Automated Posture Analysis for the Assessment of Sports Exercises

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ABSTRACT

Numerous studies in the medical field correlate the maintenance of human posture in static and dynamic situations with the muscle-skeletal health. One of the most widely used methods for assessing human posture is through visual inspection by professionals. However, this observational assessment process requires the presence of a field expert performing a time-consuming manual analysis. Hence, a reliable automatic posture evaluation system would be of great help for professionals to detect postural misalignments. In the recent years, significant progress has been achieved in pose estimation through state-of-the-art deep learning techniques, competent to estimate human body landmarks fast and accurately from RGB images. In this paper, we describe a methodology scheme to estimate human posture and detect postural misalignments in static and dynamic exercises in real-time. The MediaPipe Pose algorithm is employed to detect human pose and the vector geometry of the pose is evaluated to detect postural misalignments. Furthermore, in order to not limit the applications of this work by preselecting rule parameters for only a certain set of exercises, the rule parameters of any form of exercise are automatically extracted from an example of a single correct execution through machine learning. The datasets of the videos utilized in this work were provided and annotated by a clinical exercise physiologist.

CCS CONCEPTS

• **Healthcare**; • **Fitness**; • **Posture Assessment**;

KEYWORDS

MediaPipe Pose, Computer Vision, Deep Learning, Machine Learning

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1 INTRODUCTION

Human posture has been a subject of clinical and scientific interest, with numerous studies researching its correlation with musculoskeletal health [1–5]. Poor posture arises when the body produces increased pressure on the supporting structures and reduced balance over the base of support. This occurs to many individuals due to congenital disorders or age-related alterations (e.g. loss in range of motion and muscle strength), causing changes in their body alignment, which can lead to postural deviations. Many musculoskeletal complaints are also associated with the improper execution of fitness exercises. Exercises such as squats, deadlifts, and shoulder presses although they may be very beneficial to health and fitness, they can also be very dangerous if performed incorrectly. The heavy weights involved in these workouts can cause severe injuries to the muscles or ligaments if the proper posture is not maintained. Axial misalignments while performing exercises are mainly due to the lack of formal training with a professional, and failure to correct them over time, may result in long-term adverse effects on the musculoskeletal system [6].

One of the most widely used methods for assessing human posture deviations is the visual inspection in static and dynamic situations by professionals, who can detect postures that could be contributing to an underlying problem and provide a tailored program of corrective exercises to improve the identified issues [7, 8]. A static postural assessment examines the positioning of the spine, neck, pelvis, shoulders, shoulder blades, hips, knees and feet while the patient remains stationary, and is a simple yet effective way to detect structural issues. The dynamic posture assessment monitors body movement for axial misalignments and for overactive or underactive muscles while the patient performs certain exercises. Axial misalignments may be prominent throughout an exercise, yet they may only appear at certain phases indicating a specific underlying cause. Thus, the process of evaluation requires the thorough visual inspection of the full body throughout the exercises performed, in order to detect potential posture deviations. The observational assessment process, apart from requiring a field expert performing a time-consuming manual analysis, it is also heavily dependent on the evaluator's subjective input, which could lead to considerable intra or inter rater variability [9].

In this paper, we describe the design and deployment of a motion analysis system, which automates the process of static and dynamic posture assessment in order to assist professionals in their day-to-day routine and facilitate the diagnostic procedure of their patients. Our main contribution lies in the effective postural axial misalignment detection in any form of static or dynamic exercise. We approach this by extracting the rule parameters for posture evaluation through heuristic and machine learning models from a single video with the correct execution of a specific exercise. Videos with executions of the same exercise are then evaluated on the extracted rule parameters in real-time. Moreover, in order to avoid quantification of wrong structures, the results summarize the identified frames that contain events of interest through display.

The remaining of the paper is organized as follows. Section 2 presents related research works, while Section 3 describes the proposed methodology. Section 4 describes the performed experiments and the corresponding results. Finally, Section 5 concludes the paper.

