A mobile platform app to assist learning human kinematics in undergraduate biomechanics courses

Hanwen Wang, Lu Lu, Ziyang Xie Bingyi Su, Xu Xu
Edward P. Fitts Department of Industrial & Systems Engineering,
North Carolina State University, Raleigh NC, USA

Abstract: Biomechanics examines different physical characteristics of the human body movement by applying principles of Newtonian mechanics to physical activities. Therefore, undergraduate biomechanics courses are highly demanding in mathematics and physics. While the inclusion of laboratory experiences can augment student comprehension of biomechanics concepts, the cost and the required expertise associated with motion tracking systems can be a burden of offering laboratory sessions. In this study, we developed a mobile platform app to facilitate learning human kinematics in biomechanics courses. An optimized computer-vision model that is based on convolutional pose machine (CPM), MobileNet V2 and TensorFlow Lite frameworks is adopted to reconstruct human pose first. A real-time human kinematics analysis then allows students to conduct human motion experiments. The proposed app can serve as a potential instructional tool in biomechanics courses.

INTRODUCTION

Biomechanics is a common sub-discipline within movement science and human factors, which addresses the integration of functional musculoskeletal anatomy and mechanical physics (Hatze, 1974; Knudson, 2010). It analyzes human body movement by applying principles of Newtonian mechanics to physical activities to avoid injury and/or enhance performance. To date, there have been a number of novel developments in new technologies used in the biomechanical analysis (Hamill et al., 2021). Nearly all undergraduate movement science students are required to complete one biomechanics course prior to graduation (Hamill, 2007; Munro, 2012; Riskowski, 2015). However, as courses in biomechanics are highly demanding in mathematics and physics, many undergraduates often fear and delay taking their required biomechanics course, even though they involve necessary biomechanical concepts in their future professions (Garceau et al., 2012; Hsieh, et al., 2012).

To help students overcome the anxiety toward this subject matter, biomechanics instructors must develop a student-centered teaching method to teach course content more effectively. Previous studies have suggested that the inclusion of laboratory experience improves learning outcomes in biomechanics (DiCecco et al., 2007; Knudson et al., 2009; Full et al., 2015) due to the self-reference effect (Symons & Blair, 1997) and self-efficacy theory (Wallace & Kernozek, 2017). Students' learning performance can be enhanced through laboratory experiments by integrating abstract concepts from lectures and real-life examples via hands-on experiences. Yet it has been reported that only 62 % of biomechanics courses were offered laboratory sessions (Garceau et al., 2011) since implementing laboratories into biomechanics curriculums is difficult due to cost and time constraints. For example, an optical marker-based motion tracking system is a general device for researchers to assess human kinematics. Such a system can obtain three-dimensional coordinates of markers that are attached to one's body in a laboratory environment. Then the joint angular velocity and acceleration can be further calculated using the marker coordinates (Skals et al., 2021). However, adopting a motion tracking system into an undergraduate course sometimes can be less practical due to its high cost, bulky size, and required expertise.

Depth sensors, such as Microsoft Kinect and Intel RealSense, are a potential solution for biomechanics education because they are low-cost, portable, and generally accurate in pose reconstruction. In one study, shoulder kinematics during computer use was captured by a depth sensor for office ergonomics assessment (Xu et al., 2017). In another study, upper-limb gestures in healthy people and post-stroke patients were evaluated by a depth sensor (Scano et al., 2019). However, the coverage area of depth sensors is limited (Shum et al., 2013; Han et al., 2013), and the accuracy can be affected by the lighting condition of the environment (Azzari et al., 2013). In addition, the hardware setup can be complicated for less tech-savvy people.

With researchers' continuous efforts and innovations on deep neural networks, computer-vision-based pose estimation methods have emerged as a promising approach to enable real-time human kinematics analysis. For example, OpenPose, an open-source library, can detect 2-D and 3-D anatomical landmarks positions with convolutional neural networks trained from single images (Cao et al., 2021). The only hardware required would be a webcam together with a computer with a high-performance graphic processing unit (GPU). A recent study assessed 3-D lower limb angular kinematics of healthy people walking on a treadmill by processing two synchronized videos in OpenPose (D'Antonio et al., 2020). The reliability and validity of the computer-vision method have also been verified during bilateral squat motion (Ota et al., 2020). Nevertheless, a computer with a high-performance GPU can still be a burden for biomechanics course experiments because of its high cost and low portability.

