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Exercise Monitoring Mechanism and Posture Correction

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ABSTRACT: The recent advancement of new technologies has resulted in the creation of an inactive living. During the tough time of the pandemic, people hesitate to visit a gym or find it difficult to keep themselves fit and healthy. A traditional gym instructor prescribes exercise programs that can help them lower the risk of non-communicable lifestyle diseases but on the other hand, they are often expensive and are not always available, or accessible. This urged us for developing an automated exercise tracking system. The study outlines a two-stage tool for evaluating exercise posture, including a count of repetitions and a recommendation for incorrect posture. The first stage consists of a real-time body tracking model, which extracts 21 key-points. These key-points are then processed via a proposed statistical algorithm in the second stage, which provides workout count and posture correction recommendations. This system will not only allow an individual to regulate the exercise but also monitor them, so they are performed correctly and hence helping in staying fit and healthy.

KEYWORDS: Body Monitoring, Exercise, Lucas Kanade, Pose Tracking, Statistical Algorithm

I. INTRODUCTION

According to the World Health Organization (WHO) data, exercising on a regular basis is an important strategy for preventing serious infections. This can forestall conditions like overweight, hypertension, and helpless cholesterol levels, prompting cardiovascular failure and stroke. At the point when everything is said and done, as people age, they become less really unique. Nevertheless, when we settle in, we require more regular exercise, not less. According to the AHA, 69 % of the people are overweight or obese, and this number is rising. The National Center for Health Statistics discovered in 2019 that every third adult who had visited a doctor in the previous year had been advised to begin or continue with a fitness program. Among grown-ups matured 85 years and more established, the rate of accepting counsel to practice almost multiplied over the previous decade (American heart Association et al, 2015). Dynamic work helps to prevent bone loss, improve coordination and harmony, and strengthen muscles. Some studies have shown that doing more genuine work reduces the risk of having a variety of contagious diseases, including cardiovascular disease.

As per the review reports of AARP, the thinking for physical inactiveness inside individuals is sub-sorted into four kinds. Regardless of anything else being ailments as high as 33% of non-exercisers (34%) express those clinical issues shield them from working out. For a few (8 percent), the possibility of being hurt is also a significant motivator for why they are currently working out incorrectly. The subsequent one being the time limitations over individuals confine them from doing any activity. People expressed that finding an opportunity to rehearse when you feel like the test is a massive issue for a few. Thirty-seven percent (37%) state they are too depleted or lacking energy to work out, the most broadly perceived clarification Americans 50-79 give for not participating in proactive errands. One out of four (26%) essentially says the individual being referred to requires more time. This is especially an issue for those so far working, diverged from those who are not (39% versus 16%). Individuals look to the third group of challenges as powerless areas or environmental factors. Having an excellent spot to rehearse that is secured and affordable—and having someone to rehearse with—are also huge reasons why people mature enough 50 and over don't work out. According to the blueprint, nearly one out of every three people (34 percent) don't practice because recreation center collaborations are prohibitively pricey, and the individual being referred to isn't working out. Additionally, Thirteen percent notice not having anyone to rehearse with as a huge inspiration driving why they don't work out. The last and fourth group is freshness or absence of information. Exercise can also be a difficult undertaking for individuals who are not used to it,

according to experts. Around one of each eight (13%) alludes to feeling uncertain as a critical inspiration driving why the individual doesn't work out. Furthermore, only about one out of every twenty (6 percent) people think they'd have to find a way to start working out.

In this paper, we describe a two-stage method for analyzing exercise postures that is both reliable and efficient. The system will provide the repetition count and also the suggestions to correct exercise posture. We have focused on developing a real-time body tracking algorithm and a robust statistical algorithm to process the body key-points obtained from the first stage for a few basic exercises like squats, push-up, plank, and skipping etc. The first stage compresses the Posenet model for body tracking, resulting in a total of 21 body key-points. At stage two, the statistical method is a phase-based model, in which the correctness of exercise is determined by the angle between significant body key-points and an ideal exercise posture.