2 RELATED WORK

Several approaches have been proposed in the literature for posture recognition and assessment, with motion capture (MoCap) systems based on wearable inertial sensors or optical markers (marker-based systems), providing high accuracy results in capturing human pose and tracking motion [10–12]. However, these marker-based systems are considered impractical for routine postural assessments, as they require trained personnel to operate, and are prohibitively expensive and non-portable. Thus, researchers focused their interest on the employment of low-cost MoCap systems based on depth cameras (markerless systems) such as Microsoft Kinect (Kinect v1 and Kinect v2). Kinect v2 automatically detects 25 anatomical body landmarks, which are retrieved from its embedded depth sensor by utilizing machine learning techniques. Therefore, by not requiring any type of markers or calibration, it has opened new horizons for pose recognition, motion analysis and musculoskeletal risk assessment. The proposed methods [13–15] analyze human posture by calculating the required joint angles from their respective landmarks generated by Kinect. Nonetheless, Kinect-based systems have lower quality tracking from non-frontal views [16] and may deliver unreliable poses especially when occlusions occur [17].

In the recent years, significant progress has been achieved in pose estimation through state-of-the-art deep learning techniques, competent to detect 2D and 3D human body landmarks from single or multiple RGB images. OpenPose [18] is one of the most popular open-source technologies for 2D and 3D pose estimation. It detects 22 2D human body landmarks with a bottom-up approach and can estimate 3D human pose by performing 3D triangulation with non-linear Levenberg-Marquardt refinement [19] over the results of multiple synchronized camera views. Another well-known and fairly recent technique for real-time pose detection is MediaPipe BlazePose [20]. It estimates a total of 33 3D body landmarks by utilizing a two-step detector-tracker machine learning pipeline, which locates the pose region-of-interest within a frame and predicts all 33 pose keypoints from it. MediaPipe has trained its depth coordinate (z-coordinate) on purely synthetic data and thus it can estimate 3D human pose via single-view capture setups. Since these methods have been validated in terms of precision and recall for keypoints, they have been widely utilized in the research field of posture analysis.

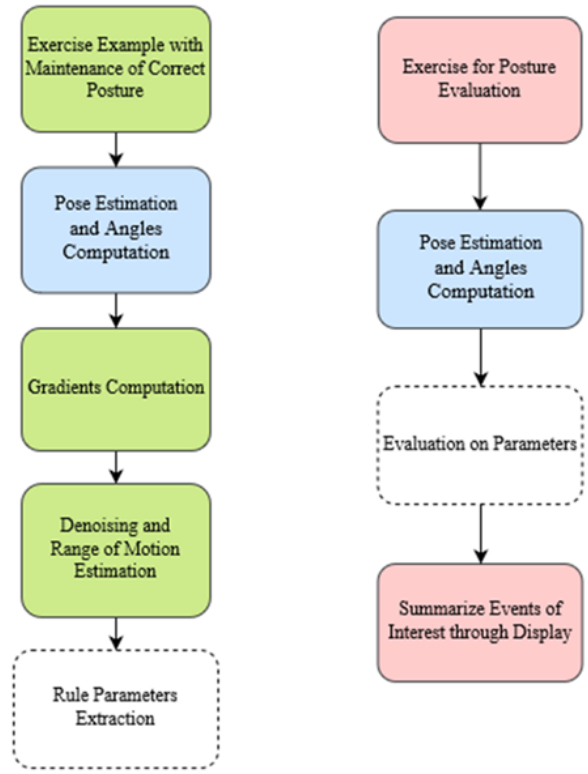

Figure 1: Overview of the proposed methodology workflow

By employing OpenPose, Pose Trainer [21] evaluates the human posture in four common exercises through geometric-heuristic and machine learning algorithms. Alatiah et al. [22] calculate joint angles after pose estimation and pass them through a neural network to classify their form of exercise. After indicating the label of the performed exercise, the model will use preselected parameters for each exercise to evaluate examples. Zell et al. [23] approach analyzes physical movements by representing the body as a mass-spring system to find the forces and torques that travel through the joints of the body.

3 METHODOLOGY

To detect postural misalignments, the utilized techniques in this work follow a methodology scheme, which consists of 4 consecutive stages: Input Data, Pose Estimation and Angles Computation, Range of Motion Estimation and Rule Parameters Extraction, Detection of Posture Misalignments and Summarization through Display. Figure 1 illustrates the proposed methodology workflow.

3.1 Input Data

In order to not preselect the rules of parameters for posture evaluation and limit the applications of the model to only a certain set of exercises, the rules of any form of exercise are automatically extracted from a single correct execution of a particular exercise. The parameters of interest along with a video example are therefore initially provided. The parameters are vector pairs from key body joints and are selected by the user according to the posture alignments related with the specific exercise.

