MyLiftingPal: A real-time camera based weightlifting form correction system

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ABSTRACT

This paper presents MyLiftingPal, a vision-based approach to track and correct the form of weightlifters while performing the squat and deadlift exercise. Utilizing a high-resolution camera facing the side of the lifter, the system tracks and evaluates eleven metrics for form and continuously provides correctional audio feedback. In addition, MyLiftingPal tracks the number of correctly completed repetitions and encourages the lifter through audio feedback as and when required. The lifters can naturally interact with the system with the use of hand gestures as these are the only effective means of interacting in a loud and busy gym. Unlike other similar systems, MyLiftingPal does not rely on Microsoft Kinect to analyze the kinematics of the body during exercises but rather uses custom wearable markers and a simple frame-based phone camera.

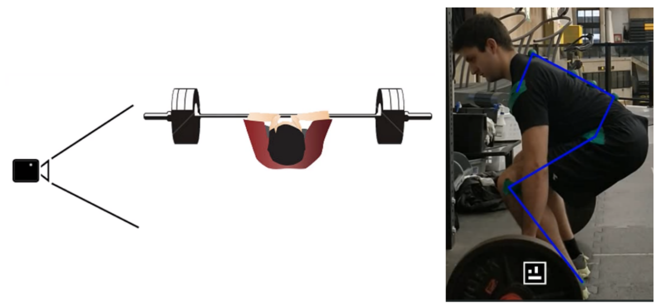
Author Keywords

Fitness; Health; Deadlift; Squat; Weightlifting; Form Correction; Phone Camera

INTRODUCTION

Resistance training with an incorrect form not only fails to activate desired muscle groups but also significantly increases an individual's risk for major injuries. An external expert such as a personal trainer can spot mistakes in the form immediately and suggest corrections. However, not all individuals who require a personal trainer has access to one. Therefore, an individual would often fail to identify their mistake before sustaining a significant injury. Even in the case of professional athletes, a lapse of form when not in direct supervision of a trainer can result in career-ending injuries.

Most of the work attempting to solve similar problems rely on the use of a Microsoft Kinect [19, 17]. Sutthiprapa et al. [19] tackle the exact problem we aim to solve by using a Kinect to perform a deadlift form analysis. They do not provide correctional feedback but provide data on forces acting on the spine which can be analyzed to practice the correct form. Rector et al. [17] use Kinect skeletal tracking to create a virtual yoga instructor that provide audio instructions and cues for blind or low-vision people. Lin et al. [12] make use of a Kinect to assess whether a patient undergoing physical rehabilitation achieves the requirements of each exercise by validating each movement. Though the skeletal tracking provided by Kinect is widely used for motion tracking, its coarse skeletal joint model and low portability makes it less than ideal for our specific problem.



(A) (B)

Figure 1. The intended set-up of MyLiftingPal in the gym environment. (A) provides an illustration of the top view of the set-up. The camera is positioned such that the side profile of the lifter along with the barbell are visible. (B) shows the view from the camera with the skeleton model of the subject overlaid in blue.

We propose an affordable and practical solution to this problem - MyLiftingPal, a system that can analyze a lifter's pose and give continuous specific correctional feedback to maintain correct form for that particular exercise. For the purposes of this project, we will focus on the deadlift and the squat exercise, both of which are tricky for beginners and present challenges even for veteran lifters. Using a high-resolution camera looking at the side profile of the lifter as seen in Figure 1, the system will track the weights and the lifter's form as they are performing the exercise and will continuously check if their form is correct. If not, it will provide vocal instructions on what action to take to fix it. The system also keeps track of the number of repetitions completed in order to provide cues and motivational phrases to encourage the lifter. In addition to that, the lifter can interact with the system through hand gestures.

Instead of using a Microsoft Kinect as seen in the literature, we chose to use a simple frame-based camera as input to establish a finer and accurate skeletal model with custom joints specific to the exercises we have chosen. This also ensures that the software is not dependent on specialized hardware and thus, it can easily be ported to other platforms such as a smartphone. Our next contribution is the evaluation of form correctness. Unlike the other techniques, we utilize the results from kinematic analysis of the deadlift and squat exercises to scientifically evaluate correct form using a variety of metrics.

