes or other estimation support techniques. The analysis conducted showed that the smallest errors were calculated for the height of centre of mass, while the biggest errors were observed for the bending angle of the knee of the trail leg.

1 INTRODUCTION

With the development of available technologies, we can observe an increased interest in research concerning the use of mobile applications in various areas of life, e.g. activity classification (Mitchell et al., 2013), fall detection (Shawen et al., 2017), light measurement (Gutierrez-Martinez et al., 2017). One of the potential applications is also the support of athletes' training through the tracking and analysis of human motion. Because of this, coaches have the ability to evaluate the athlete's technique and show where they make mistakes.

Sport experts have been exploring a wide range of applications for mobile platforms in the context of athletes' performance improvement (Yilmaz et al., 2004; Baca et al., 2010; Möller et al., 2011; Kranz et al., 2013; Weghorn, 2013; Koyama and Watanabe, 2014; Jensen et al., 2015; Xu et al., 2015; Weiler, 2016; Yamaguchi and Miura, 2016). For example, the application named GymSkill (Möller et al., 2011; Kranz et al., 2013) is a personal trainer. In this system a smartphone placed on a balance board is used to calculate the skill level of a particular exercise. GymSkill provides feedback to the user with the goal of tracking training quality and success, and to motivate regular exercise. Baca et al. (Baca et al., 2010) developed a prototype system for monitoring, transmitting and processing performance data in sports called the Mobile Coaching System. Monitored athletes are equipped with wireless sensors and a mobile device. The system gathers biomechanical, physiological and other sports related parameters. The measured data is sent to the server and provided to experts. In turn, these experts analyse the athlete's performance and return individual message feedback. Another paper (Jensen et al., 2015) discusses an IMU-based mobile system for golf putt analysis. The system performs automatic putt detection using machine learning methods. The calculation of parameters is performed in real time. Simpson et al. (Simpson et al., 2017) examined the utility of a commercial application to increase athlete knowledge and nutrition promoting behaviours. The study was conducted on a group of 17 New Zealand elite male field hockey players aged between 18 and 20. From a paper by (Xu et al., 2015), the authors describe a sensing and mobile computing system for classifying the foot angle profiles during cycling. The system provides real-time guidance to the user for achieving a correct profile. Yilmaz et al. (Yilmaz et al., 2004) developed a method which tracks the complete object regions, adapts to changing visual features, and handles occlusions. Tracking is achieved by evolving the contour from frame to frame

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by minimizing the proposed contour energy function. The paper (Koyama and Watanabe, 2014) presents a support system for golf swings consisting of perceptive sportswear and a mobile device. The wireless mobile device receives motion data from the sportswear for monitoring body motion. Another application (Weiler, 2016), called Ubersense, is a coaching tool designed to help improve the technique and movement of the athlete. The application allows for the analysis of any movement, such as running, throwing, tennis serves or golf swings, these movement are recorded by a camera. The paper (Yamaguchi and Miura, 2016) describes a vision-based speed-measuring method for baseball pitches. Authors have developed a smartphone application that uses an image processing technique. Yeo and Sirisena (Yeo and Sirisena, 2017) proposed a mobile application for the analysis of the walking and running gait. The application has been named Simi Move. The user is required to mark the positions of individual joints of the human body on every frame. On that basis, the angles between the individual parts of the body and their length are calculated. After that the user may perform a gait analysis frame by frame.

From a review of the literature, it may be seen that there is a need to create tools that can be used to support coaches in the training process and can be taken everywhere. The main contribution of this paper is therefore to develop a human motion tracking method that can be deployed and run on a mobile platform. The system was used to track the motion of hurdlers during hurdle clearance and can be used by coaches to evaluate the athlete's technique. From motion data, two distance parameters and three angle parameters have been estimated. The tracking system that we have developed does not use any markers, special clothes or other techniques supporting estimation. The applications developed are run on a Raspberry Pi 3 B+ microcomputer board equipped with a quad-core ARM-8 Cortex-A53 1.4 GHz processor and 1 GB of RAM and a NVidia Jetson TX2 development kit equipped with Dual-Core Denver 64-bit CPUs, a Quad-Core A57 Complex and 8 GB of RAM. This study is a continuation of our previous research (Krzeszowski et al., 2016).