There are no restrictions on the form of exercise or the distance from the camera. The only precondition is that the point of view should allow the performed exercise to be properly visible. In order to reduce computational cost without reducing efficiency, the frame rate is reduced to 10 fps. The videos that will be evaluated on the respective exercise type are also preprocessed in the same manner.

3.2 Pose Estimation and Angles Computation

After experimenting with multiple state-of-the-art pose estimators, the pretrained real-time system, MediaPipe Pose, was selected. By utilizing MediaPipe Pose, this work leverages the state-of-the art in pose estimation algorithms, and focuses on the extraction of exercise parameter rules for posture evaluation. MediaPipe output consists of lists containing the normalized coordinate predictions of all keypoint locations. We consider the predictions of 13 keypoints of the pose, which include the nose, shoulders, elbows, wrists, hips, knees, and ankles. Following the pose estimation, the angles between the selected body vector pairs are computed from the detected keypoints of interest. The available for selection body vectors are the following:

- Left / Right Upper Arm
- Left / Right Forearm
- Left / Right Upper Legs
- Left / Right Lower Legs
- Left / Right Side of Torso
- Left / Right Side of Neck
- Left / Right Foot
- Shoulder Blades
- Hips

3.3 Range of Motion Estimation & Rule Parameters Extraction

The exercises for dynamic posture assessment, as well as fitness exercises in general, are structured and repetitive, thus the angle values between the body vector pairs during these exercises have a specific range. As a result, the computed angles from the vector pairs through time form either a periodic or a constant type of signal. The periodic signal's highest and lowest points indicate the range of motion in angle values between the vector pairs, while the frequency indicates the repetitions of a complete motion. For example, in an overhead squat exercise, the torso and hands should mainly stay in parallel with the lower legs and not move significantly, while the knees bend repeatedly. Figure 2 depicts the correct posture for an overhead squat exercise and Figure 3 illustrates the computed vector pair angles during an overhead squat with correct posture maintenance. Under these observations we detect postural misalignments during an exercise, by comparing all vector pair angles through time, with the vector pair angle extrema from a correct execution of the respective exercise.

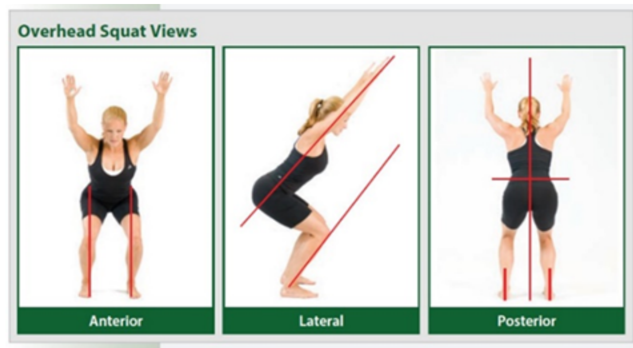

Figure 2: The correct posture during an overhead squat

The computed vector pair angles are dependent on the performance of the pose estimator. We work under the assumption that the pose estimator is accurate the majority of the time, with small measurement deviations due to noise (Figure 3), which we take under consideration. Thus, in order to determine the extrema from the angle signals of an exercise's correct execution, instead of just selecting their minimum and maximum values, we detect the values of the signal with gradients less than 1 and cluster them into two clusters by employing the k-means algorithm [24]. Algorithm 1 describes the pseudo code of the rule parameter extraction procedure. The values of the centroids of the clusters are the extrema of a pair vector. In the case of a static posture exercise, the parameter rules are the angles of the pair vectors computed after pose estimation.

Algorithm 1 The Rule Parameter Extraction Algorithm

```
Input: The computed vector pair signals
procedure:
for all s(t) ∈ Vector Pair Signals do
    T = {t | t ∈ Ds , |s´(t)| ≤ 1}
    extrema_{1/2} = KMeans (T, n_clusters = 2)
end for
```

3.4 Detection of Posture Misalignments and Summarization through Display

After the extraction of the rule parameters from the ground truth video, the rules are stored and videos with executions of the respective exercise can be evaluated on posture misalignments with an accepted deviation of 5%. It should be noted that the point of view of the posture in the videos that are to be evaluated, should be approximately the same as that of the correct execution. In order for the application to run in real-time as well, the pair vector angle values are computed at each frame and monitored for interval change (changes in ascending or descending order). With this technique, a deviation from the correct range of motion of any vector pair can be detected in real-time and displayed to the user. Algorithm 2 describes the process of postural misalignment detection. To summarize the results of an entire video, the angle value deviations