II. RELATED WORK

In recent years, methods of human posture recognition have been studied in a range of different papers. In general, these methods can be divided into two types. The first type involves wearable sensors, which are put on the body or clothes of a human to measure certain values, such as the positions of limbs and the slope degree of the body. For instance, one study asked a participant to wear a garment with strain sensors to recognize 27 upper body postures [1]. In [2] and [3], the authors proposed a smart shirt system (SMASH) with acceleration sensors to recognize 21 human exercise postures. A waist-mounted triaxial accelerometer system was developed in [4] to classify human movement status. A wireless acceleration measuring system to monitor a human's activity volume and recognize emergent situations was built in [5]. However, a disadvantage of all five of these studies was that the wearable sensors and the accompanying batteries that the participants were required to wear can be a source of discomfort or inconvenience for them.

The other type of method used to recognize posture information is based on captured images of a human body. Some posture features can be represented by specifically coloured markers on the human torso and limbs. By recognizing the relative positions of the coloured markers, human postures can be recognized using the methods presented in [6] and [7]. However, wearing coloured markers can be just as uncomfortable as wearing sensor devices. In the paper, Amit Nagarkoti et al. author [8], aims to aid people in playing out these exercises freely. In the model for Realtime Multi-Person 2D Pose Estimation, part affinity fields are used to estimate the human pose. Optical flow tracking is used to obtain body parts from adjacent frames, and the Lucas-Kanade algorithm is utilized for optical flow tracking in OpenCV. The system's only issue was that the user had to first give the trainer's video, which the algorithm would then compare.

The author Alexander Toshev et al. [9] suggested a procedure for pose estimation of the human body based on the concept of Deep Neural Networks (DNNs). They introduced a course of such DNN regressors which results in high accuracy pose estimates. The methodology has the advantage of considering posture in a comprehensive manner, and it offers a simple but effective definition that takes advantage of recent Deep Learning breakthroughs. The research also examines the condition of workmanship or improved execution on four academic benchmarks of various actual photographs in great detail.

The author Alex Kendall et al. [10] offer a monocular six degree of freedom relocalization system that is strong and continuous. It is prepared in a CNN organization to relapse the current 6-DOF camera with no additional designing or schematic enhancement required. Their algorithm has the ability to work both outdoors as well as indoors in real-time, taking 5ms per frame to quantify. It acquires roughly 2m and 6-degree precision for enormous scope outdoor scenes and 0.5m and 10-degree exactness inside.

III. METHODOLOGY

1. Outline of the system

This complete architecture is based on two key elements,

- 1) A 2D human body tracking model.
- 2) A statistical algorithm providing repetition count.

It has suggestions for the wrong posture, and a complete exercise report, as shown in Figure 1. As operating the model in real-time being the key aspect of the research, the 2D human body tracking model is enhanced using Lucas Kanade's Algorithm.

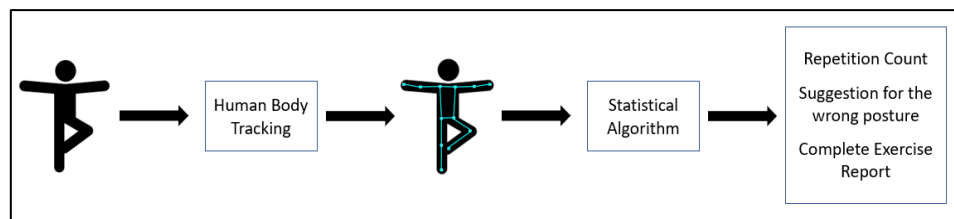


Figure 1 - Overall Proposed Architecture.

2. Enhancing 2D Body Tracking Performance

We devised an approach to track human movement that consists of three main components: recognition, including following, and strong assessment. As demonstrated in Figure 2, detection is accomplished using a cutting-edge algorithm called PoseNet. The total system starts with an input frame, then does pose estimation and the Lucas Kanade algorithm for alternate frames or based on the gap.