The aim of this paper is the implementation using a mobile device of a method of human motion tracking for hurdles clearance based on kinematic analysis and its evaluation.

2 METHODS

2.1 Monocular Human Motion Tracking

The main purpose of human pose recovery is to estimate a body pose which closely reflects a real pose registered from a sensor input (Moeslund et al., 2006). With the conjunction of cameras as sensors, vision-based approaches are widely used in human motion analysis. Estimating the 3D body pose from visual appearance features by employing vision-based approaches is a challenging problem due to the high dimensional search space of the underlying model used to represent body structure, as well as appearance variability between observed humans and environmental conditions (John et al., 2010; Kwolek et al., 2012). Those conditions may manifest as image noise, that can make background and feature detection very difficult. The monocular camera approach is also prone to increased observation ambiguity especially when some of the body parts are obscured due to the motion performed. Tracking may be applied to ensure the coherence among recovered poses over the time. The simplified human body appearance may be adequately represented by no less than 10 large body parts. More precise models are required for the purpose of tracking upper and lower extremities (Deutscher and Reid, 2005; John et al., 2010; Kwolek et al., 2012; Krzeszowski et al., 2016). For the purpose of tracking hurdling motion the underlying articulated kinematic structure of an athlete is represented by a tree consisting of 11 rigid segments (Deutscher and Reid, 2005). The manoeuvrability of each segment is determined by the number of degrees of freedom (DoF) that define its orientation, and in the case of the pelvis, its location in 3D space. Applying constraining factors to the movement of the segments allows 3D models to be used for 2D human motion recovery and tracking. By taking into account a prior knowledge of hurdle running, the motion model can operate with 19 DoFs, see Figure 1. We also assume that the hurdle runner will move perpendicularly to the camera and will not change its direction. The model can also be projected into 2D image space approximating each segment by a tetrahedron created using a simplified perspective projection of a truncated cone (Kwolek et al., 2012). The image of a model silhouette and contour can be generated by drawing filled tetrahedrons and their edges.

The likelihood function is used to evaluate the degree of similarity between real and estimated monocularly-viewed human poses. Depending on the approach, different visual features may be used to

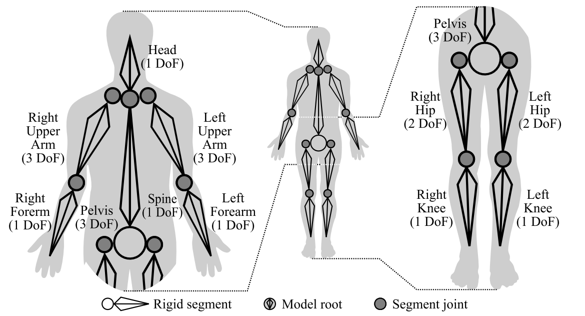

Figure 1: Hierarchical structure of 3D human body model.

define the degree of similarity between poses. In this paper, the likelihood function is determined based on the extracted human silhouette image S and the edge distance map image D (John et al., 2010; Kwolek et al., 2012). Gaussian Mixture-based Background/Foreground Segmentation algorithm (KaewTraKulPong and Bowden, 2002) is used for human silhouette extraction. The edge distance map is determined using Chebyshev distances and it is based on the edges detected by the Sobel operator and masked by the extracted human silhouette. The proposed likelihood function is determined according to the following equation:

$$f(\mathbf{x}) = 1 - \big(af_s(\mathbf{x}) + (1-a)f_c(\mathbf{x})\big) \quad (1)$$

where $a = 0.7$ is an importance coefficient of a function $f_s(\mathbf{x})$ and $f_c(\mathbf{x})$. The $f_s(\mathbf{x})$ function reflects the degree of overlap between the image of the extracted human body silhouette S and the corresponding image of model silhouette $S_{\mathbf{x}}$ in pose $\mathbf{x}$. The $f_c(\mathbf{x})$ function reflects the edge distance map-based similarity of the model in pose $\mathbf{x}$ with a silhouette contour $C_{\mathbf{x}}$ and acquired edge distance map D.

