

# An interactive motion analysis framework for diagnosing and rectifying potential injuries caused through resistance training

Jake Hall  
Northumbria University

Jacky C. P. Chan  
Caritas Institute of Higher Education

Hubert P. H. Shum  
Northumbria University

Wei Wei  
Xi'an University of Technology

Edmond S. L. Ho  
e.ho@northumbria.ac.uk  
Northumbria University

## ABSTRACT

With the rapid increase in individuals participating in resistance training activities, the number of injuries pertaining to these activities has also grown just as aggressively. Diagnosing the causes of injuries and discomfort requires a large amount of resources from highly experienced physiotherapists. In this paper, we propose a new framework to analyse and visualize movement patterns during performance of four major compound lifts. The analysis generated will be used to efficiently determine whether the exercises are being performed correctly, ensuring anatomy remains within its functional range of motion, in order to prevent strain or discomfort that may lead to injury.

## KEYWORDS

motion capture, motion analysis, resistant training, visualization

### ACM Reference Format:

Jake Hall, Jacky C. P. Chan, Hubert P. H. Shum, Wei Wei, and Edmond S. L. Ho. 2019. An interactive motion analysis framework for diagnosing and rectifying potential injuries caused through resistance training. In *Motion, Interaction and Games (MIG '19)*, October 28–30, 2019, Newcastle upon Tyne, United Kingdom. ACM, New York, NY, USA, 2 pages. <https://doi.org/10.1145/3359566.3364688>

## 1 INTRODUCTION

A study conducted by the Nationwide children's hospital found that more than 970,000 injuries directly related to weight-training were treated in U.S. hospital emergency departments between 1990 and 2007, with the frequency of cases increasing by almost 50% in 18 years [ScienceDaily 2010]. The driving force behind this work is the fact that physiotherapists require years of training to be able to diagnose the causes of injury simply by watching the patient perform an exercise. Receiving professional coaching can be costly, thus a sizable portion of these individuals are not professionally educated in how to perform these exercises optimally or the dangers associated with poor execution of these exercises.

Bodybuilding, Olympic weightlifting and bodybuilding are the most widely recognised and commonly practised weightlifting focused sports. The injuries associated with these sports can be split into two classifications - acute and chronic. A study conducted by Calhoun and Fry reported that acute injuries accounted for 59.6% of injuries with 30.4% being chronic and 10% classified as 'other' [Fry et al. 1998]. A 2016 systematic review [Aasa et al. 2017] contains 9 studies looking into injuries among weightlifters and powerlifters found that on average weightlifters sustained up to 2.4-3.3 injuries and powerlifters sustained up to 1.0-4.4 injuries per 1000 hours of training. These resultant frequencies are relatively low, however this study defined 'injury' as an "an event that causes an interruption in training or competitions" [Strömbäck et al. 2018] which may not be the case with all discomfort.

Motion capture technology has been widely applied within sports science and the healthcare sectors. Shen et al. [Shen et al. 2017] proposed a visualization framework for evaluating the skills level of the player in sports such as boxing. In the healthcare sector, optical MOCAP data has been used for Diagnosing Musculoskeletal and Neurological Disorder [Rueangsirarak et al. 2018]. Various motion features, such as relative joint positions, and feature selections techniques are evaluated on classifying the health issues from the patients' motion data. McCay et al. [McCay et al. 2019] propose a new framework to classify infants with potential movement difficulty issues by analyzing the body movement. Ho et al. [Ho et al. 2016] proposed a new classification framework which takes into account the reliability of the joint position data captured using low-cost depth cameras such as Microsoft Kinect.

In this paper, we propose a new motion analysis and visualization framework to highlight the potential injuries caused by resistance training. Specifically, the body movement of the subject is captured using an inertial MOCAP system. Next, the joint angles extracted from the skeletal motion data will be compared with the joint movement range suggested in the literature to analyze whether the subject is at risk. Finally, the joint(s) which violate(s) the safe movement range will be highlighted in the visualization interface.

## 2 METHODOLOGY

This section explains the design of the proposed framework, from the use of the inertial motion capture suit to capture the motion data, to how the system has been designed.

### 2.1 Data Gathering

This data was collected using the XSens MVN inertial motion capture system. In particular, 17 sensors are used in the capturing

Permission to make digital or hard copies of part or all of this work for personal or classroom use is granted without fee provided that copies are not made or distributed for profit or commercial advantage and that copies bear this notice and the full citation on the first page. Copyrights for third-party components of this work must be honored. For all other uses, contact the owner/author(s).

*MIG '19*, October 28–30, 2019, Newcastle upon Tyne, United Kingdom

© 2019 Copyright held by the owner/author(s).

ACM ISBN 978-1-4503-6994-7/19/10.

<https://doi.org/10.1145/3359566.3364688>

**Table 1: Range of motion of the selected body parts.**

body part	plane/direction	range (in degree)
lumbar spine	flexion	0 to 90
lumbar spine	extension	0 to 25
lumbar spine	lateral movement	-25 to 25
shoulder	all	0 to 360
hip	lateral	-20 to 20
hip	backward extension	0 to 30
knee	sagittal	0 to 150

process. In this study, 4 types of motions are selected, including Deadlift, Push-up, Overhead Press, and Squat. To ensure the health and safety of the subject, the subjects are experienced personal trainers and a detailed briefing session is conducted before every single capturing process.

## 2.2 Anatomical range of motions

As stated in Section 1, previous studies [Aasa et al. 2017; Strömback et al. 2018] suggested that the lumbopelvic region (low back), shoulder, hip and knee are the most susceptible to injuries. In this study, the range of motion in these body parts are considered to evaluate the healthiness of the postures in the captured motion. Table 1 summarizes the motion ranges obtained in previous studies.

