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Gesture based Human Computer Interaction for Athletic Training

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ABSTRACT:

The invention of depth sensors for mobile devices, has led to availability of relatively inexpensive high-resolution depth and visual (RGB) sensing for a wide range of applications. The complementary nature of the depth and visual information opens up new opportunities to solve fundamental problems in object and activity recognition, people tracking, 3D mapping and localization, etc. One of the most interesting challenges that can be tackled by using these sensors is tracking the body movements of athletes and providing natural interaction as a result. In this study depth sensors and gesture recognition tools will be used to analyze the position and angle of an athlete's body parts thought out an exercise. The goal is to assess the training performance of an athlete and decrease injury risk by giving warnings when the trainer is performing a high risk activity.

KEY WORDS Motion Analysis, Injury Risk, Kinematic

INTRODUCTION

The invention of depth sensors for mobile devices, has led to availability of relatively inexpensive high-resolution depth and visual (RGB) sensing for a wide range of applications including biomechanics analysis. The complementary nature of the depth and visual information in the activity sensor opens up new opportunities to solve fundamental problems in object and activity recognition, people tracking, 3D mapping and localization, etc. One of the most interesting challenges that can be tackled by using the activity sensor is tracking the body movements of users and providing natural interaction as a result. Human body tracking has many applications in areas of digital animation for entertainment, education, biomechanics analysis for clinical and sports applications, etc.

In recent years, many algorithms have been proposed to address the problem of human parts detection, pose estimation and body tracking from 3D data. Earlier research show focus on the use of time-of-flight range cameras (TOF). Recent technological advances have led to the development of depth cameras that allow acquiring depth and 3D images in real-time with no need for multi-camera systems.

The focus of this research is to use the Microsoft Kinect as a clinical assessment tool which can assist rehabilitation, biomechanics and training, regular exercise, and ergonomic methods. In biomechanics, having knowledge on the position and orientation of a user is vital when assessing attention, performance, injury risk and joint loading. The focus of scientists in this area has always been on obtaining information on position and orientation of body quickly and accurately. Skeleton



tracking and gesture analysis play a central role in ergonomics and biomechanical engineering. Through this scientific exploration, attempts can be made to reduce the risk of musculoskeletal injury or possibly study the system for performing ergonomic assessments. One of the frequently used exercise in strength & conditioning programs is the Olympic snatch. Snatch requires athletes to lift the weight explosively. The biomechanics of this technique is similar to activities such as running and jumping. Researchers have studied the lift extensively by examining Olympic weightlifters to get insight on this exercise. However it is difficult to acquire kinematic and kinetic parameters. Thus, an understanding of the movement would be very valuable for coaches [1].

Current devices that are capable of measuring spatiotemporal and kinematic variables are expensive. Emerging of low cost sensors that capture motion has provided a clinically feasible alternative for biomechanical validation of weightlifting.

Originally created for gaming, the Microsoft Kinect V2 enables 3D motion capturing. In particular, the Kinect has a depth sensor with a resolution of 512 x 424 pixels which provides depth information for each pixel using TOF [2]. It is possible to obtain the 3D coordinates of 25 body joints via randomized decision trees forests [3] as shown in the following Figure.

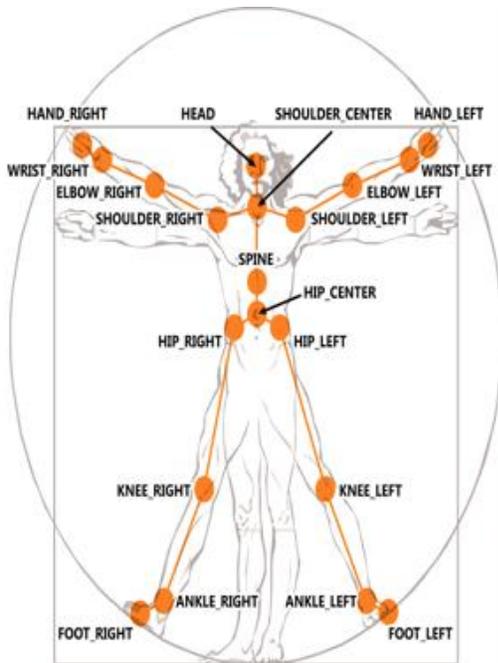


Figure 1. Kinect skeleton tracking points

Previous research studied the feasibility of using the Kinect as clinical assessment tool and found that the Kinect and Kinect V2 showed promise as a low cost alternative to lab-based multi camera

systems. In particular, in spinal cord injuries rehabilitation, the Kinect was compared with an expensive high precision optical system and was found to be an accurate low-cost and easy to use alternative [4]. The Kinect was found to be a valid tool for assessing spatiotemporal components of gait [5,6] but it is unable to accurately assess lower limb kinematics [7,8]. In order to bypass the lower extremities inaccuracy a technique that relies on knee joint relative angle has been proposed to detect foot-off and foot contact during the gait cycle [9]. The Kinect was successfully used for the classification of human movement during active video game play in relationship to fundamental movement skill [10].