A video demonstrating the functionality of MyLiftingPal is available[1] along with the code used to complete this project[2].

RELATED WORK

To better understand how MyLiftingPal will recognize correct form, a brief background of the biomechanics involved in performing the supported exercises is given below. Then we look at the most relevant research related to the development of the system.

Biomechanics

The deadlift and squat exercises require the correct activation and weight distribution of the entire posterior chain in order to avoid injury [23]. The primary injury suffered by athletes while performing these exercises is to the back, with the lower back being at a far greater risk [23]. Both inexperienced and veteran lifters are susceptible to poor form, either from lack of knowledge or by using higher resistance [23]. To properly perform these two complex full body lifts, correct form should be maintained during two stages of the lift: the set-up stage (before performing the lift), and the lifting stage (throughout the process of lifting).

Although there are many variations of the deadlift and the squat, only the conventional deadlift and the low back squat will be supported for the purposes of this paper. The guidelines for a correct and injury-free execution of both are well documented in the field of biomechanics [7, 8, 2, 18]. Based on these guidelines, the following biomechanical metrics were selected to be used during the lifter's set-up stage: the barbell placement in relation to the centre of gravity of the lifter, knee angle, hip angle, upper back position in relation to the lifter's shoulders, and the lower back position. Likewise, a different set of four metrics were selected for gauging the performance during the lifting stage: barbell path, shoulder angle, hip position throughout the lift, and lower back position throughout the lift. The initial angles as well as the range of motion provided in the literature will be used to evaluate the lifter's form.

Expert Video Analysis

Photographic methods have been used to analyze the performance of athletes for as long as cameras have existed. Development of video cameras have been especially useful for fast-paced activities. Trainers also use video recordings when they cannot directly supervise the athlete, either because of time constraints or differing location. Affordable sports video analysis software are now available for trainers which allow them to dissect the video and measure other useful information such as speed, angles, and kinematic movement patterns without attaching sensors on the body.

Kinovea [1] is an open source sports analysis tool which is especially useful for barbell path analysis and lifting techniques. Garhammer et al. [9] presents a comprehensive study of optimum camera set-ups and a review of a few video analysis software, including Kinovea, focusing on examples from weightlifting. All these systems allow for a variety of quantitative linear and angular measurements for any point of interest; for example, the centre of a barbell. But to provide useful feedback, an expert is required to both identify key points for tracking and analyze the resulting measurements.

Kinect Skeletal Tracking

With the introduction of affordable motion tracking technology, there has been an upsurge of research studies that use Microsoft Kinect skeletal tracking for fitness and physiotherapy applications. Many useful metrics can be calculated from the motion of this skeletal model without human intervention such as the position and angle of joints, velocity of movement and even rate of fatigue [10]. But these metrics still need to be analyzed by an expert in order to provide feedback. The expert need not be human and several systems exist that use these metrics to identify improper techniques. For example, training systems for factory workers have been developed to help them correct their heavy-lifting technique in order to reduce work-related musculoskeletal disorders (MSDs) [4, 13].

But for weightlifting applications, real-time feedback is more useful for the lifter as they can correct a mistake when it happens. MotionMA by Velloso et al. [21] utilizes a Kinect to record an exercise demonstration by an experienced person and compare it with the motion model of novice lifters to provide real-time performance feedback. Exergames, which combines fitness and video games, are available for a variety of activities ranging from standard exercises to yoga [17, 15]. In addition to providing correctional feedback, they also provide motivation to the player by means of milestones and challenges. But the Kinect SDK v2.0 skeletal model has only 3 joints along the spine, out of a total of 25 joints. [3] [22]. For weightlifting exercises such as the deadlift, the stress on the spine is crucial and 3 joints just do not provide enough fidelity to differentiate between a proper and improper form.

Vision-based skeletal tracking

Vision-based pose-estimation is a technique that is heavily utilized in many forms of Human-Computer Interactions. Poppe [16] offers a review on this vast topic, splitting it into two fundamental areas: model-based and model-free skeletal estimation. Models of either the known human skeletal shape [11] or human motion profiles [14] are used to create 3D skeletal models. More recently, advances in machine learning have allowed for the relaxation of the model constraints of previous systems resulting in a model-free skeletal estimation [5, 20, 6]. However, this requires a large amount of labelled training data for high accuracy.