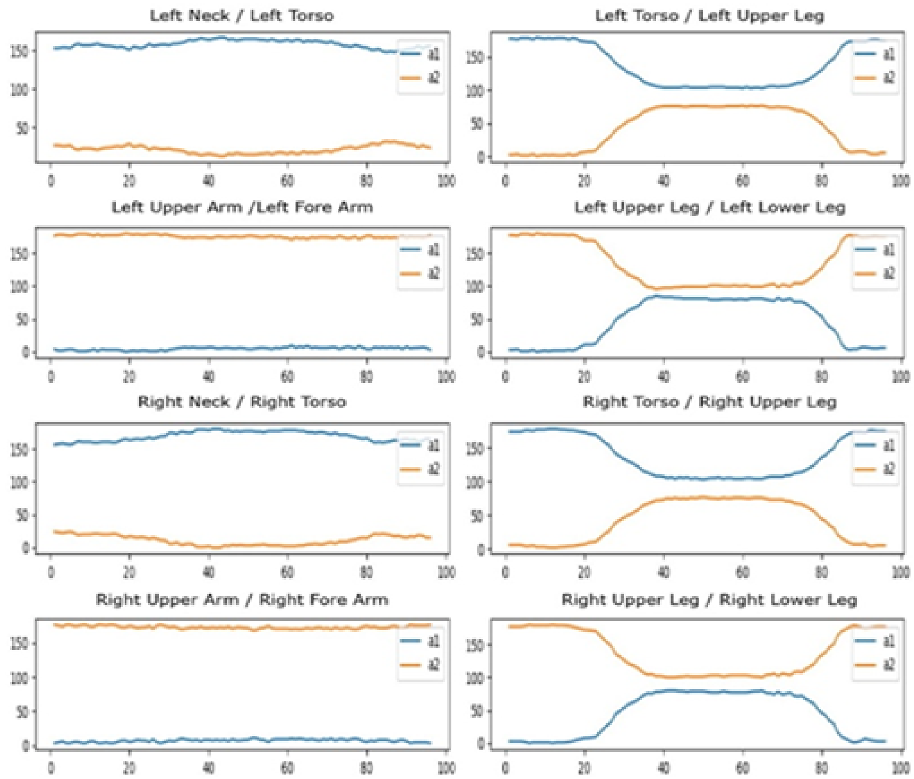

Figure 3: Vector pair signals (interior and exterior angles of the vector pairs) from a correct posture during an overhead squat from frontal view

Figure 4: Frames of the video utilized to extract the rule parameters for correct posture maintenance during an overhead squat exercise

from the extracted rules are exported and to visualize the posture misalignments detected during the exercise, the frames that contain events of interest are displayed. Additionally, the plots of the angle values from the pair vectors through time are also presented, as they may indicate additional information for the user to evaluate, such as the duration and frequency of repetitions.

Algorithm 2 The Postural Misalignment Detection Algorithm

Input: Video for posture evaluation, the extracted rule parameters and the acceptance threshold ϵ (degrees)
procedure:
$\epsilon = 10^{\circ}$
for each frame
 for all v ∈ Vector Pairs do
  compute and store in cache Vector Pair Angle sv(t)
  if (interval change for 10 consecutive frames and sv (t-10) ∉ [extrema v - ϵ, extrema v + ϵ]) then
   annotate posture misalignment
 end for
end for

4 EXPERIMENTS AND RESULTS

The dataset utilized in this work was acquired specifically for this project by a clinical exercise physiologist. It contains videos with correct executions of 8 types of exercises (overhead squat, single-leg-squat, push-up, standing overhead dumbbell press, standing row, upper extremity abduction, upper extremity rotation and lunge front) along with the parameters associated with each type of exercise. To evaluate the efficacy of the system, an additional dataset of 40 videos with exercises performed by patients was also provided along with annotations of posture misalignments on frames.

