Interactive Exercises for Computer-based Work Using a Webcam

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ABSTRACT

Sedentary behavior in office environments has become a widespread concern due to its negative impact on individuals' health and well-being. This study not only addresses this issue by providing details about the musculoskeletal disorders pertinent to the wrist, shoulders, and neck that can develop due to immobility or prolonged sitting in front of a computer workstation, but also promotes the regular incorporation of three specific exercises for office workers. In particular, this study contains a comprehensive literature review covering the trade-offs between wearable devices and computer vision techniques in monitoring and counting the repetitive movements of various physical activities. Moreover, this study utilizes the Mediapipe pose estimation technique to track exercise performance and develops algorithms using a state machine for accurately counting repetitions during active breaks in an office environment. The dataset used to evaluate the methods employed consisted of a total of 36 videos and was gathered by engaging the employees working at Fraunhofer IGD and the University of Rostock. The findings of the research validated that the state machine could count the interventions with a mean accuracy of 92%. This suggests its incorporation in the future on a larger scale by selecting more exercises, a larger dataset, and various environmental settings.

CCS CONCEPTS

• **Human-centered computing** → **Empirical studies in HCI**; • **Applied computing** → *Health informatics*; Consumer health.

KEYWORDS

occupational health, pose estimation, active breaks, exercise monitoring, finite state machine

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1 INTRODUCTION

The prevalence of sedentary behavior has increased in modern office environments, where employees spend long periods of time in a seated position with limited physical activity[2, 20]. The adoption of a sedentary lifestyle has been linked to various health consequences, such as musculoskeletal disorders, reduced performance, and an impaired well-being [1, 3]. With an increasing awareness of the adverse effects associated with extended periods of sitting [4, 6], there is a rising demand to investigate efficacious approaches for encouraging physical activity and movement among individuals employed in office settings [13, 25]. This study focuses on the implementation of active breaks during the workday with the aim of enhancing the health and well-being of office workers. Active breaks [5] refer to the integration of brief periods of deliberate exercise into a routine to interrupt continuous periods of inactivity [18]. It is postulated that by promoting physical activity and movement during these breaks, the harmful consequences of extended periods of sedentary behavior can be alleviated [14]. In addition, the incorporation of pose estimation algorithms has the capacity to augment the efficacy and involvement of physical activity intervals by providing immediate feedback and monitoring exercise execution. Apart from keeping a record of pose estimation, it is imperative to consider the counting of repetitions during active breaks as a crucial aspect that cannot be ignored [22]. The practice of tallying repetitions confers a number of notable benefits that enhance the efficiency of the workout regimen, encourage body movement, and improve overall health and fitness. Incorporating repetition counting during active breaks can facilitate progress monitoring, consistency maintenance, intensity regulation, goal setting, and motivation enhancement for individuals [28].

Although active breaks and pose estimation tracking have demonstrated potential to adress sedentary behavior and promote physical activity among office workers, there are several challanges and trade-offs in identifiying and quantifiying active breaks in office settings. These challenges pertain to the selection between wearable devices, equipment instrumentation, and the utilization of computer vision or pose estimation methods to ensure precise exercise recognition. Furthermore, the algorithms utilized for repetition counting during active breaks are pivotal in guaranteeing dependable and efficient monitoring. A significant obstacle involves the identification of a suitable technique for detecting active breaks.