Even though they have never been specifically applied to the domain of form correction while weightlifting, such vision-based skeletal model estimation algorithms can be utilized to calculate biomechanical metrics to evaluate form. However, much like Kinect based skeletal models, these also fail to create accurate high fidelity models of the spine, which are needed to effectively evaluate a lifter's form. Moreover, as outlined by the authors of many papers [5, 20], such algorithms are also highly dependent on lighting and occlusion of the subject; both of which would be an issue in a gym environment.

[1]The video can be found here: https://youtu.be/XVwOX6z8078

[2]The code is a public github repository which can be accessed at: https://github.com/milievski/myliftpal

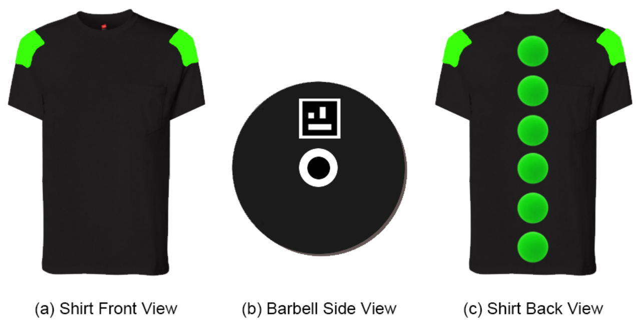


Figure 2. Markers affixed on the clothing worn by the lifter

Using wearable markers, MyLiftingPal intends to solve the above issues in an affordable manner.

METHODOLOGY

This section will provide a detailed description of the proposed physical set-up and software implementation of the system.

Physical Set-up

Camera Set-up

MyLiftingPal utilizes a single OnePlus 5 phone camera which is placed at a distance between two to six meter away from the user as seen in Figure 1(A). The camera is placed such that it views both the user's side profile and the barbell. The image, as seen by the camera, is depicted in Figure 1(B).

Wearable Markers

To improve the accuracy of recognizing the exact position of the lifter, the system relies on visual markers worn by the lifter while performing each exercise. To achieve this, all lifters are required to wear a custom black skin-tight short-sleeved shirt. Protruding coloured balls are affixed to the back of the shirt corresponding to the spine of the lifter. Coloured strips are attached to the corresponding to locations of the shoulders, hips, knees and feet of each participant. All markers are coloured a prominent green and are attached using an adhesive material. This can be seen in Figure 2.

Weight Markers

One distinct identifiable augmented reality (AR) marker generated by the ARUCO library is placed on the external weight facing towards the camera as shown in Figure 2(B). This marker is used to track the distance, orientation, and position of the barbell throughout the exercise.

Software

MyLiftingPal was programmed in python taking advantage of OpenCV3, ARUCO and simpleaudio libraries. In this section, we will discuss the software implementation details.

Lifters Position

To calculate the position of the lifter, the assumption is that the relative orientation and position of the barbell is the same as the lifter himself. Using this assumption and the identifiable markers placed on the barbell, the position of the lifter in relation to the camera is calculated. This allows the system to function independently of the lifters starting position as long as the markers present on the shirt are not completely occluded.

To calculate the relative orientation of the AR marker, first the position of the AR marker is found and its orientation is established using ARUCO library methods. For this calculation to be accurate, the phone camera was first correctly calibrated using a traditional checkerboard method. However, even after calibration, this technique proved to be inaccurate as the phone camera aperture dynamically readjusts, thus throwing off the relative orientation of the marker. Another issue with this technique is the high computational requirement of the algorithms used. To reduce the computational cost, we look for the AR marker in a 100-pixel square area of its previous location since we know that it does not move that far between frames.

Lifters Skeleton Detection

MyLiftingPal is able to quickly and accurately detect the human skeleton with the use of deformable skeleton model. First, a deformable skeleton model is fitted to the lifter by identifying a set of landmarks (in this case the markers worn by the lifter), and then the model is tracked over time using the same landmarks as a lift is performed. This method of skeleton detection is robust to minor occlusion as well as being computationally inexpensive.