The Particle Swarm Optimisation (PSO) algorithm can be successfully employed to track full body motion using single (John et al., 2010) and multiple cameras (Kennedy and Eberhart, 1995; John et al., 2010; Kwolek et al., 2012; Krzeszowski et al., 2016). The PSO algorithm is an example of population based stochastic optimization. The optimization is achieved in an iterative fashion by maintaining a swarm of I particles that collaborate with each other. Every i-th PSO particle determines its own current $\mathbf{x}_i$ and best $\mathbf{p}_i$ position in the multidimensional search space, which each particle explores with the velocity $\mathbf{v}_i$ in each iteration l.

In order to work correctly our current version of the algorithm requires: choosing the initial 3D model configuration, defining the height of the hurdle obstacle visible on the acquired image to scale the model to the correct size, defining the first frame of the sequence where the human is fully visible, and a rough 3D model pose.

In this paper each particle position $\mathbf{x}_i$ represents a hypothetical state of the 3D model. Human motion tracking is performed by a sequence of static PSO-based optimizations followed by the re-diversification of particles to anticipate the pose expected in the next frame $(t+1)$. The re-diversification of the particles at the beginning of each frame is obtained on the basis of a normal distribution centred around the best particle location $\mathbf{g}$ found in the previous frame as well as from a set of five model states $\mathbf{K}_{1\ldots5}$ representing the key phases of hurdle clearance motion (Krzeszowski et al., 2016):

$$\mathbf{x}_i^{t+1} = \begin{cases} \mathcal{N}\mathbf{g}^t & \text{if } i < 0.5I \\ \mathcal{N}\mathbf{K}_{(i \bmod 5)+1} & \text{if } i \geq 0.5I \end{cases} \quad (2)$$

2.2 Data Acquisition

The algorithm was applied to three sequences registered in the athletics stadium with a tartan track. Each sequence represents a single run performed by the same competitor. Hurdle clearance was captured in the regulation conditions of the 100 m women race (hurdle height: 0.762 m). The sequences, in the form of colour images of size 1920x1080 pixels, were captured with a HTC M8s smartphone taking 30 frames per second. The smartphone was placed on a tripod perpendicular to the running competitor. The distance from the camera to the running track was 2.44 m. The parameters of the cameras have been estimated using the TSAI calibration method (Tsai, 1987).

In this paper, the authors considered selected parameters of hurdle clearance, which are presented in Table 1. These parameters were chosen based on the literature (Čoh, 2003; Krzeszowski et al., 2016). In clearing the hurdle, three time points were distinguished (Figure 2). The first point (P_1) is defined by the moment when the athlete positions himself to clear the hurdle. The second point (P_2) is determined by the position of the athlete when both of their legs are off the ground and their feet are at the same height. The third point (P_3) is determined by the moment when the athletes put their lead leg behind the hurdle.

The repeatability of the algorithm were calculated using a coefficient of variation. This indicator is ex-

Table 1: Calculated parameters of hurdle clearance.

Parameters	Description
h	the height of centre of mass (CM)
w	the CM to hurdle distance
α	the bending angle of the knee - trail leg
β	the bending angle of the knee - lead leg
γ	the torso inclination angle

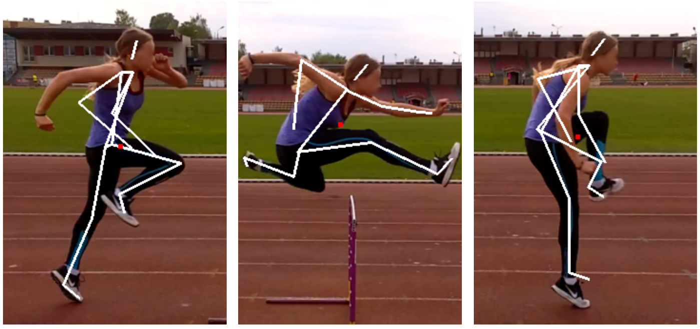

Figure 2: Example of tracking results for sequence 1, frames #55, 61 and 66.

Figure 3: Example of tracking results for sequence 2, frames #78, 84 and 90.