Wearable technologies offer enhanced convenience and ease of use, instead of necessitating the use of supplementary equipment or devices that may be inconvenient and unsuitable for certain individuals. Conversely, while instrumentation can provide accurate measurements, it often requires specialized equipment that may not be easily accessible or practical for widespread adoption in office environments. Selecting the optimal technology for detecting physical activity during active breaks presents a further obstacle. Pose estimation algorithms, which are a type of computer vision technique, have become increasingly popular due to their ability to analyze body movements and recognize particular exercise patterns without the need for supplementary sensors. The MediaPipe pose estimation framework [19] and other similar techniques have demonstrated the potential for precisely monitoring key points and joint angles, facilitating the identification of different exercises executed during active breaks. Nevertheless, these methodologies may exhibit constraints with respect to precision, different illumination settings, and real-time processing. In addition, the algorithms utilized for repetition counting during active breaks are of utmost importance in providing feedback and monitoring the physical activity performance of individuals. This study utilized a state machine methodology to quantify the number of repetitions performed during active breaks. The methodology employed in this approach involves the utilization of state transitions to identify and monitor every iteration. However, further investigation is required to determine the efficacy of the state machine in accurately counting repetitions, particularly during various active breaks in office settings. It is crucial to tackle these challenges and trade-offs in order to devise productive and easily accessible techniques for identifying and quantifying active breaks. This study endeavors to address the challenges associated with accurately tracking and counting repetitions of active breaks in an office environment by utilizing the MediaPipe pose estimation model and state machine algorithms, respectively.

1.1 Research Objectives

This paper aims to address the aforementioned research gaps and achieve the following objectives:

(1) Assess the impact of regular active breaks on the health and well-being of office workers. By motivating and encouraging office workers to perform active breaks, the objective is to evaluate the effectiveness of these breaks in mitigating the negative effects of sedentary behavior, reducing musculoskeletal disorders, and improving overall physical health.
(2) Explore the utilization of pose estimation techniques, specifically Mediapipe, in accurately detecting and tracking specific active breaks. By leveraging pose estimation, the aim is to provide real-time feedback and guidance to office workers, ensuring correct exercise form and optimizing the benefits of each active break.
(3) Develop and implement a robust repetition counting algorithm within the active break framework. This algorithm, integrated with the pose estimation system and utilizing state machine techniques, will be utilized to count repetitions, allowing office workers to track progress, regulate intensity, and maintain consistency in their exercise routines.

By achieving these objectives, this paper seeks to contribute to the understanding of the positive impact of regular active breaks, the efficiency of pose estimation techniques in detecting active breaks, and the development of a reliable repetition counting algorithm for office workers. The research findings will inform the design and implementation of effective interventions to promote physical activity, well-being, and performance in office environments.

2 RELATED WORK

2.1 Conception Of Active Breaks

Active breaks, a series of short-duration muscle contraction exercises, are designed to disperse muscle stress and minimize fatigue during extended periods of physical inactivity [11]. Their incorporation has been increasingly common in the corporate sector.

2.1.1 Significance of Active Breaks Within the Corporate Sphere. On average, people spend 8–9 hours a day sitting, making sedentary lifestyles a significant public health issue worldwide. Sedentary workers face higher risks of diabetes, obesity, cardiovascular disease, and premature mortality. Moreover, they are more susceptible to musculoskeletal disorders affecting the neck, upper limbs, and lower back. These conditions have been linked to depression, cognitive decline, dementia, and reduced quality of life. As a result, there has been a substantial loss of working days, leading to a decrease in productivity. In the United Kingdom, Germany, and the Netherlands, musculoskeletal problems accounted for 21% to 28% of all work-related absences in 2017 and 2018. In 2012, these conditions accounted for 74% of US workdays lost and cost companies and employees 5.73% of the GDP. Sedentary behaviors were associated with a global healthcare expenditure of 67.5 billion USD in 2013 [26].

Regular breaks from prolonged sitting have been linked to improved metabolic profiles, suggesting that frequent breaks from sedentary tasks may be associated with reduced health risks. Incorporating physical exercise at work can improve mental and physical performance, foster social interactions, and enhance work performance, while simultaneously reducing work-related illness, absenteeism, and injuries. Recent studies suggest that effective "micro-breaks" should involve more than just standing up and stretching [26].