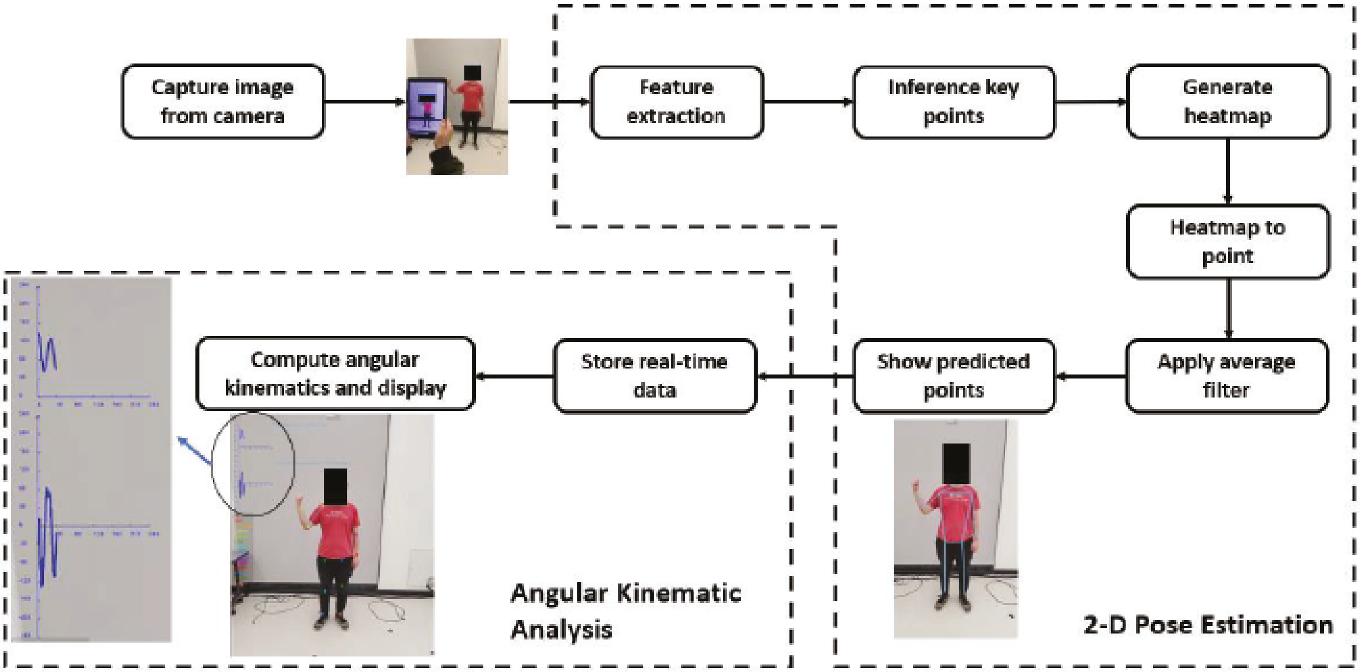


Figure 1. System overview. The input is the images captured in the app; the outputs are the selected joint angle and angular velocity.

Ideally, mobile devices, such as tablets and smartphones, can address the challenges mentioned above because they are affordable, portable, and interactive. While the computational power of mobile devices is typically not as good as a high-performance GPU, researchers have developed several advanced computer-vision algorithms for mobile device deployment. For example, Google launched the MobileNet and Tensorflow Lite frameworks (Howard et al., 2017; Abadi et al., 2016). Tensorflow Lite provides interpreter modules that can adapt different sizes of inputs to help mobile terminals optimize the trained network model and perform local calculations on human pose estimation. Considering most mobile devices also come with an embedded camera, there is a good potential to only use a mobile device as an instructional tool of biomechanics courses to help students gain laboratory experience in human kinematics.

