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THE ART AND SCIENCE OF POSTURE ASSESSMENT: EXPLORING METHODS AND ADVANCEMENTS

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ABSTRACT
This paper delves into the crucial realm of posture assessment in contemporary work environments. The introduction underscores the increasing need for posture correction tools, particularly for individuals engrossed in sedentary jobs, who often overlook their anthropological constraints during work. Sedentary work, exceeding eight hours daily, is not only detrimental to health but can result in Work-Related Musculoskeletal Disorders (WMSDs) like Carpal Tunnel Syndrome, lower back pain, and cervical spondylitis. Ergonomics plays a pivotal role in assessing the well-being of working individuals. Methods such as REBA and RULA are commonly used to evaluate posture, although these methods demand manual readings conducted at various intervals. Different work environments require distinct assessment scores, making them intricate and time-consuming. For industries with dynamic working conditions such as mining, plumbing, construction, logistics, and maintenance, 3D posture recognition proves effective. This ergonomic approach, combined with manual assessment, enhances worker safety and productivity. Conversely, an increasing number of individuals lead sedentary lifestyles due to their profession, typified by prolonged computer use, desk work, and limited physical activity. These behaviours lead to a host of health issues, both physical and psychological. Moreover, the omnipresence of smartphones and attention-diverting content have extended the average time people spend sitting or lying down, causing long-term health problems, including cardiovascular diseases, vitamin deficiencies, and migraines, compounded by the persistence of WMSDs. In the subsequent sections, this paper delves into the advancements in posture assessment techniques. With camera various pose estimation techniques with AI models table, categorizing them by year invented, model name, strengths, weaknesses, applicability to single or multiple persons, and whether they operate in 2D or 3D space. These advancements represent innovative and efficient methods for assessing posture, making it a valuable resource for researchers, ergonomists, and individuals aiming to enhance their work environments and overall health.

Keywords: Posture assessment, Pose Estimation, Ergonomics, Work-Related Musculoskeletal Disorders (WMSDs), AI models, Surveillance, Physiological-Psychological Assessment, Human Activity Recognition (HAR)

INTRODUCTION
People who are extremely focused on their work and lose sight of their anthropological limitations while working frequently need a posture correction tool[1]. According to research, sitting continuously without a break can also cause a few WMSDs, such as Carpel Tunnel Syndrome, lower back pain, and spondylitis (cervical)[2]. Sitting for more than eight hours a day is also dangerous[3]. Ergonomics frequently associates various assessment scores for working people such as REBA, RULA, and other methods that are distinct for various working environments, but those methods require a large number of manual readings at multiple intervals[4]. Workers in industry-specific work environments such as mining, plumbing, construction, logistics, and maintenance must be dynamic, as their work frequently requires movement in multiple directions, so 3 Dimension posture recognition system often seems fine, and ergonomically manual assessment is also encouraged[5], [6].

Contrary to previous case, majority of working people, are having inactive life style due to their type of labour, like sitting in offices, having desk work, few time for work out; so more or less, minimum movement generates health issues in overall body and few times psychological problem as well[7], [8]. The modern apps in cell phones are targeted to luring contents and people are habitual for using smart phones which affects their attention span as well, so briefing out with average sitting and laying down times have been increased for people because of gadgets and ignorance behaviour towards health of the people which creates problem on a longer run, including cardio vascular deceases, vitamin deficiency and migraines like situation in addition to WMSDs[9].

DISCRIMINATING BETWEEN POSE AND POSTURE:

Posture[10]**:** Posture refers to the way in which a person holds their body when standing, sitting, or lying down. It involves the alignment and positioning of various body parts, such as the spine, shoulders, hips, and limbs. Good posture is typically associated with the optimal alignment of body segments, which helps to distribute the body's weight evenly and reduce strain on muscles and joints. Proper posture can contribute to physical comfort and health. Poor posture can lead to various issues, including muscular imbalances, discomfort, and potential long-term problems like chronic pain.

