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Short communication

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

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ABSTRACT

Whole-body biomechanics examines different physical characteristics of the human body movement by applying principles of Newtonian mechanics. 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 experiment equipment can be a burden of offering laboratory sessions. In this study, we developed a mobile app to facilitate learning human kinematics in biomechanics curriculums. First, a mobile-based computer-vision algorithm that is based on Convolutional pose machine (CPM), MobileNet V2, and TensorFlow Lite framework is adopted to reconstruct 2D human poses from the images collected by a mobile device camera. Key joint locations are then applied to the human kinematics variable estimator for human kinematics analysis. Simultaneously, students can view various kinematics data for a selected joint or body segment in real-time through the user interface of the mobile device. The proposed app can serve as a potential instructional tool to assist in conducting human motion experiments in biomechanics courses.

1. Introduction

Biomechanics is a common sub-discipline of kinesiology that integrates movement science and human factors (Hamill et al., 2021). The knowledge of biomechanics can be of great help to improve sports performance and/or avoid physical injury (Knudson, 2010). Nearly all undergraduate students in movement science are required to complete at least one biomechanics course prior to graduation (Hamill, 2007; Riskowski, 2015). However, many undergraduates often fear and delay taking their required biomechanics course as they perceive it as a course highly demanding in mathematics and physics even though it involves necessary biomechanical concepts in their future professions (Garceau et al., 2012; Hsieh et al., 2012).

Biomechanics instructors must develop a more effective student-centered teaching method to help students overcome their anxiety toward this subject matter. Since motivation is considered a key factor that promotes students' cognitive engagement, self-efficacy, and learning experience (Wallace & Kernozek, 2017; Clyne & Billiar, 2016), a number of studies (Knudson et al., 2009; Munro, 2012; Full et al., 2015) have suggested that the inclusion of hands-on laboratory experience improves learning outcomes in biomechanics. Yet, these studies also indicated that dealing with human subjects and gathering meaningful data for biomechanical analysis can be challenging. For instance, human kinematics data collection could be achieved through various methods, such as using an optical motion tracking system (Skals et al., 2021; Wang et al., 2021), depth sensors (Xu et al., 2017; Scano et al., 2019), or a webcam-equipped desktop computer with computer-vision algorithms (D'Antonio et al., 2020; Ota et al., 2020). However, these alternatives can be less practical to be adopted in an undergraduate biomechanics course due to their high cost and/or required expertise.

Learning through mobile devices, such as smartphones and tablets, has been noted as an innovative approach to enhancing students' learning experience inside and outside the classroom (Malley et al., 2005) due to students being familiar with the devices. Recent studies have suggested that the use of mobile apps in the educational context positively contributes to student's motivation for learning, curiosity about the contents, and passion for team collaboration (Hwang & Wu, 2014; Hochberg et al., 2018). Meanwhile, researchers in computer science have developed several advanced computer-vision-based pose estimation algorithms for mobile device deployment in the past few years. The only hardware required is a mobile device with an embedded camera. These algorithms can detect human key joint positions through

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images by applying convolutional neural networks. For example, Google launched MobileNets and Tensorflow Lite frameworks (Howard et al., 2017; Abadi et al., 2016), where MobileNets trains lightweight deep neural networks with depth-wise separable convolutions, and Tensorflow Lite provides interpreter modules to help mobile devices optimize the trained network model and perform local calculations on human pose estimation. Therefore, there is a good potential to develop a computer-vision-based mobile app as an instructional tool for biomechanics courses to help undergraduate students gain laboratory experience in human motion.

In this short communication, we aim to present an open-access Android-based mobile app named Mobile Biomechanics Laboratory (MOBL) that could be applied to undergraduate biomechanics courses. With smartphones or tablets, students can practice real-time biomechanics analysis on body motions that are personally relevant. In the following section, we provide a detailed description of this mobile app from the overall architecture, the involved modules, and some initial ideas to utilize this app in actual biomechanics courses.