Prolonged computer usage is related to a high prevalence (33% to 65%) of eye and visual disorders, especially among younger individuals. "Digital Eye Strain (DES) is an entity encompassing visual and ocular symptoms arising due to the prolonged use of digital electronic devices. It is characterized by dry eyes, itching, a foreign body sensation, watering, blurred vision, and headache" [12]. A study by [29] examined the effects of the 20-20-20 rule (a 20-second break every 20 minutes to stare at something 20 feet away from the screen) on DES and accommodative and binocular vision systems in young, symptomatic, and regular computer users. User breaks, eye gazing, and blinking were analyzed using the laptop's webcam, which also provided customized rest reminders [29].

2.1.2 Examining the Risk of Musculoskeletal Disorders in Office Workers. In their study on the occupational risk factors contributing to musculoskeletal disorders (MSD), [9] underscored the importance of ergonomics in workplace environments to reduce MSD prevalence. Furthermore, they conducted a cross-sectional survey on a sample of 126 participants to investigate the occurrence of musculoskeletal pain among remote computer users during the COVID-19 pandemic. The findings from this data are illustrated in the subsequent bar chart (Figure 1).

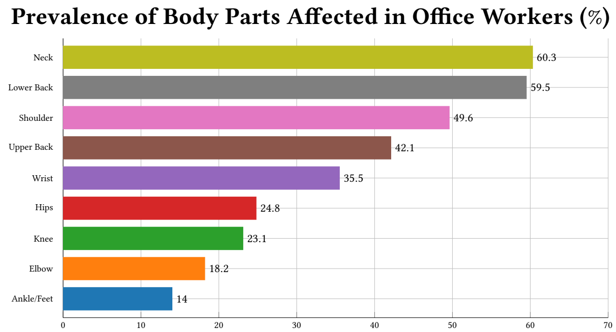

Figure 1: Prevalence of Musculoskeletal Pain among Computer Users [9]

2.1.3 Rationale Behind Selected Exercises for Active Breaks. Extended periods of sitting, sedentary lifestyles, and poor postures can disproportionately strain certain body parts such as the neck, shoulders, lower back, wrists, feet, and eyes. This strain can lead to not only musculoskeletal disorders but also potential nervous system conditions such as "Piriformis Syndrome", which can result in sciatic nerve pinching.

A concerning number of office workers (42–63% annually) experience neck pain, due to factors such as poor ergonomics, psychological stress, cervical spine immobility, aging, and minimal exercise. To address this growing issue, modifications in workstation design, adherence to good posture, physiotherapy, regular breaks, and the inclusion of stretches or strength exercises should be considered. This could aid in preventing or rehabilitating chronic neck conditions [24]. Furthermore, office workers' lack of neck mobility predisposes them to "Upper Crossed Syndrom", a condition characterized by muscular deformation in the neck, shoulders, and chest due to poor posture. Neck exercises or stretches as active breaks during the workday are recommended, but should be performed with caution, especially by those with preexisting neck conditions.

"Carpal Tunnel Syndrome (CTS) is a prevalent condition characterized by the compression or entrapment of the median nerve within the carpal tunnel in the wrist," leading to discomfort and sensory deficits in the hand [8]. A survey conducted in a large Chinese metropolis found that 9.6% of participants had CTS, with hand and wrist problems affecting 22% and 15% of participants, respectively [7]. Wrist or arm stretches are thus recommended to be incorporated into office workers' routines to prevent or mitigate CTS and other musculoskeletal strains in the hands or wrist.

Disorders related to the intensive use of computers have become more prevalent, with pain in the neck and shoulders being a common complaint [31]. Thus, shoulder disorders, such as "Rotator Cuff Tendinopathy" and "Adhesive Capsuliti" could also be a consequence. The former, often seen along with "shoulder impingement syndrome", is associated with inflammation of the tendons of the rotator cuff muscles [30]. The latter, or "frozen shoulder", restricts movement of the glenohumeral joint and can cause persistent, low-level pain that can be aggravated by certain activities [23]. Regularly incorporating shoulder exercises into work routines, such as shoulder circles, can help alleviate these issues by releasing tension and improving blood circulation in the shoulder and chest regions.