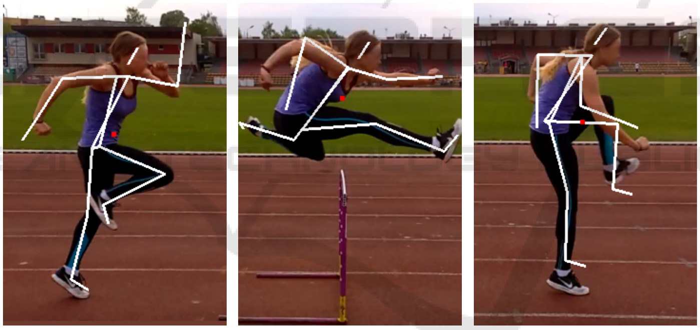

Figure 4: Example of tracking results for sequence 3, frames #44, 51 and 56.

pressed by the formula:

$$V = \frac{sd}{M} \cdot 100 \tag{3}$$

where sd is the standard deviation and M is the mean value. The parameters were calculated using the proposed method and compared with the ground truth values (manual setting of the reference model parameters). The quality criterion for the algorithm was defined as:

$$\delta = \frac{|M - GT|}{M} \cdot 100 \tag{4}$$

where δ is the relative error, M is the estimated value (determined by the mean value of 10 repetitions of the algorithm), GT is the ground truth value.

3 EXPERIMENTAL RESULTS

An example of the tracking results for all sequences for the three selected frames are shown in Figures 2, 3 and 4. As one may observe, the projected 3D model matches the athlete on the images reasonably well. As follows from the analysis, the presented method provides the correct detection of lower limbs, however, sometimes there are inaccuracies in tracking, particularly in the point (P_3), see Figure 2 frame #66 and Figure 4 frame #56. Analysis also shows that there are some problems with the correct tracking of the upper limbs arising due to the mutual covering of particular parts of the body. They are difficult to eliminate when a monocular camera from a mobile device

Table 2: Mean value and coefficient of variation for 10 algorithm repetition.

		h [mm]				α [deg]				β [deg]				γ [deg]			
		M	V	GT	δ %	*M*	V	GT	δ %	*M*	V	GT	δ %	*M*	V	GT	δ %
Seq. 1	P1	996	6.8	1057	6	164	8.2	170	4	47	50.8	42	11	74	4.8	70	5
	P2	1221	1.5	1275	4	100	29.4	49	51	140	8.7	153	9	58	14.1	44	23
	P3	1004	3.2	981	2	141	18.9	62	56	149	16.6	155	4	58	4.5	64	10
Seq. 2	P1	995	3.7	1029	3	166	7.1	170	2	38	12.8	42	11	71	6.6	70	1
	P2	1225	1.6	1270	4	101	15.8	49	52	145	5.4	153	6	52	17.1	44	15
	P3	998	2.3	965	3	89	10.8	71	20	154	2.6	155	1	54	5.1	61	12
Seq. 3	P1	954	6.1	1005	5	155	6.8	165	6	94	40.1	42	55	72	4.5	70	2
	P2	1247	0.4	1261	1	113	15.2	37	67	157	1.9	156	1	53	4.6	44	16
	P3	1034	1.3	999	3	97	16.9	74	24	165	2.4	155	6	58	7.3	64	10