2. Methods

2.1. System overview

The mobile app follows a three-tier architecture that consists of a mobile platform-based computer-vision algorithm, a human kinematics variable estimator, and a user interface. Image information is collected and processed through the computer-vision algorithm to predict joint locations. Key joint locations are then applied to the human kinematics variable estimator for further biomechanics analysis. Users can then view various kinematics data for a selected joint or body segment in real-time through the user interface. Fig. 1 illustrates the data flow of the system, which includes two major processes: 2-D pose estimation and biomechanics analysis. The input is the RGB images captured by a mobile device, and the output is the kinematics data of the selected joint or body segment.

2.2. Computer-vision algorithm

Note that real-time 3-D pose reconstruction with deep neural networks on mobile devices remains computationally challenging. Therefore, in this short communication, 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 original image input and represent the number of rows and columns of pixels, respectively. The red-Green-Blue (RGB) color channels of each pixel are represented by a 3-D vector. The outputs are the predicted 2-D joint locations of a number of key joints on the image plane. Each key point is represented by a 2-D vector (x, y) indicating the 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 the shoulder, elbow, and wrist, are selected to articulately represent human poses under different conditions (Ding et al., 2019; Yan et al., 2017). At each key point, the body joint and body segment are rendered as a sphere and a rod, respectively. The rod orientation is determined by the two adjacent joints that define the segment (Fig. 2).

Traditional convolutional neural network (CNN)-based pose detection models are not suitable for mobile app development as they demand high computational capability. In this short communication, the mobile app detects key points through a Tensorflow Lite deep learning model based on convolutional pose machines (CPM) (Wei et al., 2016). An inverted residual with a linear bottleneck module (a.k.a., 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 to immensely reduce the number of computations (Chollet, 2017). Moreover, the input image is first reshaped into $192 \times 192 \times 3$ and then converted to image features to further reduce the computational cost. The inferenced key points are then shown as a heatmap after each convolution process. Within each repeated stage, the heatmaps improve confidence for spatial detection over joint locations and provide better estimates for the localization of key points. By fitting the final heatmap to an average filter, the maximum value from the confidence map for each key point is used to estimate the 2-D coordinates of the key joints.

