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A Study on Vision-Based Posture Assessment Tools

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***Abstract* – One of the primary contributors to neck and back issues in the modern world is the increased amount of time individuals assume incorrect or uncomfortable postures during work. Many employees have been forced to spend more time than usual in front of a computer, causing them to work in bad postures for a prolonged time. Workers in various industries are required to perform tasks in awkward positions within their workstation. These workstations may or may not have the qualities required for the worker to be able to position themselves comfortably. This paper focuses on highlighting the features of the various vision-based systems developed to evaluate postures using risk assessment tools like Rapid Entire Body Assessment (REBA) and Rapid Upper Limb Assessment (RULA).**

***Index terms:* Body posture, Ergonomic risk, Pose estimation**

I. INTRODUCTION

The information technology sector has discovered that improving workplace morale and safety is essential for achieving peak productivity. Musculoskeletal disorders (MSDs) relate to long-term pain effects due to the strain on muscles, nerves, blood vessels, tendons and ligaments. Workers in many different industries and occupations can be exposed to work related risk factors, like lifting heavy items, bending, reaching overhead, working in awkward body postures and performing the same tasks repetitively.

Work-related MSDs can be prevented. Ergonomics refers to fitting a job to a person by reducing muscular fatigue and body strain. It directly increases productivity and reduces the number and severity of work-related MSDs. It is, therefore, highly essential for us to develop techniques to analyse postures and take immediate actions to prevent health issues among the people of the current generation.

Using a self-assessment tool that analyses inappropriate human postures can be very helpful in determining the main risk factors responsible for work-related MSDs. They evaluate the ergonomic risks associated with a specific position in a methodical manner.

A risk assessment tool can be regarded as the first step towards risk reduction and prevention. It can be used to determine the risk of developing MSDs due to unfavourable working postures based on information about the duration of the task, the working postures and movements that occur during the task.

A major function of posture risk assessment is evaluating the severity of a particular pose. This can be done using ergonomic risk assessment tools like RULA and REBA. Traditionally, these scores are calculated manually by interviewing the worker to gain an understanding of the job tasks and keenly observing the worker's movements during several work cycles. This can be time-consuming and takes a lot of effort. Vision-based risk assessment systems can be of great help as they are user-friendly and require minimal time, effort, and equipment. Postures can be analysed automatically using OpenCV and other pose estimation frameworks. This fastens the posture evaluation process and is very convenient to use.

II. LITERATURE SURVEY

Rithik Kapoor, Ashish Jaiswal, and Fillia Makedon [1] worked on developing a Light-Weight Seated Posture Guidance System using the concepts of Computer Vision. Their work proposed a system that monitored a worker's pose and returned a result after classifying it as a good/bad posture. Their newly developed pipeline helped workers improve their posture without any additional cost or hardware. Their work proposed a combination of a pose estimation system to extract joints and a posture classification system (good/bad).

The BlazePose model was used to extract 33 key body points from each input frame. The posture classification system used a machine learning model instead of a simple rule-based system which classified postures based on joint angles. Despite that fact that the latter could work faster and perform well, it would not be able to calculate the joint angles accurately for all profiles as the method is highly sensitive to the position of the camera. However, in machine learning models, the position of the camera plays a less significant role in calculating the accuracy as they have been trained in all positions. A limitation of this system was that it could not determine the risk associated with a posture, but was only able to classify it as a good or bad posture. They wanted to enhance the proposed system by enabling it to assist people with workout after prolonged periods and provide real-time-feedback.

Enrique Piñero-Fuentes, Antonio Rios-Navarr and Manuel Domínguez-Morales [2] proposed a Posture Detection System for Preventing Telework-Related Musculoskeletal Disorders using Deep Learning techniques. Their work used a specific hardware system that processed videos in real time using convolutional neural networks to design, implement, and test the posture evaluation system. The device was able identify how the neck, shoulders, and arms are held, and provide workers advice on how to improve their posture in order to avoid any health issues. The methodology used for the proposed work was as follows:

Images and video frames were acquired through a camera positioned correctly to capture the pose. The device was connected to a system that processed the input in two main steps:

- Estimating the worker's joints' positions usinga neural network classifier.
- Processing and analyzing the posture to provide recommendations with respect to some related parameters.

The first step involved the use of a skeleton estimator trained based on the COCO dataset which comprised of 66,808 human images. They used TRT_Pose, a pose estimation software capable of running on NVIDIA devices. After estimating the pose, they focused on evaluating three parts of the posture – the shoulder alignment, the neck lateral bend and the arms. Each of these parameters were marked in four zones ranging from 0 to 3 which defined the severity of the acquired posture. The extremes 0 and 3 correspond to correct and incorrect posture respectively.

