Advances in Intelligent Systems and Computing 392

Paul Chung
Andrea Soltoggio
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Proceedings of the 10th International Symposium on Computer Science in Sports (ISCSS)

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Preface

The 10th International Symposium of Computer Science in Sport (IACSS/ISCSS 2015), sponsored by the International Association of Computer Science in Sport and in collaboration with the International Society of Sport Psychology (ISSP), took place between September 9–11, 2015 at Loughborough, UK. Similar to previous symposia, this symposium aimed to build the links between computer science and sport, and report on results from applying computer science techniques to address a wide number of problems in sport and exercise sciences. It provided a good platform and opportunity for researchers in both computer science and sport to understand and discuss ideas and promote cross-disciplinary research.

This year the symposium covered the following topics:

- Modelling and Analysis
- Artificial Intelligence in Sport
- Virtual Reality in Sport
- Neural Cognitive Training
- IT Systems for Sport
- Sensing Technologies
- Image Processing

We received 39 submitted papers and all of them underwent strict reviews by the Program Committee. Authors of the thirty-three accepted papers were asked to revise their papers carefully according to the detailed comments so that they all meet the expected high quality of an international conference. After the conference selected papers will also be invited to be extended for inclusion in the IACSS journal.

Three keynote speakers and authors of the accepted papers presented their contributions in the above topics during the 3-day event. The arranged tour gave the participants an opportunity to see the Loughborough University campus, and facilities in the National Centre for Sport and Exercise Medicine and the Sports Technology Institute.

We thank all the participants for coming to Loughborough and hope you had enjoyed the event. We also thank the Program Committee members, the reviewers and the invited speakers for their contributions to make the event a success.

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- Prof. Arnold Baca, University of Vienna, Austria
- Dr. Michael Hiley, Loughborough University, UK
- Prof. Thomas Schack, Bielefeld University, Germany

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Part I
Image Processing in Sport

Non-Invasive Performance Measurement in Combat Sports

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Abstract. Computer vision offers a growing capacity to detect and classify actions in a large range of sports. Since combat sports are highly dynamic and physically demanding, it is difficult to measure features of performance from competition in a safe and practical way. Also, coaches frequently wish to measure the performance characteristics of other competitors. For these reasons it is desirable to be able to measure features of competitive performance without using sensors or physical devices. We present a non-invasive method for extracting pose and features of behaviour in boxing using vision cameras and time of flight sensors. We demonstrate that body parts can be reliably located, which allow punching actions to be detected. Those data can then visualised in a way that allows coaches to analysis behaviour.

1 Introduction

Recent advances in computer vision have enabled many examples of non-invasive measurement of performance in the sports domain including player position tracking [12, 10], and action recognition [14, 1]. Some work has also demonstrated action recognition in challenging conditions such as the aquatic environment in swimming [18, 19]. Broadly, the aim in much of the work for computer vision has been to measure features of performance without the use of invasive tracking devices or sensors. This can be described as non-invasive performance measurement. The historical alternative to non-invasive performance measurement (excluding the use of sensors or tracking devices) has been notational analysis, such that the analyst manually notates events from a competition using some predefined scheme of events and actions (See [9]). Human notational analysis, however, is notoriously vulnerable to errors such as inconsistent interpretation of event labels. Further, the manual nature of most notational analysis methods makes large-scale analyses difficult to implement. Additionally, for some dynamic and high-impact sports such as boxing, it could be dangerous for participants to wear devices of any type due to the potential risk of injury. Therefore non-invasive methods for reliable and accurate performance analysis are highly desirable.

Time of flight (ToF) sensors are a modern tool used in a range of computer vision and robotics applications where depth information is a desirable addition or replacement for conventional RGB cameras. Depth data has been widely

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used in gesture and action recognition [2–4, 17]. While computer vision has enabled many novel and exciting insights into sports performance, there are other instances where vision alone is insufficient for extract meaningful performance features, and in those instance 3D data may provide a practical solution. For instance Behendi et.al., attempted to classify punching types in boxing using overhead depth imagery [11]. In that work, punches were classified by six basic actions, *straight*, *hook* and *uppercut* (each for *rear* and *lead* hand). The direction of a boxer's forearm movement and the elbow angle were key features to determine punch types, and boxers usually throw uppercut punches from a lower initial glove position compared to hook or straight punches. Since it was not possible to differentiate between different glove positions from overhead vision alone (as illustrated in Figure 1), the main motivation for using depth data in that study was to exploit differences in the depth values of the forearm to classify uppercut punches.