## 2.3 Skeletal Data Visualization and Analysis

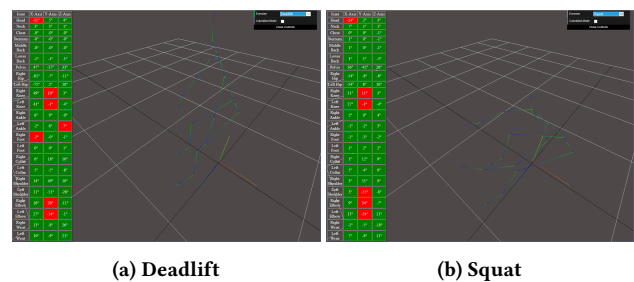
The next process is creating an interface in which the user can observe the data and how it changes during the movement of the skeleton. To perform the analysis of the data, we consider the overall anatomical range of motions of musculoskeletal joints that were outlined in Section 2.2. These values can be considered the absolute safe range of motion for the average human anatomy. These values can be used to set thresholds in which each joint of the skeleton being analysed must remain within. This allows each joint to be analysed individually and the differences between anatomies ignored as any joint exceeding this range of motion are in a dangerous position.

## 3 IMPLEMENTATION DETAILS AND RESULTS

In this work, we analyze each joint individually. Doing this allows each plane of motion to be analysed separately, as well as in conjunction with each other. An example of this would be the knee joint in comparison to the shoulder complex. As the knee is a hinge joint, it can only effectively rotate around a single axis, the X-axis, therefore a single range of motion can be specified for the X-axis and the other two can be set to minimal range to allow for capture inaccuracies without disrupting the analysis. This is in contrast to the shoulder which allows for almost 360-degree rotation upon all axis, meaning the shoulder only becomes compromised when an unfavourable pair of rotations occur. If the shoulder were to rotate 180 degrees around the Z-axis, as well as 180 degrees around the Y-axis, the glenohumeral joint would be dislocated. This can be covered using the absolute range of motion analysis method as multiple conditions can be specified. If the joint angle violates the suggested range of motion threshold, the cell of the table in which

the joint value is being displayed turns red, alerting the user of the system that during that moment of the animation clip, the joint was in a compromising position.

The interface (see Figure 1) upon start-up contains an assistance grid orientated upon the XZ plane which aids the user in orientating the camera while observing the skeleton. There will also be an interactive drop-down interface that will house the exercise selection options. Upon selecting an exercise from the drop-down menu, the skeleton loads and begins to perform the motion loaded from the captured BVH file. Alongside the skeleton, the interface features a table displaying the names of the 23 joints being analysed, as well as the corresponding joints X, Y and Z orientation. The joints are not ordered in skeleton hierarchy, instead they are ordered in relation to the kinetic chain, from head to feet, followed by the upper limbs.



**Figure 1: Screenshots of the user interface of the proposed system.**

## 4 CONCLUSION AND DISCUSSIONS

In this work, we propose a unified framework for analyzing and visualizing potential injuries in resistant training. In the future, we will capture a wider range of motion to further evaluate the effectiveness of the proposed framework.

## REFERENCES

- Ulrika Aasa, Ivar Svartholm, Fredrik Andersson, and Lars Berglund. 2017. Injuries among weightlifters and powerlifters: a systematic review. *British Journal of Sports Medicine* 51, 4 (2017), 211–219. <https://bjsm.bmj.com/content/51/4/211>
- A. C. Fry, G. Calhoun, M. H. Stone, L. W. Weiss, Y. Li, and E. L. Cantler. 1998. Injury Rates and Profiles of Elite Competitive Olympic-style Weightlifters. *Medicine & Science in Sports & Exercise* 30, 5 (1998), 53.
- Edmond S.L. Ho, Jacky C.P. Chan, Donald C.K. Chan, Hubert P.H. Shum, Yiu ming Cheung, and Pong C. Yuen. 2016. Improving Posture Classification Accuracy for Depth Sensor-based Human Activity Monitoring in Smart Environments. *Computer Vision and Image Understanding* 148 (2016), 97 – 110.
- Kevin McCay, Edmond S. L. Ho, Claire Marcroft, and Nicholas D. Embleton. 2019. Establishing Pose Based Features Using Histograms for the Detection of Abnormal Infant Movements. In *2019 41th Annual International Conference of the IEEE Engineering in Medicine and Biology Society (EMBC)*.
- W. Rueangsirarak, J. Zhang, N. Aslam, E. S. L. Ho, and H. P. H. Shum. 2018. Automatic Musculoskeletal and Neurological Disorder Diagnosis With Relative Joint Displacement From Human Gait. *IEEE Transactions on Neural Systems and Rehabilitation Engineering* 26, 12 (Dec 2018), 2387–2396. <https://doi.org/10.1109/TNSRE.2018.2880871>
- ScienceDaily. 2010. Weight training-related injuries increasing. <https://www.sciencedaily.com/releases/2010/03/100330115925.htm>. Accessed: 2019-07-22.
- Yijun Shen, He Wang, Edmond S.L. Ho, Longzhi Yang, and Hubert P.H. Shum. 2017. Posture-based and action-based graphs for boxing skill visualization. *Computers & Graphics* 69 (2017), 104 – 115. <https://doi.org/10.1016/j.cag.2017.09.007>
- Edit Strömback, Ulrika Aasa, Kajsa Gilenstam, and Lars Berglund. 2018. Prevalence and Consequences of Injuries in Powerlifting: A Cross-sectional Study. *Orthopaedic Journal of Sports Medicine* 6, 5 (2018).