In conclusion, this study recommends the inclusion of wrist circles, shoulder circles, and neck rotations as active breaks in office workers' routines. These exercises are chosen specifically to address the musculoskeletal disorders prevalent in different regions of the body — the wrist or hand, shoulder or chest, and neck or upper back, respectively.

2.1.4 Promoting Active Breaks In The Workplace: Systems And Tools For Health and Productivity. Efforts to combat the health hazards associated with sedentary behavior in the workplace have led to the development of systems and tools that encourage active breaks among employees. One such solution is the Structured Exercise Program (SEPro), a physical activity regimen designed to promote mobility among office workers and mitigate potential health risks associated prolongedsitting [21]. It incorporates stretching and strengthening exercises, and an initial study involving 10 office workers demonstrated positive outcomes. However, limitations include a lack of personalization and a focus on English-language research literature. Despite these limitations, the SEPro offers a feasible solution for integrating exercise into daily routines without interrupting work schedules or requiring additional equipment.

Another study by [10] explored digital micro-interventions for stress reduction. Comparing pre-scheduled and just-in-time delivery timings and three types of intervention content (mindfulness, cognitive restructuring, and positive psychology), the study found no significant differences in stress reduction between delivery timings. However, participants favored just-in-time interventions, perceived as more relevant and effective. The research offers valuable insights into stress reduction strategies, but it was constrained by a small sample size, limited duration, reliance on self-reported data, and the absence of a control group. Despite these constraints, the study suggests digital micro-interventions may be a useful secondary strategy for reducing workplace stress.

In our previous work, we developed CareCam [15–17], a webcam-based system aimed at facilitating health-promoting interventions during computer-based work. This system was evaluated through qualitative semi-structured interviews, albeit with a small sample size [27]. Through this exploration, we were able to identify the need for further development of the system and its interventions. One example of these interventions is a dynamic sitting reminder, designed to encourage movement when no major activity is detected within a 2-minute period. In addition, we introduced straightforward exercises for improving posture, promoting eye health, and fostering mindfulness, which were presented in a simple design combining text and pictures. Our initial findings also indicated a demand for more advanced interventions to enhance the quality of exercise execution. This identified need has steered the course of our current research, as we aim to further improve these exercises and interventions, as presented in this study.

In conclusion, promoting active breaks and offering stress reduction interventions are promising approaches to enhance employee health and well-being. Both the SEPro and digital micro-interventions can contribute significantly to this cause, although future research should address their limitations and broaden their scope.

3 METHOD

The methodological approach of this research was designed to develop a computer vision-based system capable of accurately identifying exercise forms and counting repetitions. To achieve this, we utilized a real-time camera feed and the MediaPipe library for pose estimation. The goal was to detect predetermined landmarks associated with each exercise and calculate the angles between them. The initial phase of the study involved data collection, which entailed capturing a real-time camera feed of participants performing a set of pre-designated exercises. This data served as the foundation for the succeeding steps in the research. We then employed the MediaPipe library, an open-source cross-platform framework, to build the machine learning pipelines needed for pose estimation. The accuracy of this estimation was essential for the next steps in the methodology, which involved the selection of critical keypoints or landmarks from the estimated poses for each exercise. Once we had identified these keypoints, we proceeded to compute the angles between these points. This computation was crucial as it enabled our system to monitor the form of the exercise being performed. The final step in our methodological approach involved repetition counting. This was achieved by using a state machine to track the changes in the calculated angles, allowing the system to count the repetitions of each exercise.