(a) Lead Uppercut (b) Lead Hook

Fig. 1: Visual similarities between hook and uppercut punches [11].

Sports analytics research in boxing is limited, and remains a difficult problem due to the high speed of action, and occlusions in the visibility of performance features from most viewing angles. Most examples of performance analysis or activity profiling in boxing rely on slow-motion review of video footage (e.g.[5, 6]). Some efforts, such as "Box-Tag" have been made to automate scoring in boxing, which can provide additional insight to coaches about certain features of performance [7, 8]. Additionally, Morita et al [16] described a system to differentiate between punches based on gyroscopic signals providing insight on the offensive patterns of boxers.

However, despite these innovations, there are additional features of performance that are not easily extracted with existing methods. For instance, the relative position of boxers in the ring may be of significant interest to coaches, but there are no existing, non-invasive positioning methods for available for boxing. Also, the vertical movements of a boxer might be used to infer features of performance such as fatigue. Since there are no existing methods for estimating the "bouncing" of a boxer in competition, new solutions are required.

In this paper we propose a combat sports video analysis framework and demonstrate a method for extracting specific performance features in boxing using overhead depth imagery.

2 Methods

The general framework of the method is given in Figure 2. In this framework athletes are tracked to obtain their trajectories and analyse their movement. In the first frame, athletes are detected and trackers are assigned. Detected athletes are represented by their contour and head position. Contour tracking is used to handle partial occlusion between athletes. Finally, athletes trajectories are obtained and mapped on the ring canvas for further analysis. These stages are further described in the following sections.

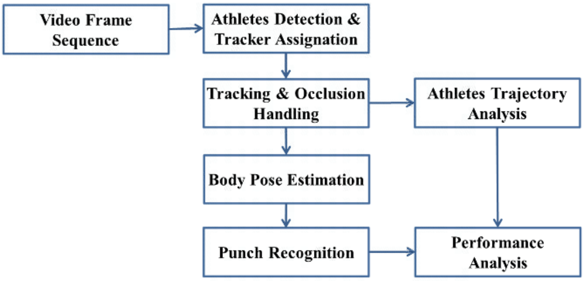
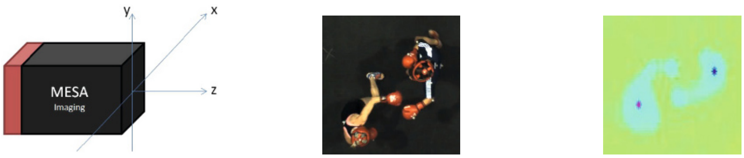


Fig. 2: Combat-sport movement analysis framework.

2.1 Depth Sensor

A MESA Imaging SwissRanger (SR4000) ToF sensor was used to measure activities in the boxing ring. The device was mounted approximately 6 meters above the level of the canvas ring surface. The SR4000 device generates a point cloud with a 176(h)×144(w) pixel resolution, a functional range of 10 meters, and a 69 × 55° FOV. The maximum sampling rate is 50 f.p.s. The output from the device consists of a 3×176×144 element array for calibrated distances in 3-dimensional cartesian coordinates. Viewed from above, a representation of calibrated distance values corresponding to a vision camera (mounted in tandem) is shown in Figure 3.



(a) Coordinate System (b) Machine Vision (c) Depth Image

Fig. 3: Swissranger SR-4000 Coordinate System (Courtesy Mesa Imaging AG), Machine Vision Image and Matching Depth Image.

2.2 Athlete Detection

This section describes the process of detecting boxers from overhead depth data. Previous research using overhead depth data leverages the shape of the head and shoulders for finding head candidates[13]. However, low resolution overhead data from ToF can make detecting the those features difficult especially when their hands are closed. A histogram of the depth data is obtained to extract the boxing canvas depth level and depth values are translated based on the obtained ring depth level. A precise contour of the boxer's form is obtained using the normalised histogram of foreground contours at different depth levels (Fig. 4). Detecting boxers head position can be challenging since boxers frequently lean to different angles, such that the visible shape of head varies. However, detecting the posterior location of a boxer's neck in overhead images is more reliable. A 2D chamfer distance of a boxer contour is obtained to estimate the boxer's neck position. The properties of a boxer's contour can be "fuzzified" by assigning a continuous probabilistic range to the boundary state, as opposed to a discrete binary state. The neck position of the boxer is selected using the product t-norm of fuzzified values of the candidate boxer's contour chamfer distance and depth value [11],