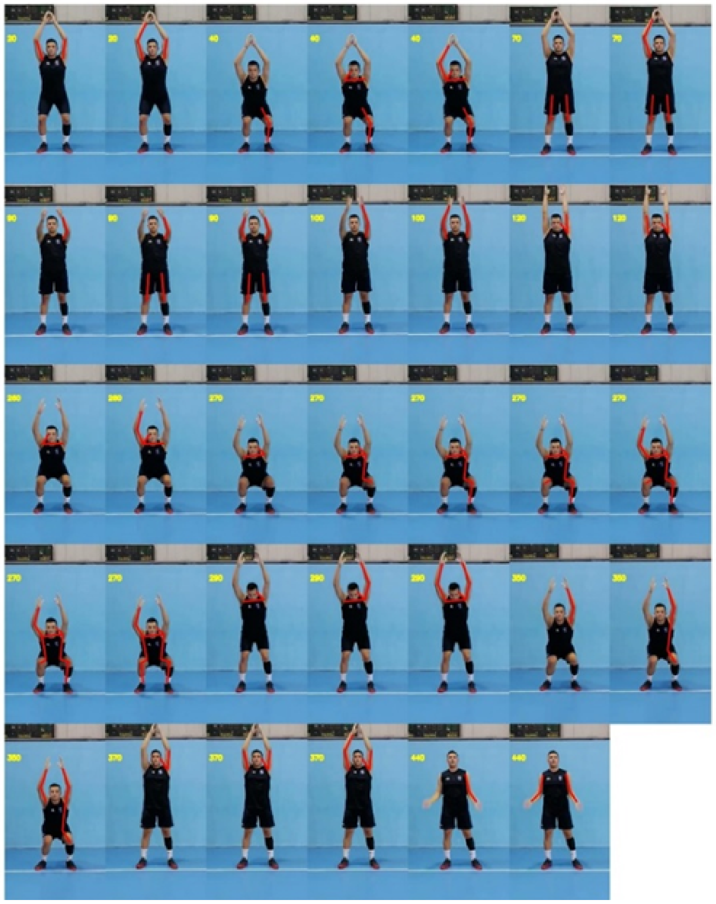

Figure 5: The detected frames with posture misalignments during an overhead squat

Body Lines	angle	best angle	best angle index	distance	seconds	frame
Left Upper Arm Right Upper Arm	23	40.95	0	17.95	0.67	20
Right Upper Arm Right Fore Arm	42	8.44	1	-33.56	0.67	20
Left Upper Leg Left Lower Leg	33	17.35	1	-15.65	1.33	40
Right Neck Shoulder Blade	124	112.88	1	-11.12	1.33	40
Right Upper Arm Right Fore Arm	47	8.44	1	-38.56	1.33	40
Left Upper Leg Right Upper Leg	8	18.52	0	10.52	2.33	70
Right Upper Arm Right Fore Arm	41	8.44	1	-32.56	2.33	70
Left Upper Arm Left Fore Arm	45	10.3	1	-34.7	3.0	90
Left Upper Leg Right Upper Leg	8	18.52	0	10.52	3.0	90
Right Upper Arm Right Fore Arm	36	8.44	1	-27.56	3.0	90

Figure 6: Pair vector angle values during the exercise of overhead squats in Figure 5

The extracted parameter rules from the application were confirmed as valid for all exercise types by the qualified professional, and the frames with annotated posture misalignments (1213 in total) were accurately detected and described. Figures 4, 8 illustrate frames from videos with correct posture maintenance that were