Participants

The investigation commences with an evaluation of the algorithm and the execution of pose estimation procedures by the researcher to ascertain the precision of the system. After the algorithm has undergone refinement, supplementary participants are enlisted to evaluate the system. While the camera is recording, the participants perform the exercises. The dataset is being collected by recording 36 videos of twelve individuals, where each individual performed three exercises selected as active breaks namely *wrist circles*, *shoulder circles*, and *neck rotations*. Since the number of keypoints to be detected for each exercise is different, two models, namely MediaPipe Hands and MediaPipe Pose, are being used for the pose estimation task. So, the dataset is divided into three datasets, where each dataset contains 12 videos of the person performing the relevant exercise. The total number of frames or instances for 36 videos equates to 25,523 out of which 8173, 8873, and 8477 frames are reserved for the feature extraction and evaluation of the wrist circles, shoulder circles, and neck rotation, respectively. More details about the collected data are mentioned in `Table 1`.

Equipment Setup

These videos of active breaks are recorded in a room using a webcam. The camera is strategically positioned to effectively capture the complete upper torso of the subject from the front.The algorithm for real-time pose estimation and feature extraction is executed through the utilization of a computer or laptop with an embedded camera.

Data Collection Procedure

The exercises are executed by the participants while being monitored by the camera. The algorithm functions in real-time concurrently with the camera's acquisition of video footage. The aforementioned video material is employed to estimate the postures of the individuals, recognize significant keypoints, determine the angles between the identified keypoints through mathematical computation, and enumerate the iterations for the specified physical activity.

Table 1: Statistics of our collected data

Exercise	Participants	Time (Sec.)	Repetitions	Fraction of Time
Wrist Circles	12	279	181	32.75 %
Shoulder Circles	12	293	79	34.39 %
Neck Rotations	12	280	96	32.86 %
Total	-	852	356	100 %

Technical Details

The implementation of the system involved capturing the user's video feed using OpenCV, processing the data using the MediaPipe framework to extract the user's pose landmarks, calculating the angle between them, and detecting the user's movement using the State Machine model.

3.1 Pose Estimation

This section delineates the methodology employed for pose estimation leveraging the MediaPipe library, a widely used open-source tool for real-time computer vision tasks. For this study, we used the MediaPipe Pose and MediaPipe Hands models to estimate the pose for three distinct exercises: Wrist circles, shoulder circles, and neck rotation. The MediaPipe Pose model is a machine learning solution that estimates 33 different keypoints for each individual captured in an image, video stream, or real-time camera feed. These keypoints represent anatomical landmarks including the nose, eyes, ears, shoulders, elbows, wrists, hips, knees, and ankles. It uses a deep neural network architecture pre-trained on a large dataset of annotated images. Similarly, the MediaPipe Hands model can predict 21 landmarks for each hand captured in a similar setting. This model is adept at identifying and interpreting hand gestures and movements. To obtain the keypoints for each stretch, a frame is extracted from the real-time camera feed using the OpenCV library and then preprocessed. The preprocessing steps include transforming the frames from the default BGR color space to the RGB color space, marking the image as non-writable to enhance model performance, processing the image, converting it back to the BGR color space, and marking it as writable for subsequent visual and textual annotations. Both models are then applied to each frame of the camera feed to identify and track the keypoints of relevant body regions and their corresponding (x, y, z) coordinate values. The pose estimation process thus involves real-time detection of body joints, outputting their keypoints, and extracting corresponding coordinates for every landmark.

3.2 Keypoints Selection and Angle Estimation

Our approach to calculate the repetitions consists of employing the following equation to specific keypoints:

$$\theta = \text{atan2}(c_y - b_y, c_x - b_x) - \text{atan2}(a_y - b_y, a_x - b_x) \qquad (1)$$

$\mathtt{atan2}(c_y - b_y, c_x - b_x)$ function is used to calculate the angle between points 'c' and 'b' with respect to the positive x-axis, and $\mathtt{atan2}(a_y - b_y, a_x - b_x)$ is used to calculate the angle between points 'a' and 'b' with respect to the positive x-axis, and the difference between these two angles is calculated in radians.