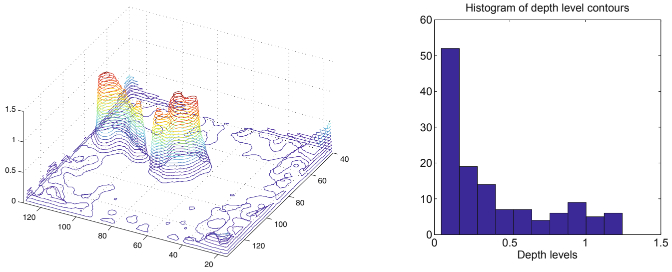


Fig. 4: Depth level contours and histogram of contour elements.

$$\begin{aligned} neck &= argmax_{(x,y)\in ROI}(f_z \cdot f_d),\\ f_z &= \frac{1}{1+e^{-a(z-c)}}, f_d = \frac{D_{ch}}{max_{(x,y)\in ROI}(D_{ch})} \end{aligned} \quad (1)$$

where z is the normalized depth value, and D_{ch} is the chamfer distance computed over the detected boxer contour.

2.3 Tracking and Occlusion Handling

Once candidate boxers have been detected in first frame, they can then be tracked over consecutive frames to obtain a continuous movement trajectory.

Boxers are non-rigid objects and occlude each other frequently (Fig. 5). The boxers' head and shoulders are relatively stable features and provide continuity of position over successive frames such that contour tracking can be used to obtain boxers trajectories. Contour tracking handles topological changes, such as merging and splitting of object regions. When occlusion occurs, the contours of the athletes are merged. At the end of the occlusion, the group contour is split and each athlete is tracked individually. The main problem in an occlusion situation is identifying each boxer and determining their positions after the occlusion. Although boxers occlude each other and their contours are merged, it is usually partial occlusion from overhead view. Regional maxima of the $f_z \cdot f_d$ for the merged contours are obtained and neck positions are estimated, which is illustrated in Fig. 5. Detected heads in occluded contour are shown by red and pink points in Fig. 5(e).

Robust position tracklets can then be derived using the calibrated x-y position coordinate system provided by the raw data files. Tracking data is then retained in the form of frame-based rows, each consisting of X, Y, Z cartesian coordinates where the origin is at the canvas level in the approximate centre of the ring.

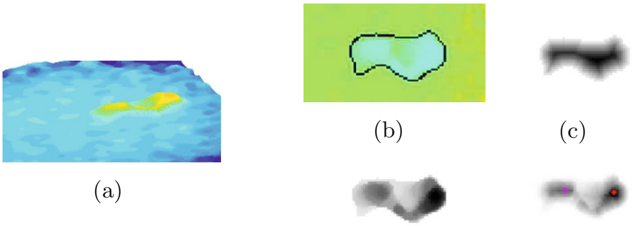

(a) (b) (c) (d) (e)

Fig. 5: Intermediate results of boxers detection: (a) the depth 3d mesh, (b) contour of the merged boxers, (c) f_d, (d) f_z, and (e) $f_z \cdot f_d$.

2.4 Athletes Movement Analysis

Performance Analysts for combat sports are frequently interested in physical proximity of two boxers, and the extent to which they each move in and out of an effective striking range. Using the position estimates extracted using the methods described above the momentary distance between the boxers can be derived as a 3-D Euclidean distance using:

$$dt(p,q) = \sqrt{\sum_{i=1}^{3} (p_i - q_i)^2} \tag{2}$$

Local point values can be visualised for coaching purposes using a bespoke interactive visualisation tool developed using OpenGL at the Australian Institute of Sport [15]. Exemplar results are shown in Figure 6.

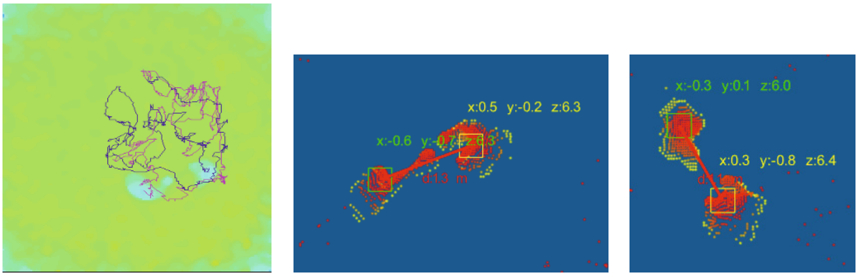


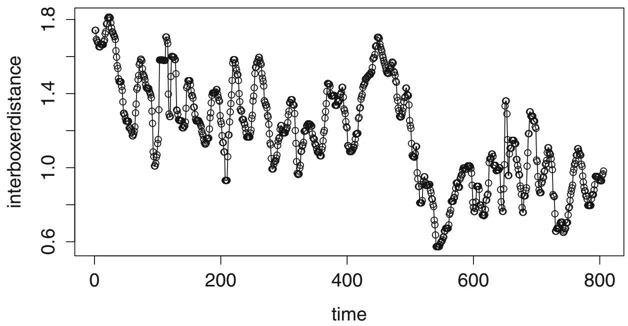
Fig. 6: Tracking and Inter-boxer distance estimates derived from position tracking.