To isolate the green markers worn by athletes, the image is first converted into the YCrCb colour space. Once converted, the image is segmented with a lower bound threshold set at (1, 60, 120) and an upper threshold at (200, 118, 135). These bounds, however, prove to be ineffective at isolating the desired markers in all lighting conditions; further research is needed to identify a better method of isolation. Nonetheless, once a segmented image was created, opening and closing Morphological Transformations with a kernel size of 5x5 was applied to the image to reduce noise. The clean image was then used to create a deformable skeleton model.

To create the model several assumptions were made: (1) the user would be standing upright (2) the users shoulder would be a uniform large contour near the top of the image (3) the shoulder, hip and knees would mostly in the same vertical line, and (4) there would be four balls which comprises the spine of the model. Once the model was fully fitted, tracking could begin. The tracking algorithm used is quite naive. Given the previous location of a given joint, it searches for any contour within a set distance; if found, it updates the location of the joint to the centre of the found contour. Even though it is simple, the tracking algorithm proved quite reliable in practice.

Lifter Form Evaluation

The skeletal model is subsequently used to calculate a set of metrics to evaluate the lifter's form while weightlifting. There are two main evaluation stages: the set-up stage and the lift performance stage. During the lifter's set-up stage the following static metrics are calculated: the barbell placement, knee angle, hip angle, shoulders angle, and the lower back position. A more dynamic set of four metrics are utilized during lifting stage: barbell path throughout the lift, knee angle difference, hip position throughout the lift, and lower back position throughout the lift.

All metrics are transformed from absolute measurements of the lifter to relative metrics based on body proportions, and position using the transform established from the AR marker placed on the barbell. All relative metrics are then compared to the ideal metrics [18, 2] to provide feedback on any metric that needs improvement.

User feedback

The user is provided continuous information on their progress using pre-recorded audio messages. This is communicated to the user as soon as the system identifies any problem in the form. The audio feedback begins as the users approaches the weight and continues throughout the lifting process. An issue encountered with the pre-recorded audio was that frequent lapses in form resulted in the lifter being overwhelmed with simultaneous auditory information since the audio overlapped each other. This results in the user getting confused. While many solutions exist, this is still an open research question.

User Input Recognition

The MyLiftingPal system allows user interaction at a distance using hand gestures. The hand gestures allow users to set the number of sets and repetitions they want to perform for each exercise by using the number of fingers they hold up. Also, the user can use a thumbs up or thumbs down gesture for yes or no inputs.

Multiple techniques were employed to make the hand gesture recognition robust across different lighting conditions and environments. The first step, which is also the hardest, is hand segmentation. This is primarily achieved using skin colour segmentation in the YCrCb colour space using a lower threshold (10,137,90) and an upper threshold of (230,180,123). In order to make this bound tighter, we crop a square (of about 1 percent of the frame height which is 20x20 pixels here) patch of skin from the face and uses the minimum and maximum values in it to get a more accurate threshold range corresponding to the subject. We perform this calibration step every 30 frames so that if a new user steps in, it will automatically adapt. HAAR cascade classifiers for face (frontal face, profile face and faces with glasses) were used to find the largest face in the scene, which is assumed as the subject, and an area under the left eye is cropped. This guarantees that we always get a patch of skin without any unwanted features such as hair or nose. To make the hand detection more robust, background subtraction using KNN (history: 10000 and detectShadows: False) is used along with skin detection so that other skin coloured objects in the environment are not included. Also, CLAHE (Contrast Limited Adaptive Histogram Equalization) algorithm is applied just on the Y channel so that the thresholding works across various lighting conditions. The resulting mask is then cleaned up using morphological operators.

From this mask, we need to find the region which corresponds to the hand. For this, we made a few assumptions after observing how users performed the gestures: 1) the user uses the right hand to perform gestures (however, it is relatively easy to extend it the left as well), 2) the user raises their hand during a gesture, and 3) the hand is not too far from the face plane. All size constraints applied on the hand in the following paragraphs are ratios of the face width or area, which makes it invariant to the distance at which the user is standing. These ratios were obtained by empirical analysis of gesture data. On the mask, the contours that have areas above a certain threshold (face area/9) are filtered and the leftmost one is fixed as the right arm. In order to remove the forearm and elbow, which are almost always included in the contour, it is cropped to a rectangle (1.5x by 1.2x face width) from the top-left corner.