For Wrist Circles. The MediaPipe hands model is being opted for the purpose of tracking the location of the hand and wrist while performing the wrist circle exercise. In order to assess the quality of wrist circles, the angles formed by designated keypoints during their rotation around the wrist are computed. This exercise involves the calculation of four angles that are crucial for comprehending the efficacy of the wrist circles. These angles are estimated with the wrist serving as the vertex, and they specify the degree of mobility exhibited by the fingers in relation to the wrist joint. Any divergence from the anticipated angles indicates an incorrect execution of the wrist circle. **Angle 1** refers to the angular measurement formed by the intersection of the keypoints located at the *thumb_tip*, wrist, and *index_fingertip*. It facilitates comprehension of the movements of the thumb and index finger during the wrist circle. **Angle 2** is generated through the utilization of the anatomical landmarks designated as *index_fingertip*, wrist, and *middle_fingertip*. It is helpful in recognizing the movement of the index and middle fingers during the wrist circle. **Angle 3** is formed through the point of intersection of the keypoints of the *middle_fingertip*, wrist, and *ring_fingertip*. It makes it easier to understand how the middle and ring fingers move during the wrist circle. **Angle 4** intersects two line segments, where the first one connects the *ring_fingertip* and wrist landmarks, and the second one adjoins *pinky_fingertip* and wrist keypoints. It helps in understanding the movement of the ring and pinky fingers during the wrist circle. By analyzing these angles, it is possible to determine if the wrist circle is identified correctly or if there is any deviation in the movement of the fingers. The aforementioned data is utilized to provide feedback to the user and facilitate them in accurately executing the exercise. The repetition counting task is performed using a state machine-based approach (see figure 2). The methodology utilized involves the quantification of the angles that are created between the wrist and the fingertips. It has five distinct states namely start state, upward state, overhead state, downward state, and end state. The occurrence of state transitions is contingent upon the magnitude of the threshold angle. Every time the wrist circle completes after these state transitions, the repetition counter keeps incrementing by one.

The repetition counter can be utilized to furnish the user with feedback concerning the precision of the exercise executed. Furthermore, it is possible to employ performance metrics for the purpose of evaluating the precision of the repetition counter.

Approach to Tracking Shoulder Circle Repetitions. The repetition counting task for shoulder circles involves the use of a state machine (see figure 3) with five states named start state, upward state, overhead state, downward state, and end state. The algorithm used for the state transitions is as follows: To calculate the angle between the selected keypoints, basic trigonometry principles are used. In the case of shoulder circles, the angle is calculated for each side of the upper body. The angle is computed between the upper arm and body torso, where the upper arm is a line segment connecting the shoulders and elbow keypoints, while the body torso represents a line segment adjoining the shoulder and hip keypoints. The difference resides in the choice of keypoints for either the left or right side of the human frame when calculating the angle for each side of the upper body. This angle is important in identifying the shoulder circles as it provides quantitative measurements of the