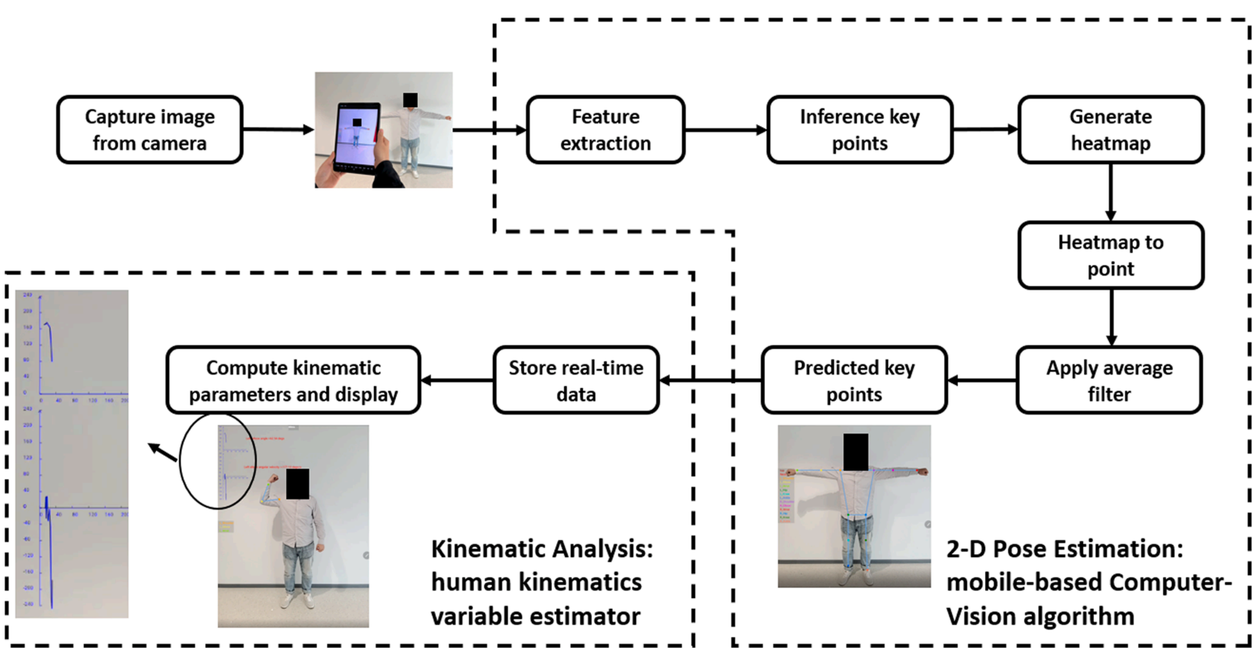

Fig. 1. System overview. The input is the images captured by the app; the outputs are the selected joint angle and angular velocity (the elbow joint angle and angular velocity shown in this figure).

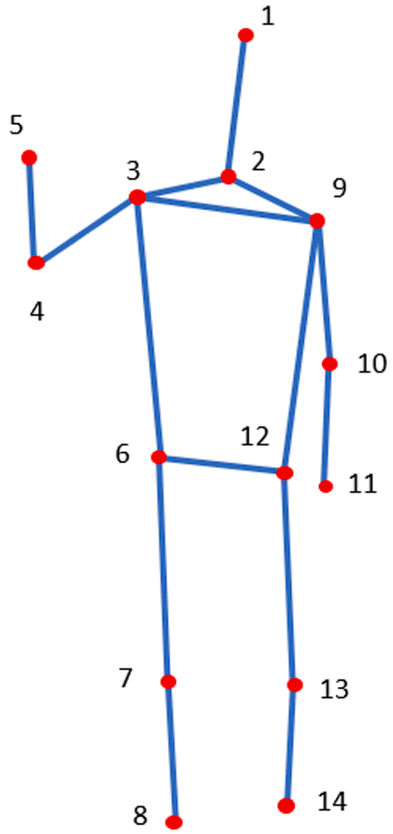

Fig. 2. Indexing for the 14 key points. 1-head; 2-neck; 3-left shoulder; 4-left elbow; 5-left wrist; 6-leftt hip; 7- left knee; 8-left ankle; 9- right shoulder; 10-right elbow; 11- right wrist; 12- right hip; 13- right knee; 14- right ankle.

2.3. Biomechanics analysis

After key point coordinates are generated from the pose estimation process, the app will automatically choose the corresponding coordinates following the user's selection and run a real-time calculation for biomechanical analysis. At present, the proposed app can demonstrate joint angular kinematics, body segment center of mass, and jumping height in real-time, respectively. Particularly, the app can automatically detect and calculate angles for elbow flexion/extension (EF/E), shoulder abduction/adduction (SA/A), and knee flexion/extension (KF/E), and trunk lateral bending (TLB). The app can also plot the location of the center of mass (CoM) of upper arms, forearms, upper legs, and lower legs for females and males using anthropometric parameters (Chaffin & Anderson, 1991). The jumping height is measured based on the distance between the highest position that the mid-hip of the captured person can reach and the original mid-hip position and expressed as a ratio of the height of the person being captured in the video. It should be noted that joint detection may fail and lead to inaccuracy in pose reconstruction when the camera view of a body segment is briefly blocked by other objects or other body segments. Therefore, the captured person is recommended to show all body segments in the camera view during the use of the jump module. In addition, since the kinematic analysis of vertical height is based on the size of the reconstructed human body in each image, the distance between the camera and the person should be controlled for each module. Let C_i denote the 2-D coordinate of the i_{th} key point and V_{i-j} denote the body segment from the i_{th} key point to the j_{th} key point. Let angle (V_{i-j}, V'_{i-j}) represent the angle between the two body segments. The definition of joint angles, centers of mass, and jumping height are summarized in Table 1.