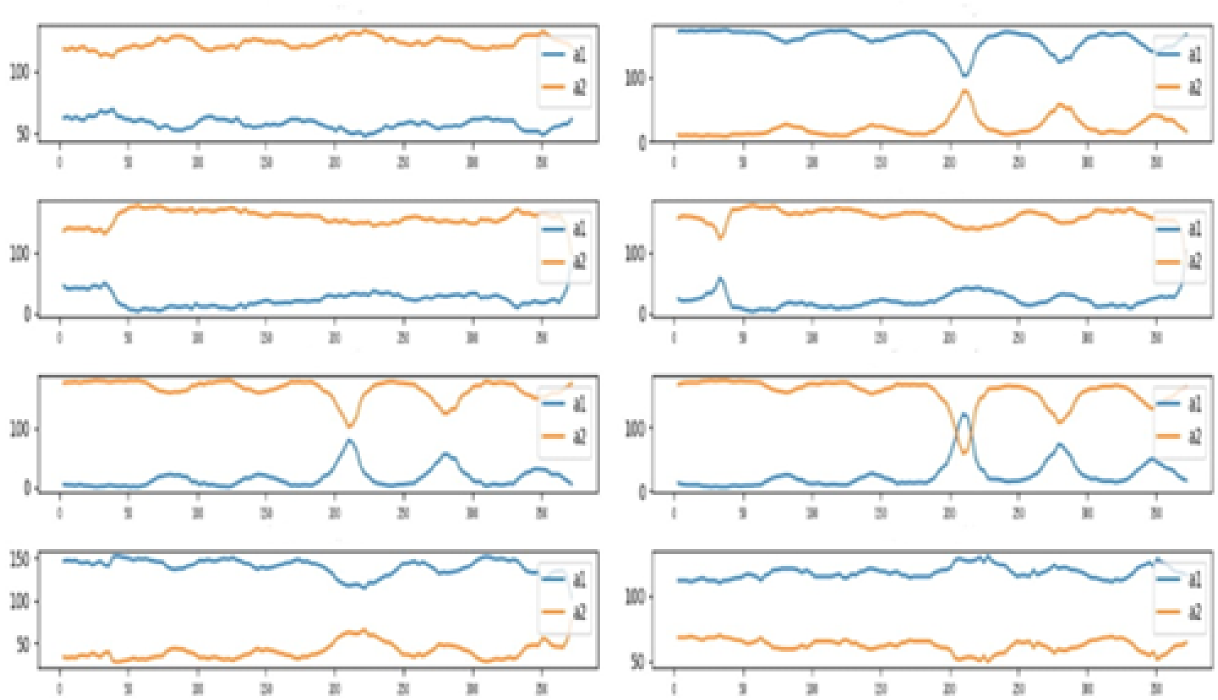

Figure 7: Pair vector angle values (interior and exterior angles of the vector pairs) during the exercise of overhead squats in Figure 5

utilized to extract parameter rules, and Figures 5, 9 illustrate the detected frames with posture misalignments from videos of patients that performed the corresponding exercises. Figures 6, 10 describe in detail the deviations of vector pair angles from the accepted values in each frame and Figures 7, 11 depict pair vector angle values during the exercise.

5 CONCLUSION AND FUTURE WORK

In this paper, we describe an end-to-end real-time application that utilizes pose estimation, vector geometry and machine learning to extract rule parameters, detect postural misalignments and provide feedback on any form of exercise. The MediaPipe pose estimator is utilized to estimate posture and the k-means algorithm is employed to extract the exercise parameter rules from a single video with correct posture maintenance. Videos of the corresponding exercise are evaluated in real-time on the extracted rules from the ground truth video and feedback is provided to the user by summarizing the events of interest through display. The results were evaluated on 40 videos of 8 different exercises by a clinical exercise physiologist.

Future work will be focused on the improvement of feedback, by providing suggestions of targeted actions for improvement according to the detected postural misalignments. Another extension of the project would be silhouette evaluation along with skeletal posture, in order to detect posterior pelvic tilts, which usually occur towards the bottom of squat exercises. Finally, the real-time feedback could be improved by illustrating the users pose diagram and comparing it with the pose diagram of the correct execution.

Figure 8: Frames of the video utilized to extract the rule parameters for correct posture maintenance during a deep lunges exercise