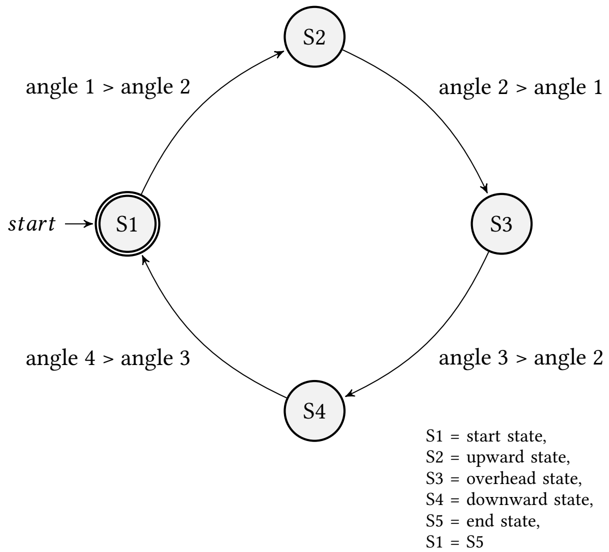

Figure 2: State Machine for Wrist Circles Repetition Counting

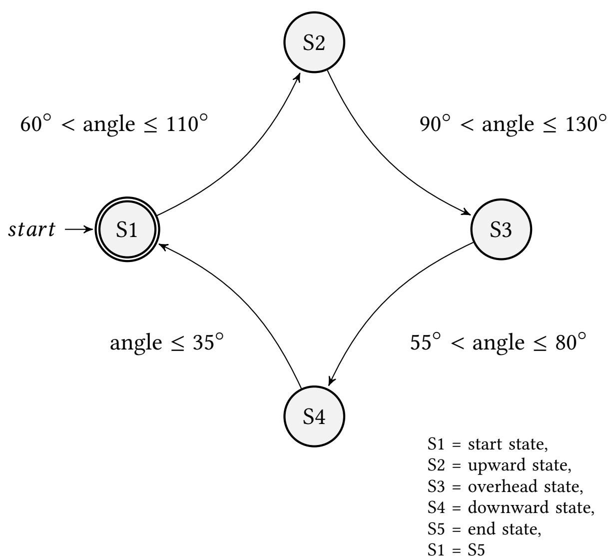

Figure 3: Finite State Machine for Repetition Counting of Shoulder Circles

movement and is used to evaluate the correctness and effectiveness of the exercise.

Methodology to Calculate Iterations of Neck Rotations. The task of counting repetitions for neck rotation is approached through a State Machine (see figure 4) methodology that involves two distinct states, namely right and left. The process of state transitions algorithmically entails the assessment of the angle formed by the left shoulder, the midpoint of the shoulders, and the nose. The algorithm operates in the following manner:

(1) If the angle is greater than 90 degrees, the state transitions to the right side.
(2) If the angle is less than 90 degrees and the current state is the right state, the state transitions to the left state and increments the repetition counter by one.

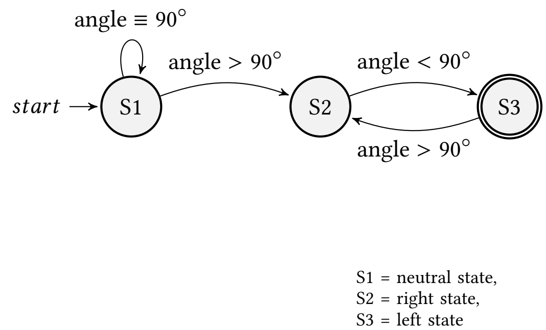

Figure 4: State Diagram for Neck Rotation Repetition Counting

In order to enhance the efficacy of the exercise, it is imperative to refine the algorithm by augmenting the states of the state machine to enable the detection of both clockwise and counterclockwise movements. Additionally, it is essential to count the completion of a full neck circle as a single repetition. The revision of the range of angles utilized for state transitions is recommended. Regarding feedback, it is advisable to notify the user that the present algorithm exhibits limitations and necessitates enhancement to ensure precise repetition quantification.

4 RESULTS

The proportion of accurately identified repetitions in relation to all the repetitions executed regardless of whether they were performed correctly or incorrectly by the state machine equates to 87.57%, 98.73%, and 90.48% for wrist circles, shoulder circles, and neck rotations, respectively (see table 2). Precision refers to the percentage of true positive repetitions tallied out of all the repetitions counted by the state machine. The state machine precisely recorded 95.29%, 100%, and 91.35% repetitions of wrist circles, shoulder circles, and neck rotations, in sequence. The sensitivity or recall of the state machine in estimating the true positives out of the total number of correctly performed repetitions refers to 91.53%, 98.73%, and 98.95% for wrist circles, shoulder circles, and neck rotations, respectively. The F1-score is utilized to describe the overall effectiveness of the state machine in identifying true positive repetitions while simultaneously minimizing the occurrence of false positives and false negatives, which in this scenario approximate 93.37%, 99.36%, and 95% for wrist circles, shoulder circles, and neck rotations, respectively.