In this study, we aim to design an Android-based mobile app named Mobile Biomechanics Laboratory (MOBL) that could be applied to undergraduate biomechanics courses. With smartphones or tablets, students are able to practice angular kinematics analysis on several body segments in real-time. Below, the method section introduces the overall app architecture and the underlying computer-vision algorithms; the result section shows the analyzed human kinematics data displayed in the user interface; the discussion section discusses the ideas to utilize this app in actual biomechanics courses as well as the future work.

METHODS

System Overview

The app follows a three-tier architecture that consists of a computer-vision algorithm, a user interface, and a database. Image information is collected and processed through the computer-vision algorithm to predict joint locations. Key joint locations are then used for further angular kinematics analysis. Regarding the user interface, users can view various kinematics data for a selected joint in real-time. Figure 1 illustrates the system's data overflow, which includes two major components: 2-D pose estimation and angular kinematics analysis. The input is the RGB images captured by a mobile device, and the outputs are the joint kinematics of a selected joint.

2D Pose Estimation

Note that real-time 3-D pose reconstruction with deep neural networks on mobile devices remains computationally challenging. Therefore, in this study, pose estimation is treated as a 2-D regression problem. The input RGB images are represented by a series of $M \times N \times 3$ matrices where M and N are determined by the resolution of the raw image and represent the number of rows and columns of pixels, respectively. For each pixel, a 3-D vector represents RGB color channels (R-red, G-green, B-blue). The outputs are the predicted 2-D joint locations of a number of key joints on the image plane. Each key point is a 2-D vector (x, y), representing its 2-D coordinate on the input image. With a consideration that the key points must possess certain distinguishable and invariant image features, such as scaling and viewing angle rotation under different conditions (Lowe, 2004), 14 key points, including shoulder, elbow, and wrist, are selected to articulately represent human poses under different conditions (Figure. 2).

Traditional convolutional neural network (CNN)-based pose detection algorithms are not suitable for mobile application development as these algorithms demand high computational capability. In this study, we adopted a deep learning model based on convolutional pose machines (CPM) (Wei et al., 2016)

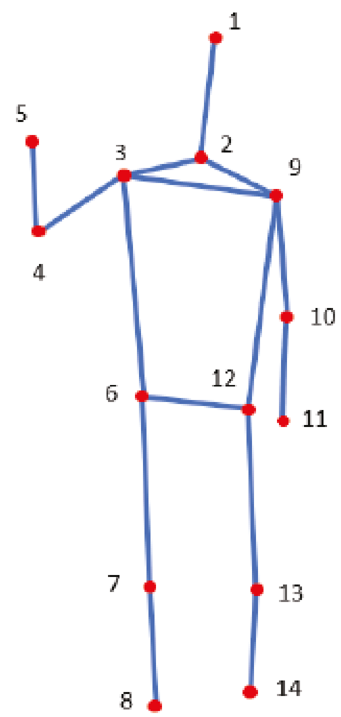


Figure 2. Indexing for the 14 key points. 1-head; 2-neck; 3-right shoulder; 4-right elbow; 5-right wrist; 6-right hip; 7-right knee; 8-right ankle; 9-left shoulder; 10-left elbow; 11-left wrist; 12- left hip; 13-left knee; 14-left ankle.

and converted it to the Tensorflow Lite model to detect key points through the app. An inverted residual with a linear bottleneck module (also known as MobileNet V2) is adopted for real-time inference (Sandler et al., 2018). Instead of applying normal convolution, this method performs a sequence of depth-wise separable convolutions introduced in MobileNet V2 to immensely reduce the number of computations (Chollet, 2017). Moreover, the input image is reshaped into 192 × 192 × 3 at the first step and then converted to image features to further reduce the computational cost. In the neural network, the inferenced key points were shown as a heatmap after each convolution process. Within each repeated stage, the heatmaps improved confidence for spatial detection over joint locations and provided better estimates for localization of key points later on. By fitting the final heatmap to an average filter, it takes the maximum value from the confidence map for each key point and estimates the 2-D coordinates of the 14 key joints.