Pose[11]**:** A pose refers to a specific position that someone intentionally takes for a specific purpose, such as in photography, art, modelling, or yoga. It's often a deliberate arrangement of the body for a particular aesthetic or functional objective. Poses can vary widely depending on the context. For instance, a yoga pose could involve a specific arrangement of the body to achieve a particular stretch or meditative state. In photography or art, a pose might be chosen to convey a certain emotion or message. Poses are not necessarily related to proper ergonomic alignment or health considerations, as they are often chosen for their visual or expressive impact.

In summary, posture primarily relates to the natural alignment and positioning of the body in everyday situations, focusing on ergonomic considerations and physical health. Pose, on the other hand, refers to a deliberate and often temporary arrangement of the body for visual, artistic, or functional purposes, often with less emphasis on ergonomic alignment.

MANUAL POSTURE ASSESSMENT METHODS

Posture assessment can be done manually through various methods that involve observation, measurements, and subjective analysis. Here's a basic outline of how posture can be measured manually.

Visual Inspection[12]**:**

Stand in front of the person being assessed and observe their body alignment. Look for any imbalances, asymmetries, or deviations from the neutral posture.

Landmarks and Reference Points[13]**:**

Identify key anatomical landmarks that are used as reference points for posture assessment, such as the ears, shoulders, hips, knees, and ankles.

Plumb Line or String Method[14]**:**

Use a plumb line or a string with a weight attached to it. Align the plumb line with specific reference points (e.g., earlobe, shoulder, hip, knee, ankle) to assess deviations from the ideal alignment.

Goniometer[15]**:**

A goniometer is a tool used to measure joint angles. Assess joint angles at specific body joints (e.g., shoulders, hips, knees) to determine if they fall within the normal range.

Photographic Analysis[15]**:**

Take photographs from different angles (front, side, back) of the person's posture. Compare the photographs to reference images of optimal posture to identify deviations.

Subjective Evaluation[13]**:**

Ask the person being assessed about any discomfort, pain, or limitations they experience. Assess their self-perception of their own posture.

Postural Assessment Grid[16]**:**
Create a grid with vertical and horizontal lines to assess alignment. Compare the alignment of body parts to the grid lines to identify deviations.

Functional Movement Tests[17]**:**
Have the person perform various functional movements (e.g., squat, lunge, reach). Observe any compensations, imbalances, or limitations in movement.

Palpation[18]**:**
Use touch to feel for any muscle imbalances, tension, or soft tissue abnormalities.

Postural Deviation Analysis[19]**:**
Analyse the extent and direction of any postural deviations. Determine if the deviations are within acceptable limits or if they indicate potential issues.

The study of posture goes beyond mere aesthetics; it plays a crucial role in overall health and well-being. Manual posture assessment methods have long served as a fundamental tool for evaluating body alignment and identifying deviations from the optimal posture[13] . However, it's important to acknowledge that while these methods offer valuable insights, they might not comprehensively capture all nuances, and their accuracy can vary. To address these limitations and delve deeper into posture analysis, modern advancements have introduced sophisticated tools such as 3D motion analysis systems, pressure mapping devices, and computerized posture analysis software[20]–[22].

THE DEPTH AND LIMITATIONS OF MANUAL POSTURE ASSESSMENT

Manual posture assessment involves the trained eye of a healthcare professional or practitioner who observes and evaluates an individual's body alignment. This approach relies on visual inspection, identifying anatomical landmarks, and using tools like plumb lines and goniometers. While these methods provide a solid foundation for understanding posture, they may fall short in capturing subtle deviations and intricacies that can influence musculoskeletal health[21]. Moreover, manual assessment can be subjective to some extent, as it depends on the observer's expertise and perception. The precision of measurements might vary between different practitioners, leading to potential discrepancies in the assessment outcomes[20].

ADVANCEMENTS IN POSTURE ASSESSMENT

Recognizing the need for more comprehensive and accurate posture assessment, technological advancements have ushered in a new era of analysis. Three notable advancements have emerged:

3D Motion Analysis Systems[23]–[25]: Leveraging advanced cameras and sensors, these systems create a dynamic three-dimensional model of an individual's posture and movement. By tracking joint angles and body positions in real time, they offer a holistic view of how the body functions in various postures and activities.

Pressure Mapping Systems[26]–[28]: These systems utilize sensor-equipped mats to measure pressure distribution across the body's contact points with a surface. They provide insights into weight distribution, identifying areas of excessive pressure that might indicate poor posture habits.