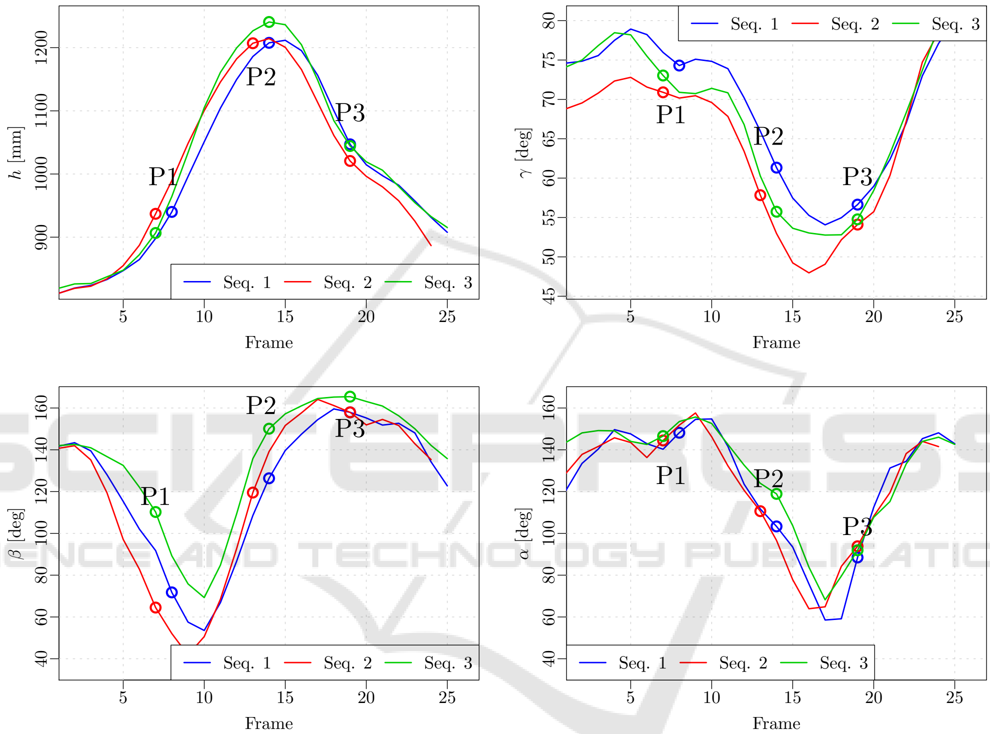

Figure 5: Parameters of hurdle clearance for the sequences analysed.

is used. Therefore, the authors only considered the parameters associated with lower limbs. As a consequence, incorrect arm motion tracking does not impact the measurement of the parameters analysed.

The results were obtained for $N = 10$ repetitions of the tracking algorithm for each sequence. Parameters were calculated on the basis of the athlete's estimated body poses. Table 2 presents the mean value (M), coefficient of variation (V), ground truth values (GT) and relative errors (δ) of the parameters analysed. An analysis of the results showed that the greatest dispersion of the solutions generated by the algorithm is observed for the angle of the lead leg β (50.8 for point P_1 in Seq. 1 and 40.1 in Seq. 3). However, the smallest dispersion and, consequently, the highest repeatability of the algorithm was observed for the height of CM in point P_2 for each sequence (1.5, 1.6, 0.4 correspondingly).

An analysis of errors showed that the most accurate estimation is observed for the height of the centre of mass h. In all running trials (sequences) this error did not exceed 6%, while the smallest one was equal to 1% (P_2 in Seq. 3). The smallest accuracy of determining the analysed parameters is observed for the parameter α. For this parameter, the largest error was noted in P_2 for Seq. 3 ($\delta = 67\%$), while the smallest one occurred in P_1 for Seq. 2 ($\delta = 2\%$). The values of errors generated for β are much smaller than the errors generated for α, but in one case a high error is also observed ($\delta = 55\%$ in P_1 for Seq. 3). The remaining errors calculated for the β parameter do not exceed 11%. An analysis of the errors for the last parameter showed that this parameter in most cases is generated with an error below 17%, with the smallest error observed in P_1 for Seq. 2 ($\delta = 1\%$), and the largest in P_2 for Seq. 1 ($\delta = 23\%$).

The presented method also allows for an observation of the analysed parameter changes over time. Figure 5 presents the parameters of hurdle clearance as a function of time (frames). The key points of hurdle clearance have been marked on the charts (P_1—P_3). The charts present the mean value of the parameters for 10 repetitions of the algorithm, additionally a moving average filter with the window equal to three was used. The analysis showed that the hurdle clearance parameters in the individual sequences are close to each other, which indicates the repeatability of the movement performed by the competitor.

4 CONCLUSIONS

This paper has proposed a human motion tracking method that can be deployed and run on a mobile device. The method can be used by coaches for the evaluation of the athlete's technique. This system was tested on two mobile development platforms and three image sequences of an athlete clearing a hurdle which were recorded using a smartphone. In the performed experiments, the hurdle clearance parameters were estimated based on the human poses obtained. An analysis of the errors received showed that the most accurately estimated parameter was the height of the centre of mass h, while the biggest errors were observed for the bending angle of the knee for the trail leg α.

Our future work will focus on improving the proposed method and preparing the application for the Android platform.

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