Kinematics Analysis

The current study focuses on joint angular kinematics analysis and presentation. Figure 3 shows the architecture of the angular kinematics estimator. The inputs are the key point coordinates from the pose estimation process. After a user selects a specific joint, the estimator will choose the corresponding coordinates and calculate joint angles by estimating the angle between two body segments. Currently, the proposed application can calculate angles for elbow flexion/extension (EF/E), shoulder abduction/adduction (SA/A), and trunk lateral bending (TLB). Let C_i denotes the 2-D coordinate of i_{th} key point and V_{i-j} denote the body segment from the i_{th} key point to the i_{th} key point. Let angle(V_{i-j}, V_{i-j}) represent the angle between the two body segments which can be calculated by using arccos function and vector multiplication. The joint angles can be defined as:

$$EF/E_R = angle(V_{4-3}, V_{4-5}) \quad (1)$$

$$EF/E_L = angle(V_{10-11}, V_{10-9}) \quad (2)$$

$$SA/A_R = angle(V_{3-4}, V_{3-6}) \quad (3)$$

$$SA/A_L = angle(V_{9-10}, V_{12-9}) \quad (4)$$

$$TLB = angle\left(\tfrac{1}{2}(C_3 + C_9 - (C_6 + C_{12})), (0,1)\right) \quad (5)$$

Note that the estimated 2-D coordinates do not include any depth information. Thus, the person being captured needs to face the camera without trunk rotation.

Next, the system uses the estimated joint angles (a) and the corresponding time (t) for angular velocity calculation. To denoise, the joint angles are first filtered by a width = 5 moving average window. The angular velocity at T = k is given by:

$$Angular\ velocity\ = \frac{\Delta angle_k}{\Delta T_k} \quad (6)$$

The joint angle and the angular velocity at each time instants are then plotted in the user interface.

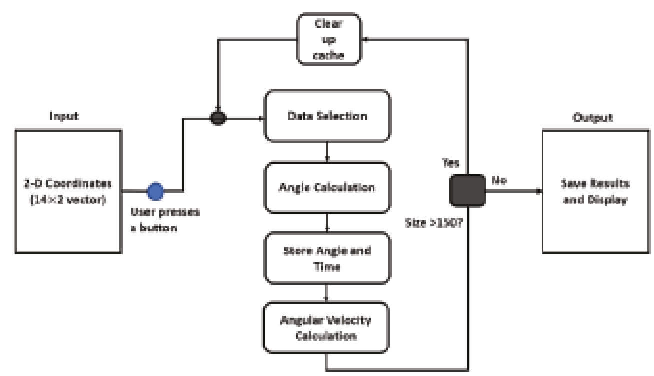


Figure 3. Angular kinematics estimator

RESULTS

We have deployed the proposed app on a Samsung S7 tablet with a Qualcomm SDM865 Pro processor. A “model” was asked to face the tablet’s back camera without trunk rotation. Meanwhile, a “user” chose a proper distance from the model to capture the model’s whole body (Figure 4). Figure 5 shows the user interface where all 14 key points are displayed with different colors. Five buttons are placed at the bottom of the interface, indicating angular kinematics analysis of different joints of interest. Figure 6 provides screenshots of a representative trial in which the model repeatedly performed right forearm flexion/extension in the coronal plane.

DISCUSSION

Potential Applications

With this proposed mobile app for analyzing basic human kinematics, we can develop a curriculum module that facilitates the education of undergraduate biomechanics concepts. For example, the curriculum module could first show a short animation during which a virtual instructor guides students to illustrate the placement of the mobile device camera and perform certain activities. Next, the computer vision algorithm recognizes the human body, reconstructs the pose, and overlaps the reconstructed pose on the model's image. Then the curriculum module will automatically calculate basic descriptive statistics of all measured kinematic variables (e.g., peak, quantiles, ranges, and distribution patterns) within and across all activities performed. In data science, basic descriptive statistics provide exploratory and knowledgeable insights of data. Thus, these statistics could further augment students' comprehension of the scale of human kinematics variables.