Because the estimates are 2D coordinates of the unblocked body key points without any depth information, the data would be more accurate in describing the motions in the sagittal or frontal plane. Thereby, in practice, the camera should be set perpendicular to these planes of the person being captured. For the angular velocity calculation, the joint angles are first filtered by a width = 5 moving average window for denoise. The angular velocity is then calculated by using a two-point finite difference approximation (Chaffin & Anderson, 1991). The joint angle and the angular velocity at each time instants are then plotted in the user interface.

Table 1
The mathematical definition for each module measurement in MOBL. C_i denotes the 2-D coordinate of the i_{th} key point, V_{i-j} denotes the body segment from the i_{th} key point to the j_{th} key point, and angle (V_{i-j}, V'_{i-j}) represents the angle between the two body segments.

Module in MOBL	Mathematical Definition
Left and right elbow flexion/extension (EF/E)	$EF/E_L = angle(V_{3-4}, V_{5-4})$; $EF/E_R = angle(V_{9-10}, V_{11-10})$
Left and right shoulder abduction/adduction (SAA)	$SA/A_L = angle(V_{4-3}, V_{6-3})$; $SA/A_R = angle(V_{10-9}, V_{12-9})$
Knee flexion/extension (KF/E)	$KF/E = angle(V_{12-13}, V_{14-13})$
Trunk lateral bending (TLB)	$TLB = angle\left(\frac{1}{2}(C_3 + C_9 - (C_6 + C_{12})), (0,1)\right)$
Center of mass (Male)	$CoM_{upperarm_L} = C_3 + 0.5269(C_4 - C_3)$; $CoM_{upperarm_R} = C_9 + 0.5269(C_{10} - C_9)$ $CoM_{forearm_L} = C_4 + 0.4172(C_5 - C_4)$; $CoM_{forearm_R} = C_{10} + 0.4172(C_{11} - C_{10})$ $CoM_{upperleg_L} = C_7 + 0.6070(C_6 - C_7)$; $CoM_{upperleg_R} = C_{13} + 0.6070(C_{12} - C_{13})$ $CoM_{lowerleg_L} = C_7 + 0.5909(C_8 - C_7)$; $CoM_{lowerleg_L} = C_{14} + 0.5909(C_{14} - C_{13})$
Center of mass (Female)	$CoM_{upperarm_L} = C_3 + 0.5322(C_4 - C_3)$; $CoM_{upperarm_R} = C_9 + 0.5322(C_{10} - C_9)$ $CoM_{forearm_L} = C_4 + 0.4217(C_5 - C_4)$; $CoM_{forearm_R} = C_{10} + 0.4217(C_{11} - C_{10})$ $CoM_{upperleg_L} = C_7 + 0.6248(C_6 - C_7)$; $CoM_{upperleg_R} = C_{13} + 0.6248(C_{12} - C_{13})$ $CoM_{lowerleg_L} = C_7 + 0.5928(C_8 - C_7)$; $CoM_{lowerleg_L} = C_{14} + 0.5928(C_{14} - C_{13})$
Jumping height	$Jumping\ height = \dfrac{\left\lvert \frac{1}{2}(C_{6,highest} + C_{12,highest}) - \frac{1}{2}(C_{6,t=0} + C_{12,t=0}) \right\rvert}{\left\lvert (C_{1,t=0} - \frac{1}{2}(C_{8,t=0} + C_{14,t=0}))/(1 - 0.039) \right\rvert}$

3. User interface description

We have deployed the proposed app on an Android-based Samsung S7 tablet with a Qualcomm SDM865 Pro processor. When a "user" records a video of a "model" from the front view (for body motions in the coronal plane) or the side view (for body motions in the sagittal plane), all key joints are displayed in an augmented reality fashion where the identified joints overlap on the physical joint. Ten module buttons are placed at the bottom area of the interface, indicating different kinematics analyses of interest (see Fig. 3, Module 1). Fig. 3 presents screenshots for all ten modules currently included in the app, which consist of the 2D pose reconstruction result (module 1), elbow flexion/extension in the coronal plane (module 2–3), trunk lateral bending in the coronal plane (module 4), shoulder abduction/adduction in the coronal plane (module 5–6), centers of mass for upper arms, lower arms, upper legs, and lower legs for males and females (module 7–8), knee flexion/extension in the sagittal plane (module 9), and jumping height (module 10). This app can be found at https://www.ise.ncsu.edu/biomechanics/MOBL/ for open access. Source code developed in Android Studio, as