3 Results

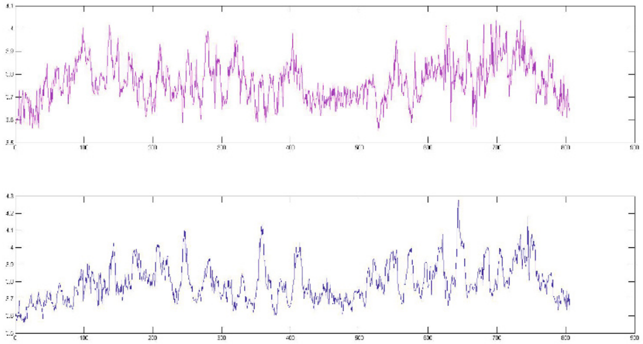
We evaluated our method using a sequence of depth arrays taken at the Australian Institute of Sport from boxing sparring. A time series of the inter-boxer distance can be calculated for greater understanding of the fluctuations in proximity between boxers as a function of various actions and behaviours (Figure 7a). In this instance the raw distance estimates are smoothed using the Tukey's (Running Median) Smoothing function: smooth {stats}, in R (version 3.2.0). Similarly, the vertical oscillations of two boxers in sparring may be related to evidence of physical fatigue. As such performance analysts are interested in monitoring the amount of "bouncing" that occurs over time in a bout. These data can be simply extracted as time series data from the calibrated z-axis, and an exemplar is show in Figure 7b. Discrete estimates of the degree of vertical oscillations could be further derived using measures of dispersion over a sample, or to analyse the data in the frequency domain.

4 Conclusions

Computer vision is becoming increasingly important in sports analytics as a non-invasive method for extracting the occurrence of actions in competition, and for understanding the features of sports performance without impacting on the performance environment with physical motion sensors. Boxing and combat sports represent a particularly challenging domain for action recognition with vision, and demonstrate a method for extracting features of performance using ToF sensors. Our results demonstrate that it is possible to track multiple boxers in a sparring contest, and to extract additional features including punch types, ring position, vertical movement, and the inter-boxer distance. Future work will aim to integrate previous punch classification work with athlete positioning to demonstrate a unified performance analysis system.



(a) Time series analysis of exemplar inter-boxer distances in sparring.



(b) Time series analysis of exemplar vertical oscillations for two boxers.

Fig. 7: Performance feature extractions from boxer head/neck tracking.

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Comparison between Marker-less Kinect-based and Conventional 2D Motion Analysis System on Vertical Jump Kinematic Properties Measured from Sagittal View

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Abstract. Marker-less motion analysis system is the future for sports motion study. This is because it can potentially be applied in real time competitive matches because no marking system is required. The purpose of this study is to observe the suitability and practicality of one of the basic marker-less motion analysis system applications on human movement from sagittal view plane. In this study, the movement of upper and lower extremities of the human body during a vertical jump act was chosen as the movement to be observed. One skilled volleyball player was recruited to perform multiple trials of the vertical jump (n=90). All trials were recorded by one depth camera and one Full HD video camera. The kinematics of shoulder joint was chosen to represent the upper body extremity movement while knee joint was chosen as the representative of the lower body extremity movement during the vertical jump's initial position to take-off position (IP-TP) and take-off position to highest position (TP-HP). Results collected from depth camera-based marker less motion analysis system were then compared with results obtained from a conventional video-based 2-D motion analysis system. Results indicated that there were significant differences between the two analysis methods in measuring the kinematic properties in both lower (knee joint) and upper (shoulder joint) extremity body movements ($p < .05$). It was also found that a lower correlation between these two analysis methods was more obvious for the knee joint movement [38.61% matched, $r = 0.12$ (IP-TP) and $r = 0.01$ (TP-HP)] compared to the shoulder joint movement [61.40% matched, $r = 0.10$ (IP-TP) and $r = 0.11$ (TP-HP)].