5 DISCUSSION

This study collected data from Fraunhofer IGD participants performing wrist circles, shoulder circles, and neck rotations, encompassing a varied demographic for wide-scale analysis. Participants' skill levels varied, and immediate feedback was given to promote

Table 2: Performance Metrics of Repetition Counter

Exercise	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)
Wrist Circles	87.57	95.29	91.53	93.37
Shoulder Circles	98.73	100	98.73	99.36
Neck Rotations	90.48	91.35	98.95	95

correct exercise execution. Despite accurate metrics obtained in a controlled laboratory setting, the dataset lacked variability in exercises and recording environments. The unique range of motion in individuals highlighted the need to refine angle calculations between joints, promoting accurate repetition counting via a state machine. Most repetitions were true positives, with few false positives and minuscule false negatives. The state machine effectively counted repetitions, despite no true negatives, indicating no incorrect movements were erroneously counted.

5.1 Limitations

This work uses the MediaPipe pose model for upper body pose estimation during seated active breaks. The model's limitations include potentially erroneous results if the user's face isn't visible during leg or glute exercises. The MediaPipe hands model doesn't require face visibility but needs visible hands. A state machine identifies activities and their transitions, but its application for exercise repetition counting is not without limitations due to specific programming and pose estimation mechanisms.

Persons Anatomy: In scenarios where the physical activity involves intricate maneuvers and adjustments, and owing to the distinctiveness of the extent of movement and articulation of joints, specifically the anatomical structure of the joints of a specific individual, the state machine may not effectively identify repetitions owing to its limited robustness or flexibility in recognizing the repetitions that are not pre-configured.

Distance from the Camera: The spatial distance between the camera and the object of interest may have an impact on the accuracy of pose estimation. As the distance between the camera and the subject increases, the resolution and level of detail in the captured image or video may decrease. This can pose a challenge for the pose estimation, which may struggle to accurately detect the keypoints of the human body.

Orientation of the Camera: The regions of the body and their relative posture may look different depending on the camera's orientation. Due to this inconsistency, the algorithm may have trouble reliably detecting and estimating posture in all orientations. The precision of the pose estimation might be further hampered by the fact that certain stances may be obscured or unclear from particular camera angles.

Inadequate Performance: The process of pose estimation necessitates substantial computational resources in the context of real-time processing. The insufficient processing capacity of the computer or hardware utilized for posture estimation may result in prolonged completion time for the requisite calculations or real-time inoperability. This phenomenon is primarily observed when working with videos of high resolution.

Poor Lighting Conditions: The accuracy and reliability of pose estimation process may be constrained by fluctuations in lighting circumstances. Inadequate lighting conditions, including shadows and uneven illumination, may lead to diminished visibility of anatomical features, thereby posing a challenge for the algorithm to precisely detect and track keypoints. In order to improve the performance of the model, it is therefore crucial to optimize and control the lighting conditions.

6 CONCLUSION AND OUTLOOK

This study aims to address the prevalence of musculoskeletal disorders among workers who use computers intensively, which also involves a sedentary lifestyle. Employees, particularly in the IT sector, risk developing conditions such as muscle atrophy, unilateral overload, or even carpal tunnel syndrome from extensive typing. To counter these issues, we advocate specific active breaks incorporating wrist circles, shoulder circles, and neck rotations, potentially preventing disorders like upper cross syndrome and rotator cuff tendinopathy. A dataset of 36 videos was collected from participants at Fraunhofer IGD, demonstrating these exercises. Execution quality was gauged using MediaPipe Pose and Hands models to detect keypoints of movement. A finite state machine tracked exercise stages based on joint angles, tallying complete repetitions. While manual annotation could improve these values, the state machine accurately counted 93.37%, 99.36%, and 95% repetitions of each exercise type. These findings warrant further exploration on larger datasets and other exercises.

We suggest that a short exercise is better than none, so it's extremely useful to incorporate short exercise episodes into your daily office routine that also don't disrupt your workflow.

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