Computerized Posture Analysis Software [20]-[22]: Designed to enhance accuracy and consistency, software applications process images or videos of an individual's posture. Algorithms analyze key alignment points and provide quantitative data on deviations from the ideal posture.

While manual posture assessment methods remain valuable tools in understanding body alignment, they may not capture the full complexity of posture deviations[20]. To attain a more detailed and accurate evaluation, especially in clinical or specialized settings, the integration of advanced technologies like 3D motion analysis systems, pressure mapping devices, and computerized posture analysis software offers a comprehensive approach. By combining the art of observation with the precision of technology, it becomes easy to foster a deeper understanding of posture's impact on health and pave the way for tailored interventions that promote musculoskeletal wellness.

Various models have been used for pose estimation of various body parts[29], however keen observation and training is needed for posture evaluation as pose is just instantaneous image but posture is similar to how person is holding the body parts through the working hours or all day routine, in majority of cases it may be similar but sometimes kind of activity often changes the posture of people after repetitive working[30], following are methods for evaluation of physiological and psychological pose analysis using body style and face expression, each model can be useful for distinct application or activity assessment.

Year Invented	Model Name	Strengths	Weaknesses	Single/Multiple Person	2D/3D
2022	Transpose[31]	Fast, accurate, and lightweight	Less accurate in challenging occlusion and/or complex background	Single/Multiple Person	2D/3D
2021	Scene-Aware Pose[32]	Considers scene context to refine pose estimation	Requires scene understanding	Single/Multiple Person	2D/3D
2020	Efficient Pose2D[33]	Improved version for accurate 2D pose estimation with efficiency	Lightweight and efficient	Single Person	2D
2019	HRNet(Lite)[34]	High-resolution pose estimation, Captures fine details	Requires significant computational resources	Single/Multiple Person	2D
2019	MediaPipe[35]	Real-time performance, Robustness to diverse poses, Integration with other components	Limited to predefined key points, may require additional tuning	Single/Multiple Person	2D/3D
2019	EfficientPose[36]	Lightweight and efficient	Sacrifices some accuracy for efficiency	Single Person	2D
2019	3d UPose[37]	Offers 3D pose estimation from 2D images	Requires careful handling of depth estimation	Single Person	2D/3D
2019	PifPaf[38]	Captures body part associations	May have increased complexity due to additional connection estimation	Single Person	2D
2019	JTA[39]	Considers task context for better pose estimation accuracy	May require additional task-specific annotations and training	Single Person	2D
2019	Temporal Pose Machines[40]	Utilizes temporal information for	Sensitive to noise, occlusions, less	Single/Multiple Person	2D

		improved pose estimation accuracy	robust, computational expensive		
2019	Pose Invariant Person Re-identification[41]	Recognizes individuals across different poses	Not solely focused on accurate pose estimation	Single/Multiple Person	2D
2019	Monocular Total Capture[42]	Estimation of 3D poses, shapes, and textures of clothed humans	Specialized for clothed humans	Single Person	3D
2019	Pose Uncertainty Estimation[43]	Estimates uncertainty for pose predictions, Robustness to Ambiguities	Adds complexity to the model, fine tuning problems	Single/Multiple Person	2D/3D
2019	SimpleBaseline[44]	Lightweight and efficient architecture	Focuses on simplicity while maintaining decent accuracy	Single Person	2D
2019	GraphCMR[45]	Combines 3D body mesh recovery with 2D pose estimation	sensitive to noise and large pose changes	Single Person	2D/3D
2019	GraphPoseGAN[46]	Generative model using graph-based structure	Complex graph-based structure	Single Person	2D
2018	DensePose[47]	Provides detailed pose estimation, can handle articulated poses	Computationally intensive, Requires high-quality input images	Single/Multiple Person	2D/3D
2018	CPN[48]	Captures detailed pose information	May struggle with occlusions and complex poses	Single/Multiple Person	2D
2018	SimplePose[49]	Optimized for real-time performance on mobile devices	May not handle complex poses as well	Single Person	2D
2018	V2V-PoseNet-Moon[50]	Accurate 3D hand pose estimation and full body pose estimation, robust	Complex, data availability, depth noise	Single Person	3D
2018	HMR[51]	Provides 3D shape estimation	Requires complex multi-task training	Single Person	2D/3D
2018	Pose Residual Networks[52]	Uses residual blocks for enhanced accuracy	Requires training with ground-truth key points	Single/Multiple Person	2D
2018	Multiview 3D Poses[53]	Accurate 3D pose reconstruction from multiple camera views	Requires multiple camera views	Multiple Person	3D
2018	VideoPose3D(Ershadi-Nasab and al)	Accurate 3D pose estimation from	Leverages temporal information	Single/Multiple Person	3D