Keywords: Motion analysis, marker less, depth camera, vertical jump

1 Introduction

The capture technique of human movement is one of the crucial parts recently used by biomechanics to study the musculoskeletal movement and is also being used by physiologists to diagnose an injury problem. According to Krosshaug et al (2007), analysis of human motion is very useful in establishing injury risks through joint position

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measurement and orientation of body segments, as well as analyzing the technique in sports (Lees, 2002). Thus, it is important to obtain the robustness and accuracy of the results in order to detect every single motion involved in particular human movements.

There are several approaches recommended for use as simple setup tools in order to obtain stable, accurate, and real-time motion capturing performances. The marker-based system tool has been proven to be suitable for in-vitro (laboratory based) studies where the subject has to wear an obstructive device, a marker which is more complicated, hard to maintain, and even quite expensive. Although the application demands to use these tools have increased during a real-time competitive sporting event, but it is difficult for athletes to do their normal routines with the marker placed on their body (Wheat, Fleming, Burton, Penders, Choppin, & Heller, 2012; Zhang, Sturm, Cremers, & Lee, 2012).

The marker-less based system tools have come out with attractive solutions to solve problems associated with marker-based system tools. Microsoft launched the low cost marker-less camera-based Kinetics which originally was used for Xbox 360 gaming, with the capability for tracking the users' body segment positions and 3D orientations in real situations. These cameras require minimal calibration by standing in a specific position only for a few seconds with no marker required on the body. However, this tool also has their own limitations resulting in low accuracy and less supported on motions with high speed (Choppin & Wheat, 2012). With a lower price compared to other depth camera, these cameras are only capable of capturing 30 frames per second. It means that these cameras have the capability only for capturing certain basic motions or movements like walking or jumping, rather than fast movements (Corazza et al., 2006; Zhang et al., 2012).

Therefore, this study was designed to observe the suitability and practicality of depth camera applications in vertical jump focusing on upper and lower extremity body movements when located at the sagittal plane with respect to the movement.

2 Method

2.1 Subject

One skilled amateur volleyball player (age 24 years, height 178 cm, weight 75 kg with 10 years of competitive volleyball playing experience) was recruited to participate in this study. Consent from the subject and approval from the research ethics committee from the research organization was obtained before the study was conducted.

2.2 Instrumentation

One depth camera (Microsoft's Kinect) and one Full HD video camera (Sony-60 FPS) were utilized in this study. The depth camera has the capability of depth data capture at 30FPS with a resolution of 640 x 480 pixels. It is capable of tracking various types of joint angles. Depth Biomechanics by Sheffield Hallam University (Depth Biomechanics, 2015) was the software utilized in this study to process the data captured by the depth camera. KINOVEA software (v. 0.8.15) (Kinovea, 2015) was used to analyze the video. Two units of reflective markers (d=14mm) were located at the right side of the subject's shoulder and knee joint. Subject was asked to perform warm up and stretching exercises for 5 to 10 minutes prior to performing the jump. All cameras were set at the sagittal view of the subject's body, as shown in Fig. 1. Typical calibration of the depth camera (front view calibration) was performed before the recording took place.

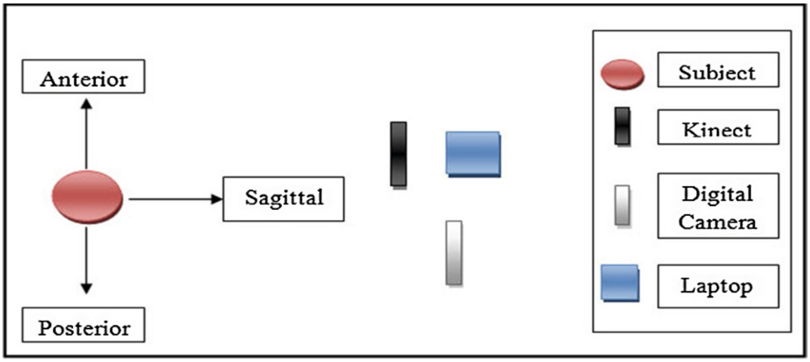

Fig. 1. Instrumentation setup (Top View)

2.3 Data collection and processing

In this study, the shoulder joint was chosen as a representative of upper body extremity, while the knee joint represents the lower body extremity. From these two major parts, each part consists of two different types of phases to be analyzed, which include initial position to take-off phase (IP-TP), and take-off position to the highest phase (TP-HP), as shown in Fig. 2.