The purpose of this study is twofold. First, this study assesses the ability of the Kinect, a low-cost easy to use device, to accurately acquire kinematic and kinetic parameters during the Snatch lift. A second purpose of this study to classify movement frames into 6 phases of the snatch and then assign a score to each frame that indicates the deviation from good form.

METHODS

The Kinect V2 allows us to retrieve the 3D coordinates of the body joints. We use these coordinates to obtain the angles between various joints as follows:

The joint angles were determined as follows:

- Knee joint angle for each leg was calculated using the Cartesian coordinates of the hip, knee and ankle joints.
- Hip joint angle was calculated using the Cartesian coordinates of the hip, knee and shoulder center joints.
- Back joint angle was calculated using the Cartesian coordinates of the hip, shoulder center and a unit vector.

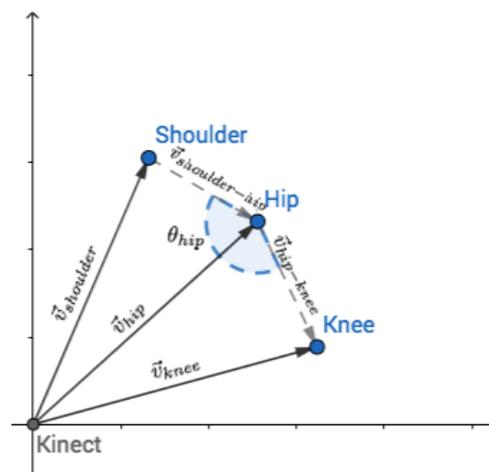


Figure 2. Calculating knee, hip, back joint angles using Cartesian coordinates

Let \vec{v}_{ij} be vectors in 3-D space between joints i and j where $i, j \in \{\text{shoulder, hip, knee}\}$ and \vec{u}_{ij} be their unit vectors (Figure 2).

We compute the angles of joints using the following:

$$\theta_{hip} = \cos^{-1}(\vec{u}_{hip-knee} \cdot \vec{u}_{shoulder-hip})$$

$$\theta_{knee} = \cos^{-1}(\vec{u}_{hip-knee} \cdot \vec{u}_{ankle-hip})$$

$$\theta_{back} = \cos^{-1}(\vec{u}_{shoulder-knee} \cdot \vec{x})$$

$$x = (1, 0, 0)$$

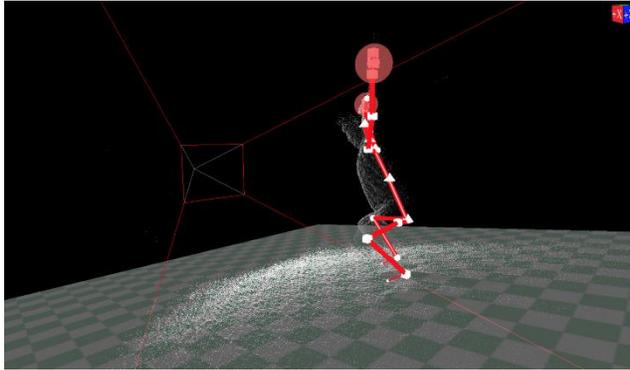


Figure 3. Kinect skeleton tracking map

The analysis focused on the pulling phase from the beginning of the barbell lift-off to the second pulling phase, turnover and rising above head. The different phases of the snatch are explained in the following.

1. First Pull: This phase begins with the barbell at rest on the ground and ends when the knees reach their first maximum extension.
2. Transition: At this stage the knees are flexed and pushed toward the barbell. This phase ends at maximum knee flexion.
3. Second pull: This phase begins when the knees reach maximum flexion during the transition phase. By the end of this phase, the displacement of the hips, knees and ankles are maximum extension range of motion.
4. Turnover: This phase begins at maximum knee extension and ends when the barbell reaches its maximum height. The lifter begins moving the body downward to be positioned underneath the barbell.
5. Catch: This phase is when the lifter locks the arms and stabilizes the barbell overhead while slowing its downward movement.
6. Rising: This phase follows the catch and is when the lifter rises from the squat position to stand fully erect at the completion of the lift.