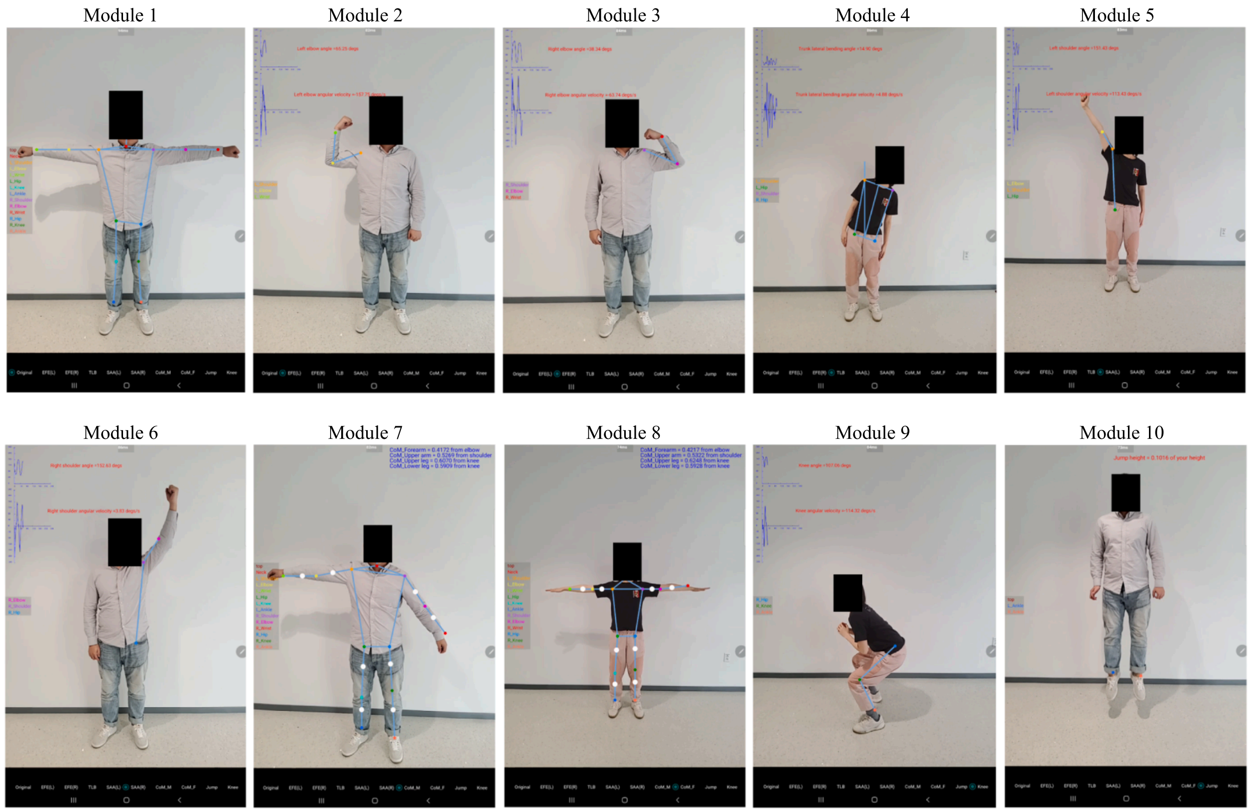

Fig. 3. Screenshots of kinematics analysis for each module in MOBL. Module 1- original 2D pose reconstruction; Module 2- left elbow flexion/extension in the coronal plane; Module 3- right elbow flexion/extension in the coronal plane; Module 4- trunk lateral bending in the coronal plane; Module 5- left shoulder adduction/abduction in the coronal plane; Module 6- right shoulder adduction/abduction in the coronal plane; Module 7- center of mass for male; Module 8- center of mass for female; Module 9- knee flexion/extension in the sagittal plane; Module 10- jumping height.

well as a tutorial demo that shows the included functional modules are also available on this website.