Gesture detection begins when the hand is near the face. From the cropped hand contour, the supported gestures, namely finger count and thumbs up, can now be identified. For both, the centre of the largest circle that can be inscribed in the hand contour is considered as the centre of the palm. The convex hull vertices of the contour are the candidate fingertip points. These candidate fingertips are eliminated as follows: 1) vertices too close together (less than 0.05x face width) are considered as a single fingertip, 2) distance between the palm centre and vertex should be within a range (0.5x to 2x face width), 3) vertices should be above the centre of the palm always (thumb may be a little below) and finally, 4) if more than 5 fingertips are remaining, the shortest ones are eliminated until only 5 remain. When the system prompts for a number from the user, the most accumulated finger count over the next few frames is considered as the intended number from the user.

For the thumbs up gesture, we opted to use a rather simple interpretation of the hand contour. A finger count of 1 is considered a thumbs up, while a finger count of 0 with one convex hull vertex below the palm centre is considered a thumbs down.

APPLICATIONS

To demonstrate the strengths of the system and vast potential of MyLiftingPal in the wide and growing strength training community, we present three applications. First, we show how the system can be used by new lifters to better educate themselves on proper lifting form and mechanics. Next, we demonstrate how even the most knowledgeable lifters can utilize MyLiftingPal in their everyday training to prevent injuries through the continuous monitoring process of the system. Finally, we demonstrate how this system can be used by the pinnacle of the strength training athletes to provide an empirical evaluation during competitions.

Educating inexperienced lifter

Strength training is intimidating to many beginners as the technique required to execute correct form is hard to learn and even more difficult to master. MyLiftingPal assists inexperienced lifters by teaching them the correct techniques by providing continuous auditory feedback and allowing the users to adjust to this feedback. This approach will ensure that beginners learn quickly and effectively without injury.

The system begins to provide feedback before the lift has started during the setup stage of the lift as seen in Figure 3(B). To prevent injury and to ensure that the user understands the correct setup technique which is the base for the rest of the lift, MyLiftingPal provide feedback while observing the lifter's response. This processing is completed only when the correct setup form is realized by the user for 1.5 seconds. Once

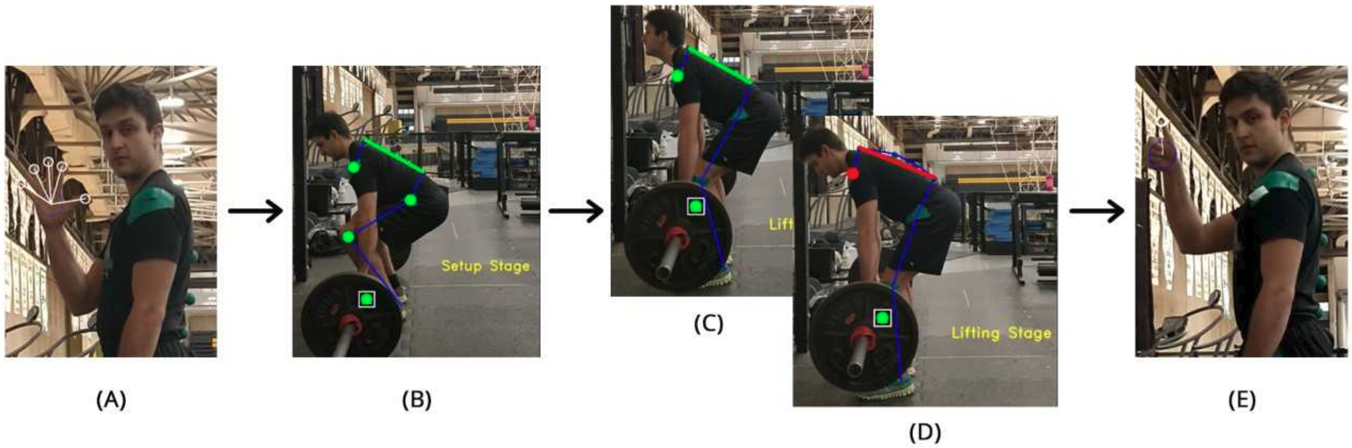


Figure 3. A) The lifter is asked to input the number of sets and reps, B)The system waits for lifter to get into position in setup stage, C)The system evaluates a lift and gives visual and auditory feedback on incorrect form, D)Correct form is visually highlighted in green, E) After finishing the reps, the lifter is asked whether the weight was too much if the user was struggling.