The joint angle: in Figure 4, the angular displacements of the ankle, knee and hip joints in the sagittal plane were calculated.

EXPERIMENTAL SETUP

A Kinect sensor was placed at the following distances and angles from the subjects which were healthy athletes familiar with Olympic weightlifting.

Table2. The experimental setup

Kinect Placement	Angle	Distance
Lateral	90°	2m
Inclined 45	45°	2.5m
Inclined 20°	20°	2m

A frontal placement of the Kinect did not yield accurate measurement of all angles. Each subject executed four snatches. The video is recorded in 30 frame per second. We determined that the most accurate data (compared to a multi-camera system) is the 2nd configuration (Inclined 45° at a distance of 2.5m)

After filtering and removing noise the remaining frames were classified into each of the 6 positions. The features generated for each frame are: the angular displacements of the ankle, knee, hip and back joints. We used time series segmentation using Hidden Markov Model to label each frame.

Image processing is used to identify the location of barbell and determine the bar path in respect to the vertical line. We used bar path, amount of time spend in each phase of the lift and joint angles to determine the risk level of the subject in each position.

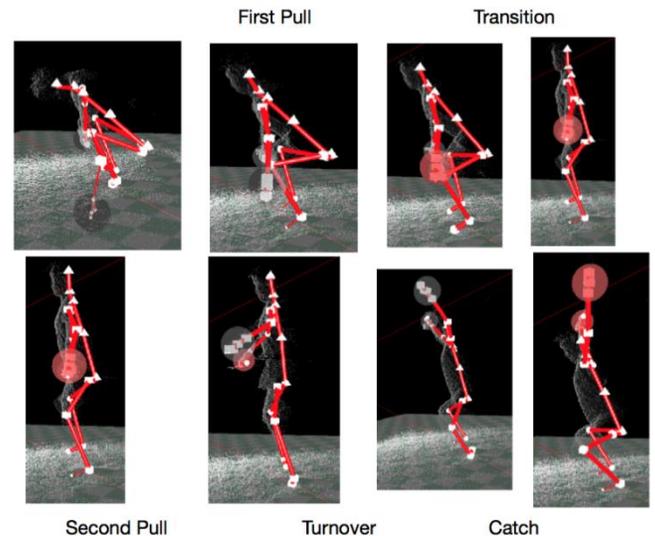


Figure 4. Phases of snatch

STATISTICAL RESULTS

The following charts (Figure 5) show the angular displacement of the hip and knee as well as the trajectory of the barbell during the Snatch. The kinematic variables of the snatch were calculated and used to interpret the healthy form.