They focused on evaluating their system, which is why they extracted random frames from the video input instead of assessing the entire video. A future enhancement to their proposed work was to develop an automatic recommendation system that could detect incorrect poses during real work scenarios. Another would be to modify the neural network used to evaluate more than a single straight segment such as the spine.

Using quantitative approaches to evaluate postures can be of great help in industries to optimize and redesign workspaces according to the comfort of the workers [6]. REBA and RULA are quite popular for postural analysis as they divide and assess the body as segments that are observed individually. These risk assessment tools analyze the neck, trunk and legs in one section and the arms and wrist in another section. This helps identify the root cause of the incorrect posture. A research work on Ergonomic Evaluation to improve Work Posture explains how REBA and RULA can be used to assess postures using the collected data obtained through detailed observation.

Ze Li, Ruiqiu Zhang, Ching-Hung Lee, and Yu-Chi Lee [3] worked on evaluating postures based on Rapid Entire Body Assessment (REBA) for determining MSDs. They developed a system called Quick Capture, which helped determine the risk levels of various working postures using the REBA tool.

REBA considers a series of factors that influence body postures. These may include the load handled by the worker, coupling tools, and how repetitive the particular task is. The REBA tool defines five risk levels based on the score. A higher REBA score implies greater risk associated with the posture and may require immediate correction.

The Quick Capture system had 4 main components: (1) An image and data acquisition scheme, (2) A human skeletal recognition system based on Convoluted Pose Machines (CPM), (3) A REBA based risk calculator and (4) a report generation module. The system calculated the REBA score after acquiring image/video input via a smartphone camera or any recoding. The score for the corresponding posture was displayed as a report on the device (smartphone).

Quick Capture was unable to consider factors like force/load and coupling only through images. These variables were usually noted down as operational observations to calculate the REBA score, and hence, were directly entered as known variables into the system.

Prabesh Paudel and Kyoung-Ho Choi proposed a Worker's Pose Estimation [4] system based on Deep Learning. It was capable of calculating the body angles of a worker and indicate which angles were not good for performing tasks in various work environments. They proposed a system that calculated RULA and REBA scores for 2D poses. CMU Open Pose was used as the baseline algorithm for detecting key points in the posture.

In order to calculate the angles of the neck and arms, the body had to be divided into two parts: (a) upper body and (b) lower body. The upper body includes the neck, limbs and wrist. This is called the sagittal plane. The shoulder and head key points were used to calculate the angle of the neck using 2D angular evaluation vectors. The body was divided into segments to evaluate the posture and movement with the help of REBA.

The system was suitable for images focusing on a single worker only. It also showed that Open Pose may not define all body angles correctly always. Their wanted to collect more data on work-related postures that can be used with deep neural networks to obtain the desired results. The system needed to be modified for different conditions, where the presence of obstacles could block the vision of the camera.

A work by Li Li, Edward P Fitts and Xu Xu [5] showed a method for real time estimation of RULA score from 2-D articulated postures. It proposed a method of using RULA on 3-D poses containing 17 key points in the body.

An articulated pose is one of the most widely used method to represent human postures as it clearly identifies the spatial location of the joints. The degree of freedom of a human body pose is mainly brought by joints. The coronal plane and the sagittal plane of body are essential to assess posture risk. The coronal plane divides the body into dorsal and ventral sections.

Their deep neural network took 3D poses projected onto a 2D plane as inputs to obtain the final RULA score. The pose was fed to the neural network after flattening it into a 1D vector. They calculated the final RULA score by finding the maximum out of the left and right side of the body. This made sure that only the worst out of the two sides were considered to calculate the severity of the posture.

The system was observed to be less robust for postures with a lower risk level. This could be because an unbalanced dataset was used for training. Since the markers were attached to the lateral side of the limbs, the joints angles were overestimated.

III. CONCLUSION

A person's physiological and psychosocial well-being are both guaranteed by proper body posture. Additionally, it provides optimal productivity while working and reduces the strain on various body parts. We can examine the associated risk factors causing work-related MSDs using computer vision and other approaches to human posture identification. Vision-based systems do not directly interact with the worker. They are efficient and easy to operate. The use of risk assessment tools like RULA and REBA can significantly help increase the accuracy of the system to determine the risk of the identified pose.

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