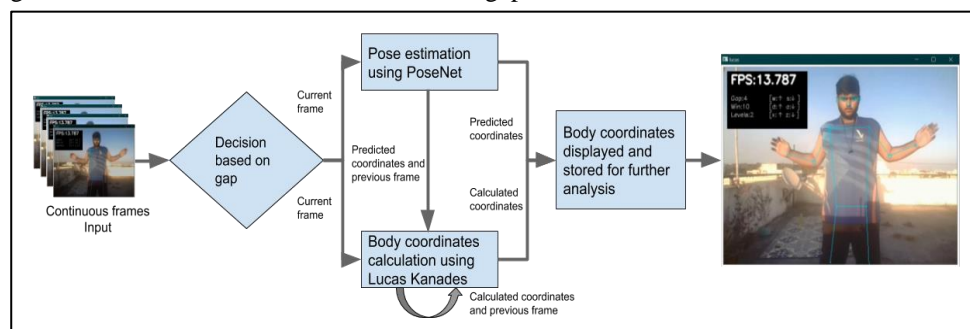


Figure 2 - Overall Architecture of the System

The Highlight following is accomplished with the Lucas-Kanade technique executed with pyramids, i.e., it runs iteratively over the Gaussian pyramid of images, as shown in Figure 3. The pyramid approach is adapted to track the more considerable object movement or object moving with larger speed [11].

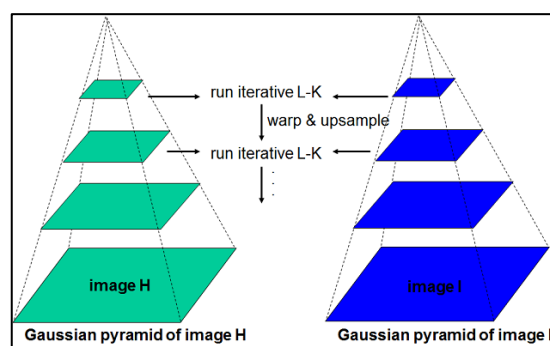


Figure 3 - Pyramid Structure used in Lucas Kanade

2.1. PoseNet – Body Pose Detection

Body present central issues are at first recognized, which yields 21 2-dimensional body points. As per info picture, it gauges the area of the key-points of the relative multitude of bodies found in the scene and all the while gauges the probability of each central issue to be associated with different ones. It explores the data RGB picture with a significant convolutional neural association to discover the body tourist spots, and a while later, it interfaces them through a heuristic computation. Operation moreover releases an extent of sureness (going from 0 to 1) for each perceived central issue and customarily sets to (0,0,0) any undetected purpose of a body.

2.2. Lucas Kanade's Algorithm for Feature Tracking

We can utilize the Lucas Kanade technique to detect key-points in future video frames once the pose has been assessed and key-points are discovered. By examining the degree of fluctuation in pixel intensity in the neighborhood of the key pixel, Lucas Kanade's algorithm estimates the movement of a pixel in two consecutive frames [12]. As stated in Equation 1, u represents the development w.r.t. x , v represents the development w.r.t. y , and $I(x, y)$ is the intensity of the pixel at location (x, y) LK. as shown in Equation 1.

$$\frac{dI}{dx}(x, y, t) \cdot u + \frac{dI}{dy}(x, y, t) \cdot v = -\frac{dI}{dt}(x, y, t) \quad \text{- Equation 1}$$

Similarly, with a pixel, we have two queries (u, v) and one condition, with the expectation that a neighboring pixel will receive more conditions. As a result, the framework tends to over-decide, and Lucas Kanade chooses the most un-square (LSQ) arrangement that approximates the optical stream's midpoints over the area. LK is made up of optical flow vectors that are generated using the procedure below.

Step 1: Calculate the frame x and frame y derivatives.

Step 2: Calculate the difference frame $I_t = \text{frame 1} - \text{frame 2}$.