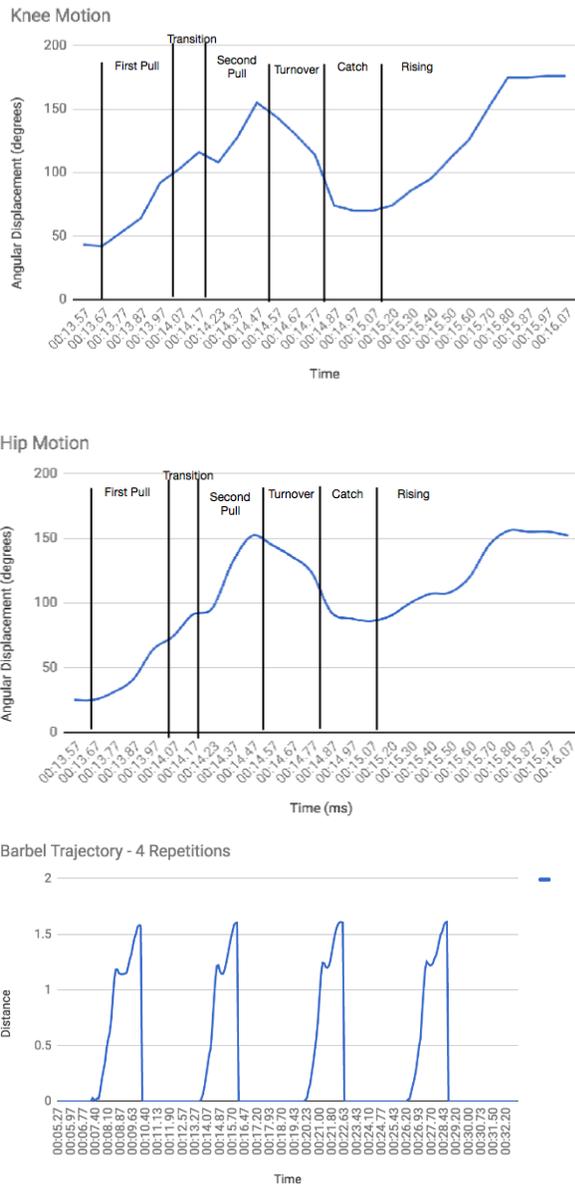


Figure 5. Angular displacements

The motion results on knees and hips are in line with previous literature and data from an optical motion tracking system, however the information gain of ankles motion was low and inaccurate. This is due to noisy data stemming from lower extremities inaccurate tracking by the Kinect as indicated in [7,8].

Once the video for skeleton tracking was recorded and annotated, the classification and feature ranking were performed. Classification analysis was performed using Naive Bayes and Support Vector Machine (SVM). 10-fold cross validation was used to evaluate the predictive models. By using both methods, a better understanding of the classification accuracy and speed boundaries for the data can be determined.

The annotated training set has a high class imbalance. To address this issue, SMOTE oversampling technique was used. As can be seen in Table 2, both classifiers performed well on the classification task. The data has been classified in 6 different clusters and the results show promise for this type of classification task.

Table 2. Classification result

	Naïve Bayes			SVM		
	Precision	Recall	FMeasure	Precision	Recall	FMeasure
First Pull	0.773	0.85	0.81	0.692	0.9	0.783
Transition	0.21	0.15	0.175	0.05	0.08	0.06
Second Pull	0.692	0.56	0.621	0.733	0.69	0.71
Turnover	0.867	1	0.929	0.917	0.85	0.88
Catch	0.727	1	0.842	0.7	0.88	0.778
Rising	1	0.84	0.914	0.941	0.84	0.889
Weighted AVG	0.817	0.81	0.808	0.789	0.8	0.791

Results of the feature analysis using the information gain ranking technique can be seen in Table 3. From these results, it can be seen that the hand and hip positions have the highest contribution to classification accuracy. Additionally, it can be seen that back and knee features have a higher contribution than time. Time series was used to identify the correlation of time feature in segmentation however that did not have an impact on the accuracy of the model. In the future work Hidden Markov Model and sliding window approach will be used.

In addition, the algorithm is able to assess each frame against predetermined rules for a health snatch. Healthy snatch will be identified using a rule-based algorithm based on displacement from centroid of clusters regarding of weight category, gender, and age of lifters and rules based on physics of lifting. For each class, the pulling style might be different for example taller lifters may need to extend the knees somewhat more to bring the bar past the knees properly.

This added validity and reliability is beneficial to assessing the variables that have previously been identified and correlate to the injury level of lifter. For example the angle of the back should remain more or less constant during the first pull, the hips and knees should be fully extended during the second pull, rules regarding speed and accuracy of both barbell path and turnover etc... a deviation from these rules in any frame will result in an alert flag and an unhealthy classification for that frame.

Feature ranking was performed using information gain based feature ranking.

Table3. Feature ranking

Rank	Score	Feature
1	0.78	LeftHandYPos
2	0.77	RightHandYPos
3	0.74	RightHandXPos
4	0.7	LeftHipAngle
5	0.67	RightHipAngle
6	0.63	BackAngle
7	0.59	LeftHandZPos
8	0.57	LeftHandXPos
9	0.53	RightHandZPos
10	0.5	RightKneeAngle
11	0.47	LeftKneeAngle
12	0.37	Time
13	0.35	RightLiftAngle

DISCUSSION

The kinematics of snatch lifting were analyzed using Kinect and provide insight into this technique. In this paper the Kinect was used to track skeleton joints of athletes performing snatch. Machine learning was used to classify the 6 phases of this technique. The proposed approach gave promising results for a systematic assessment the training performance. In conclusion, the Kinect sensor can potentially be an effective clinical tool for evaluating knee and hip joint kinematics and some spatiotemporal variables during lift. Given the advances in depth sensor technology and ease of data acquisition and processing, the Kinect can be a feasible and cost-effective alternative to the expensive marker-based 3DMA systems for use in clinic and at-home applications

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