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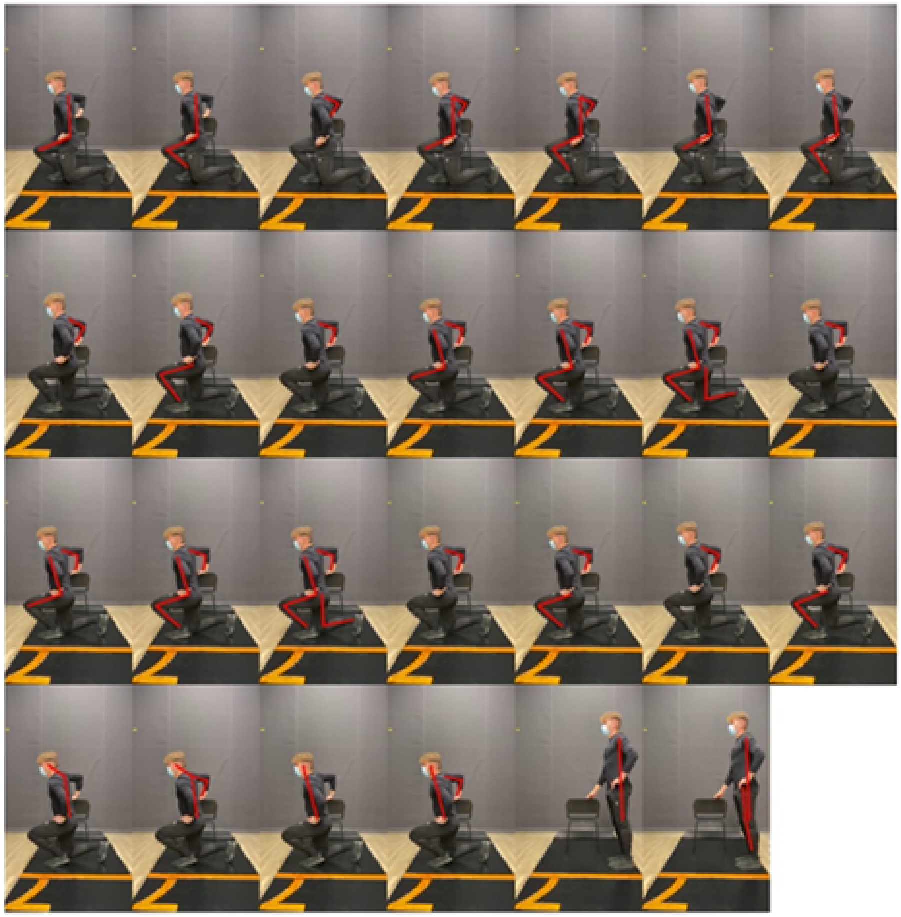

Figure 9: The detected frames with posture misalignments during a deep lunges exercise

Body Lines	angle	best angle	best angle index	distance	seconds	frame
Right Torso Right Upper Leg	110	134.73	0	24.73	3.5	210
Right Upper Leg Right Lower Leg	117	88.51	1	-28.49	3.5	210
Right Upper Arm Right Fore Arm	96	41.89	1	-54.11	8.33	500
Right Torso Right Upper Leg	113	134.73	0	21.73	8.33	500
Right Upper Leg Right Lower Leg	102	88.51	1	-13.49	8.33	500
Right Torso Right Upper Leg	110	134.73	0	24.73	8.5	510
Right Upper Leg Right Lower Leg	99	88.51	1	-10.49	8.5	510
Right Upper Arm Right Fore Arm	91	41.89	1	-49.11	12.67	760
Left Upper Leg						

Figure 10: Pair vector angle values during the exercise of deep lunges in Figure 9

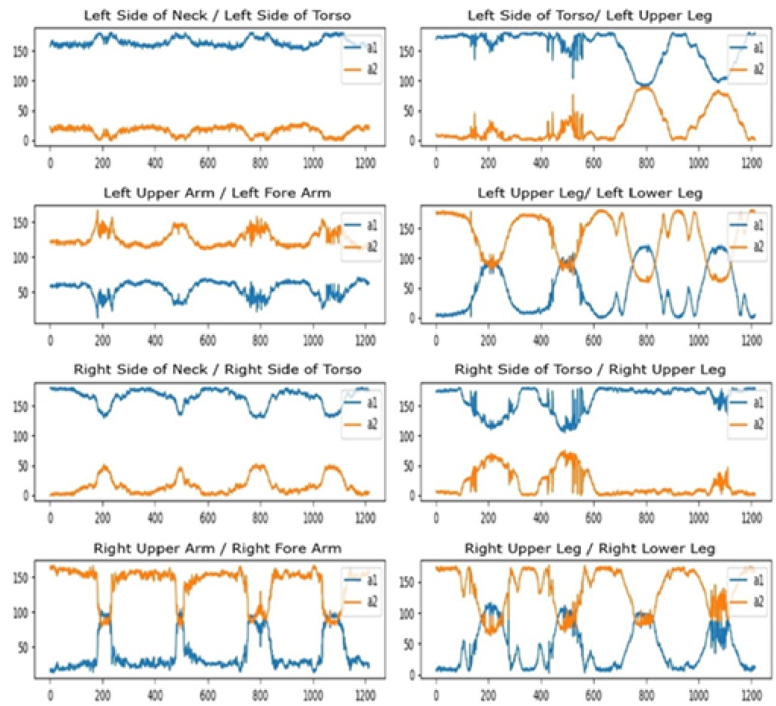

Figure 11: Pair vector angle values during the exercise of deep lunges in Figure 9

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