Step 3: Smoothen the frame components I_x , I_y , and I_t .

Step 4: For computing the Eigenvalues, solve the Linear Equations for every pixel.

Step 5: After Eigenvalues are obtained, depending on that, solve the equations using Cramer's rule.

Step 6: Optical Flow vectors are plotted.

Because the unpredictability of this method is based on the number of following focuses rather than the whole number of pixels in the image, it is much faster than the key-points recognition algorithm. The main problem with this algorithm, like with all visual highlight-based algorithms, is that it is incapable of dealing with obstacles. The posture assessor's speed can be increased by combining the central issues indicator with the Lucas Kanade algorithm. It does not, however, ensure that human movement is reproduced in a liquid state.

As shown in Figure 4, the experimentation was carried out in the real-time paradigm, altering the gap after an instance. During the experiment, the gap was changed as 1, 2, and 3. The respective FPS obtained by increasing the gap can be seen in Figure 4.



Figure 4 - Results with and without Proposed Architecture

3. Statistical Model of Proposed Model

The statistical model is proposed to process the two-dimensional body coordinates from Section 3.2 and create the repetition count as well as incorrect posture advice. To reduce single frame processing time, a statistical model is chosen over a machine learning model in this case. Figure 5 shows the algorithm for counting repetitions. The steps of the algorithm are detailed as indicated in the diagram.

Step 1: Take the stream of 2D body coordinates from the proposed model in Section 3.2 for the current frame.

Step 2: Drop all the unnecessary key points and store all the essential key points in a dictionary. Also, check for all necessary key points, if the confidence of all points is above a threshold or not, as shown in Equation 2.

$\forall x, \text{Confidence of } x \geq \text{Threshold Confidence}$ - Equation 2

where x is the necessary key points.

E.g., For Exercise class Squats, necessary body key points are – Nose, Shoulder, Hip, Knee, and Ankle.

Step 3: Calculate the angles using filtered key points from previous step using Equation 3.

$$a = (p1.x - p2.x, p1.y - p2.y)$$

$$b = (p1.x - p3.x, p1.y - p3.y)$$

$$\theta = \cos^{-1} \left(\frac{a \cdot b}{|a| \cdot |b|} \right) \quad \text{- Equation 3.}$$

where $p1, p2, p3$ are 3 key points. i.e., a and b being two vectors and θ is the angle between those two vectors.

Step 4: Calculate the deviation of angles with the reference pose angle and classify current posture into one of the reference phases.

Step 5: Furthermore, store the body coordinates, calculated angles, and current phase for posture correction suggestions.

Step 6: Increment the repetition counter using the stream of current phases. i.e., a phase pattern like 0,0,0,1,1,2,3,3,2,2,1,0 means to increment the counter by 1.

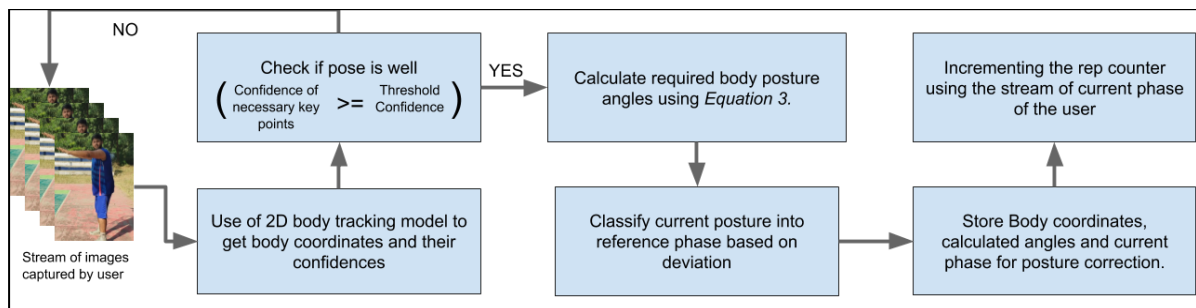


Figure 5 - Architecture of Proposed Statistical Model

IV. EXPERIMENTAL RESULTS

1. Real-time 2D Pose Estimation

Figure 6 represents the execution time plots with varying gaps from 1 to 6, giving avg fps up to 25.6. The execution time of PoseNet being greater than 0.2 sec while for the frames with the Lucas Kanade algorithm is nearly equal to 0.05. Thus, avg execution time can be determined using Equation 4. Hence the best-obtained execution time for the proposed model is 0.0783 sec.