the users correctly perform the setup posture, the system will prompt the user to start performing the lift. The system provides guidance and feedback during each repetition of the exercise to ensure that the user understands the correct form throughout the entirety of the lifting motion(see Figure 3(C) and Figure 3(D). The feedback is continuous to allow the user to correctly apply the provided feedback to the lift being performed. MyLiftingpal counts each repetition performed by the user letting them know once they have reached their goal. The application does this to allow the user to focus on the mastery of form without any additional mental burdens. Finally, MyLiftingPal is able to recommend the correct weight by asking the user if the weight felt comfortable for them. The response by the user can be seen in see Figure 3E.

Preventing injuries by continuous monitoring

Many experienced strength athletes have a good understanding of proper technique in all stages of a lift. However, whether due to fatigue or overreaching their abilities, even experience lifter has lapses in form. It is this lapse in form that is most likely to cause injury to these athletes. By using MyLiftingPal, these experienced lifters will be able to identify the exact point during which incorrect form occurred and immediately stop. MyLiftingPal goes one step further by recommending athletes to lower the weight used to a more manageable level.

Providing an empirical evaluation

High-level strength competitions such as powerlifting or Olympic weightlifting utilize three judges positioned at different locations to conclude if each lift performed was correctly executed by each participant. These judges are vital to the sport as it is their decision that determines if the weight lifted by an individual counts towards his final score. However, whether due to bias or error, humans are not always consistent when making such judgments. MyLiftingPal, on the other hand, can be used in this situation to provide a consistent judgment for all athletes. Along with consistency, MyLiftingPal will be able to provide unbiased ruling for all athletes. Furthermore, MyLiftingPal can be used by the athletes of such sports during training to become more accustomed to the rules and regulations.

Unlike Olympic weightlifting, the sport of powerlifting also has auditory cues informing athletes when they are able to perform each part of the lift. For instance, a judge audibly must inform a lifter when they are allowed to perform the downward motion followed by an additional audibly cue for the upwards motion of each lift. A delay in the audible cue may make an athlete unable to complete a lift due to no fault of his own. However, with MyLiftingPal's faster than real-time abilities, the audible cue is guaranteed to be consistent and on time.

EVALUATION

The performance of the system depends solely on the accurate tracking of the body markers since this ensures a perfect skeleton model and consequently, will ensure that accurate lifting metrics are obtained. In order to assess the accuracy of the tracking algorithm, we compare the tracked markers with the ground truth, which is a hand-labelled video recording of the detection and tracking stages of the algorithm consisting of 623 frames. The distance between the ground truth marker position and the tracked marker is considered as the error and for each frame, the error for each relevant marker is summed up to get a total error for that frame. Root Mean Squared (RMS) error is then calculated over all frames in a stage.

During the detection stage, if a marker has not been detected, the error for that marker is 0 since the algorithm has yet to label it. As seen in Figure 4 the RMS error was found to be 4.442 pixels. The small error demonstrates that the deformable model fitting algorithm did not mislabel any of not occluded markers during detection. Whereas, though the tracking stage, the RMS error was 77.001 pixels. The result was fairly good considering that the video resolution is 1920x1080 and that markers get occluded throughout the lifting process. In fact,

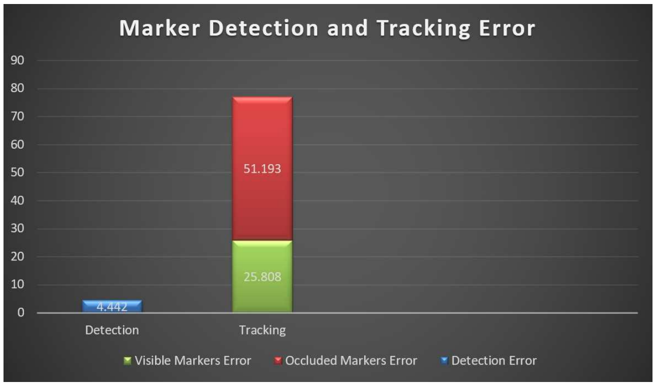


Figure 4. Root mean squared error between the labelled ground truth and detection result.

by observing the tracking stage, we can see that much of the error comes from markers getting occluded by the hand and barbell, makes the occluded markers difficult to track. In the labelled video, these are the hip, knee and foot markers. Without including the occluded markers the RMS error drop dramatically to 25.808.