4. Discussion

While learning through mobile devices can engage and motivate students to explore subject matters that they may not possibly experience otherwise, there is only limited work done within the area of biomechanics education (López-Moranchel et al., 2021). In the current work, we sought to fill this gap by developing a mobile platform app for undergraduate biomechanics curriculums. Either the back camera or the front camera can be utilized in this app, depending on whether the app is used to capture a class partner's motion or self-motion. Previously, some other studies have used low-cost mobile apps, such as Dartfish Express (Dartfish, Fribourg, Switzerland) and OnForm (OnForm, Inc., USA), to measure body joint range of motion and center of mass displacement, and reached impressive results (Kassay et al., 2021; Walker et al., 2022). With these apps, temporal and spatial joint kinematics analysis can be achieved using recorded videos of the anatomical region of interest. Yet, Dartfish Express and OnForm can only post-process recorded videos, and the users have to manually mark the body key points frame by frame for joint angle estimation. Additionally, these two apps do not include any functions for joint angular acceleration calculation. As a comparison, MOBL is able to automatically track body key points in real-time, perform 2D pose reconstruction, and implement human kinematics data calculation and visualization with an embedded computer-vision algorithm.

As this app provides an easy outlet for undergraduates to perform human motion experiments, it could serve as an efficient instructional tool that facilitates learning of a number of biomechanics concepts, such as range of joint motion and instantaneous angular velocity. For example, students can perform a variety of body motions and use the app to collect joint angles (Module 2 to Module 6 in Fig. 3). Students can then compare the measured joint range of motion with the reference values listed in textbooks. This way, students use the self-relevant data to facilitate learning the concept of the joint range of motion. Previous studies in education have found that hands-on experiences and self-relevant data can improve knowledge transfer (Ruvolo & Markus, 1992; Catena & Carbonneau, 2019). Besides, the joint angle and the instantaneous joint angular velocity can be displayed numerically and graphically at the same time in the user interface. Thus, students are able to learn that the instantaneous joint angular velocity is the derivative of the joint angle change. In addition, this mobile platform app could also demonstrate basic descriptive statistics of all measured kinematics variables (peak, quantiles, ranges, and distribution patterns) within and across all activities performed. From the perspective of data science, these basic descriptive statistics provide exploratory and knowledgeable insight view of the variable of interest and could further augment students' comprehension of the scale of human kinematics variables. It should be noted that the measures from the mobile device have not been fully evaluated against a laboratory-based motion tracking system yet. According to the findings from a previous study (Wang et al., 2021), the accuracy of computer-vision-based pose reconstruction is probably not satisfactory for conducting clinical biomechanics studies. Yet the reconstructed pose through computer-vision is adequate to demonstrate the basic concepts in human kinematics for undergraduate study. In our future work, we will aim to evaluate and improve the accuracy and robustness of the reconstructed pose in the application.

There are a few limitations that need to be discussed. First, because the adopted computer vision algorithm is originally developed for capturing a single person without any view block, pose reconstruction and kinematics analysis results can be negatively affected when the body segments are blocked by other objects or other body segments, or the camera captures multiple persons simultaneously. Second, due to the computational cost of processing 3-D poses on mobile devices, the current app is unable to reconstruct 3-D poses from the images in real-time and thus unable to perform accurate joint kinematics analysis for 3-D joints, such as the glenohumeral joint. In future work, additional biomechanical analyses covered in undergraduate courses, such as gait and running analysis, can be added in this app. In addition, its performance in supporting biomechanics knowledge learning and transfer, as well as students' self-efficacy, needs to be quantitatively investigated.

CRediT authorship contribution statement

Hanwen Wang: Methodology, Software, Validation. **Ziyang Xie:** Software. **Lu Lu:** Software. **Bingyi Su:** Software. **Sehee Jung:** Software. **Xu Xu:** Supervision, Methodology.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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