$$\text{Avg Execution Time} = \frac{\text{Posenet Execution Time} + (\text{Gap} - 1) * \text{LK Execution Time}}{\text{Gap}} \quad \text{- Equation 4}$$

2. Repetition Counter Mechanism

The acquired phases stream is used by the repetition counter mechanism. The phase list is initially empty, and the corresponding posture is added to the phase list after each phase categorization. Call the function update Counter for each update in the list to see if the counter should be updated or not. Updating the counter is determined by two factors:

1. Min-Max-Min Phase Pattern: It checks if the phase list pattern is present in the form of 0-3-0 as min-max-min phase.
2. Mountain Array Pattern: It checks whether the list is in the mountain array format, as shown in Figure 7. Both the mountain array with strictness and without strictness pattern is acceptable for the update counter.

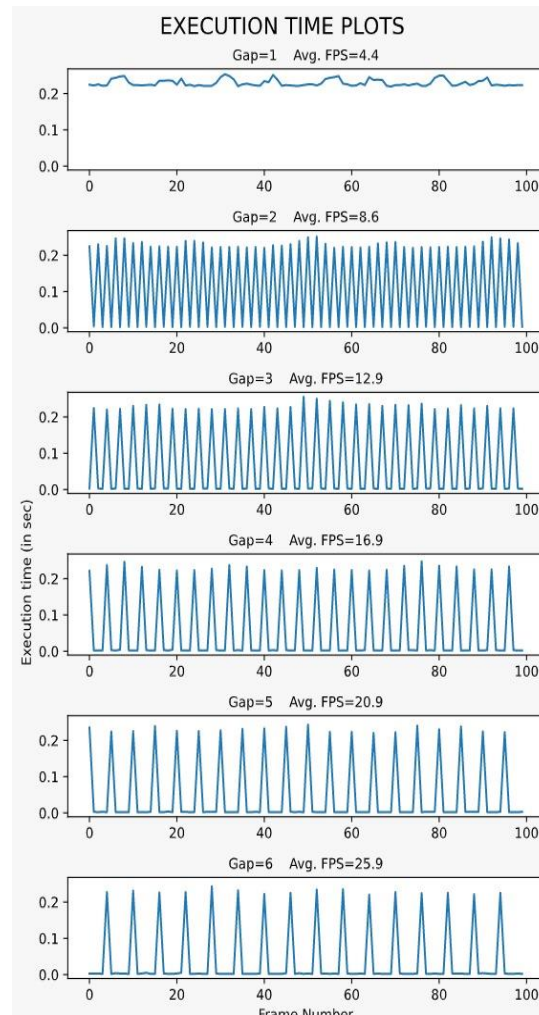


Figure 6- Execution Time graph of Proposed Body Tracking Model

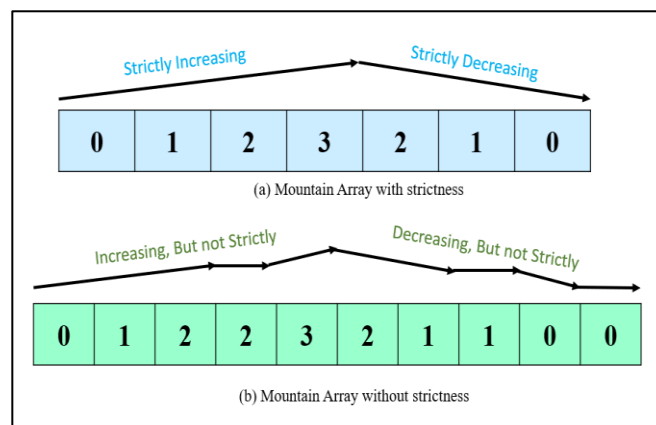


Figure 7 - Phase List Pattern for updating repetition counter

3. User feedback and Posture Correction Mechanism

After the user has completed his exercise, the user feedback mechanism is activated. The most deviated frame (incorrect posture frame) per phase is selected from each phase, and a report is prepared using the stored body coordinate angles. Furthermore, these frames are compared to the reference frames side by side, and the wrong angles are highlighted in red for the user. The improper posture frames and corresponding correct posture are given as an output at the end of the exercise or if the user performs incorrect posture in 5 frames continuously during the exercise, as shown in Figure 8.