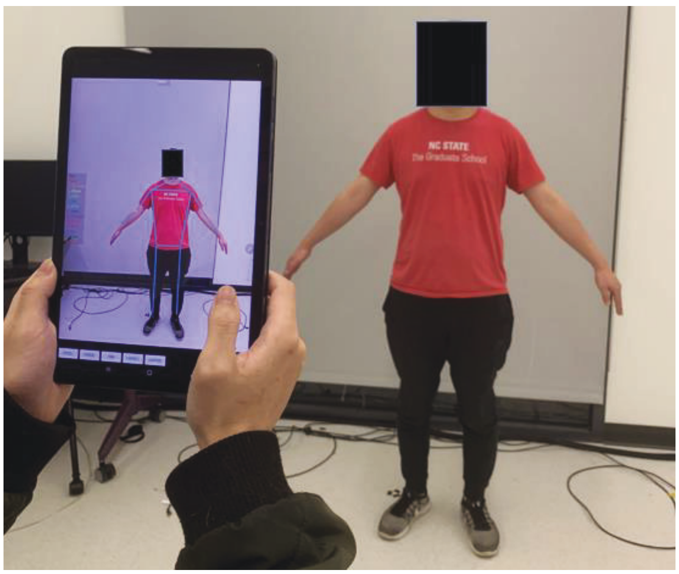
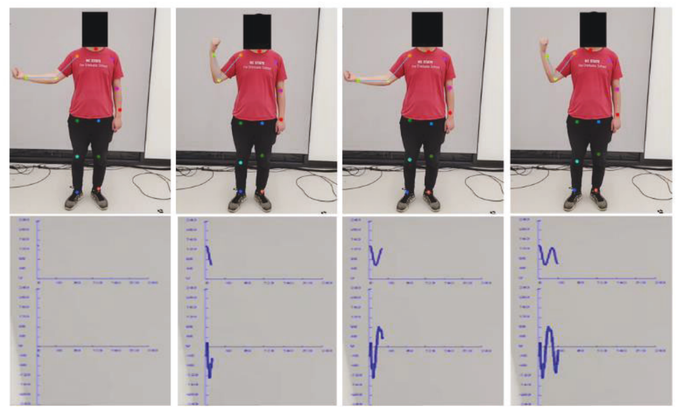


Figure 4. A scenario that a user launches MOBL to detect a model's joint kinematics data.

Figure 5. A screenshot of the user interface. The legends of 14 key points are displayed at the center-left. The bottom buttons are EF/E_L (left forearm flexion/extension), EF/E_R (right forearm flexion/extension), TLB (trunk lateral bending), SA/A_L (left upper arm flexion/extension), and SA/A_R (right upper arm flexion/extension), respectively.

Limitation and Future Work

There are a few limitations that need to be discussed. First, the computer-vision algorithm we adopted is originally developed for capturing a single person without a view block. Pose reconstruction can be inaccurate when other objects block the body segments, or the camera captures multiple persons simultaneously. Second, due to the computational cost of processing 3-D poses in mobile devices, the current app is unable to reconstruct 3-D poses from the images and thus unable to perform joint kinematics analysis for 3-D joints, such as the glenohumeral joint. Third, to what extent the knowledge that students can gain through this app has not been examined. In future work, additional biomechanical analysis covered in undergraduate courses, such as gait analysis and the center of mass (COM) calculations, can be added into this app. In addition, the app performance in knowledge transfer needs to be further quantitatively investigated.



a) Start b) First flexion c) First extension d) Second flexion

Figure 6. Screenshots of angular kinematics analysis for a representative trial (right forearm flexion/extension).

CONCLUSION

This study presented a mobile platform app that performs angular kinematics analysis based on real-time captured videos. It allows undergraduate students to conduct biomechanics experiments without using a high-cost laboratory equipment. While additional learning modules and functions can be introduced into this app in the future, the current app can be used as a potential instructional tool in biomechanics courses.

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