DISCUSSION AND FUTURE WORK

While MyLiftingPal provides a great proof-of-concept design for a camera-based lifting form correction system, we realize there are still opportunities for enhancement. In this section, we will highlight some issues faced and interesting areas of future research.

Skeleton Detection Issues

The skeleton model relied quite heavily on two assumptions: the wearable markers being correctly and fully isolated with no external noise and strong assumptions made regarding the exact position of the skeleton at initial detection stage. These assumptions, however, does not always hold true. One large issue on the correct isolation of the markers was the lighting conditions of the environment. Another issue with the isolation of the markers was similar colours in the background. Another large issue faced while using this algorithm is the strong assumptions made to fit the initial skeleton model. Many of the assumptions proved incorrect in many application situations.

Wearable Marker Design

The design of the wearable markers is an aspect that should be revisited. The current design of attaching the markers with the use of an adhesive to the shirt or skin is both uncomfortable and does not stay in place. An alternate approach would be to fully incorporate all markers into the lifter outfit, much like how the balls are currently attached.

Gesture Detection Issues

Our hand gesture recognition system performs well for the selected gestures in controlled environments with a single user, but it fails when other people pass through the scene. To take it further to a practical setting such as a crowded gym will require solving a number of problems. The first thing is to make the system contextually aware of the current user to be able to differentiate between his and another person's hand in the background. One solution would be to fit a deformed skeleton model and look for the hands at its expected position according to the body posture. Another problem is the limited number of gestures that can be detected by just looking at a hand contour mask. More details are needed for complex gestures, such as even a thumbs up. Training a classifier using feature descriptors such as Histogram of Oriented Gradients (HOG) or Speeded Up Robust Features (SURF) is one avenue to explore.

Markerless Skeleton Detection

The marker-based approach of MyLiftingPal does improve the accuracy of the deformable model matching, but it has its limitations. One is that many users were uncomfortable in wearing the markers, especially in public places. Another limitation of the marker-based approach was the requirement that the shirt needs to fit the body tightly to correctly estimate the user's skeleton. Due to this, different sized shirts were needed by different users. To solve many of the issues which marker-based approaches face, we suggest exploration of a markerless approach to skeleton detection. It should be noted, however, that all markerless approaches should strive to never compromise the accuracy of skeleton fitting as this might result in the incorrect metric calculation and ultimately, injury to the user.

Future Experimentation

The final aspects that we feel would strengthen the application of MyLiftingPal is further testing and experimentation. The study conducted in this paper, while very important in laying the groundwork for future studies, is not sufficient in demonstrating the accuracy of the algorithm across multiple users, environmental conditions, and finally different exercises. Furthermore, it is our belief that even though the skeleton detection and tracking error are important metrics to quantify, the overall evaluation of lifter's form is more important. Thus, to more concretely demonstrate the merits of MyLiftingPal in the future, we would like to conduct a comparison study between a personal trainer evaluating a lifter's form and the evaluation from MyLiftingPal. This would not only demonstrate the aspects of form which MyLiftingPal captures or fails to capture, but also would provide metrics about how well each captured aspect is evaluated. Additionally, we would like to perform a user study to gather data about how comfortable users would feel about wearing the recommended markers to public and personal gyms.

CONCLUSION

In this paper, we introduce MyLiftingPal, a single camera marker-based approach to weightlifting form correction. By only using a phone camera, we ensure that our system is portable and practical in a gym environment. With the utilization of kinematic data, we scientifically evaluate the correctness of a user's form. We also demonstrate that MyLiftingPal can be applied in the real world to fill an important gap within the strength training community.

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