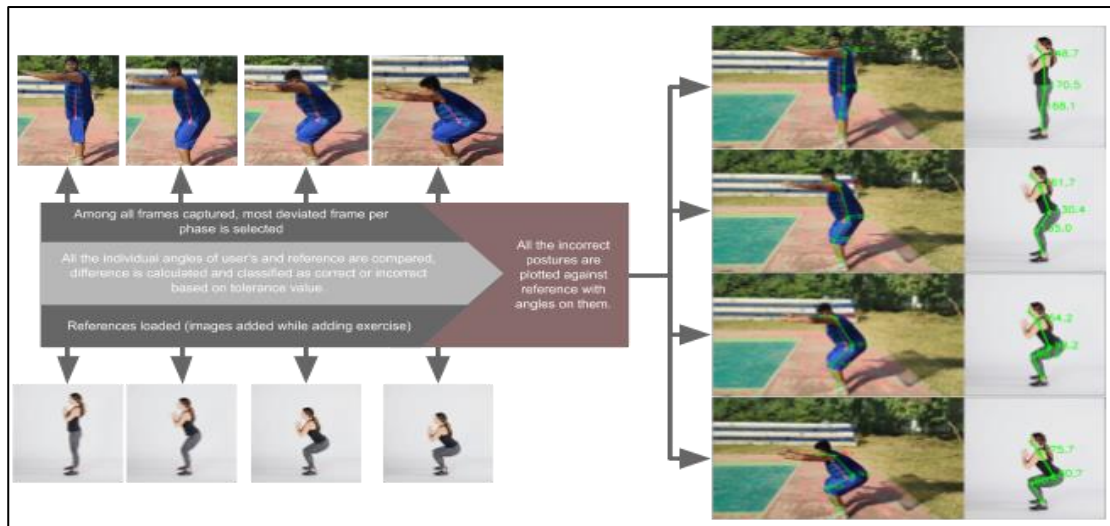


Figure 8 - Incorrect Posture Suggestion

IV. CONCLUSION

This research met all the primary objectives and secondary objectives specified in Section I. The Virtual Gym Instructor boasts a stable algorithm that tends to the shortfalls of the Pose system. Virtual Gym Instructor monitors a user's form continuously and gives real-time feedback during workouts. Perfect real-time object detection and tracking was achieved up to four meters away from the camera, whereas 60% of the motions were successful at eight meters away. The detection and tracking algorithm is thus an important contribution that can also be used in other systems, such as for the rehabilitation of injuries or gait recognition. The reports from Keep Up can motivate users to break their prior records and keep track of their total points and last workout. The system as a whole is promising, and in future, can be extended for greater functionality subsequent to more testing

This study accomplished all of the key goals for a virtual gym trainer. The proposed model is a stable method that addresses virtual gym trainer's shortcomings. It continuously monitors an individual's form and delivers real-time feedback throughout workouts. Following the workout, the system generates a full report. With frame rates up to 25.6 frames per second and an execution time per frame of 0.783 seconds, perfect real-time human pose detection and tracking was accomplished, allowing the proposed model to include fast-paced training. The system as a whole appears promising, and it may be expanded in the near future for further capabilities.

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