		monocular videos			
2017	Openpose[54]	Accurate multi-person pose estimation, Handling occlusions	Computationally intensive, less suitable for real-time applications	Single/Multiple Person	2D
2017	VNect[55]	Accurate 3D pose estimation	Requires depth data, Performance affected by limited depth resolution, Accuracy	Single Person	3D
2017	AlphaPose[56]	Supports multi-person pose estimation, Works with diverse scenes	Requires powerful GPUs for real-time performance	Single/Multiple Person	2D
2017	ArtTrack[57]	Specialized for artistic images	May not generalize well to other types of images	Single Person	2D
2017	DenseReg[58]	Designed for dense regression tasks, provides detailed pose information	needs GPU, occlusion problem	Single Person	2D
2017	Pose Transfer[59]	Transfers pose from one individual to another	Primarily focused on pose transfer	Single Person	2D/3D
2017	Pose Homography[60]	Preservation of Identity, Pose Invariance, Potential for Real-world Applications	Data Dependency, Complexity, Pose Limitations	Single/Multiple Person	2D
2017	CascadePose[61]	high accuracy in facial landmark detection, head pose estimation in video sequences.	High-quality training data with accurate annotations, Robustness to Variations	Single/Multiple Person	2D
2017	Spatio-Temporal Pose[62]	Incorporates spatial and temporal information for improved accuracy in videos	Requires temporal data	Single	2D/3D
2017	Vision + IMU Integration[63]	Enhanced accuracy and robustness with visual and IMU data	Combining different data sources can be complex	Single/Multiple Person	3D
2016	DeepCut[64]	Capable of multi-person scenarios, Works with RGB images	Requires substantial training data, Complex training process	Multiple Person	2D

2016	Stacked Hourglass[65]	Iterative refinement for accuracy	Can be computationally intensive	Single/Multiple Person	2D
2016	SPPE[66]	Real-time capable	May not achieve the same accuracy as some multi-stage models	Single/Multiple Person	2D
2016	CPM[67]	real time performance using heatmap, accurate, efficient, versatile	Occlusion Handling, Complexity, Data Requirement, Fine Tuning Problems, low light or crowded scene problems	Single/Multiple Person	2D
2016	RMPE[68]	crowd analysis, sports analytics, and surveillance.	The accuracy of RMPE models can be affected by occlusions, overlapping people, and complex poses.	Single/Multiple	2D
2015	PoseNet[69]	Real-time capable	May not handle complex or multi-person poses well	Single Person	2D
2015	Skeleton-free Pose[70]	Estimates pose without predefined key points	Versatile for various scenarios	Single/Multiple Person	2D/3D
2014	DeepPose[71]	Able to estimate pose from RGB images, Works with limited training data	Prone to overfitting without sufficient data augmentation	Single Person	2D
2014	Simultaneous Pose and Shape Estimation[72]	Estimates both body pose and shape	Requires handling of complex multi-task training	Single Person	3D
2014	Object Localization Using Convolutional Networks[73]	learn hierarchical features from data, light weight CNN	Efficiency, Complexity, resource availability	Single/Multiple	2D/3D
2012	Face Pose Estimation[74]	Estimation of face pose (orientation)	Specialized for facial poses	Single Person	3D
2010	HumanEva[75]	Benchmark dataset and model for multi-view pose estimation	Focused on multi-view scenarios	Single/Multiple Person	3D
2003	Pose from Silhouette[76]	Estimates pose from object silhouettes or outlines	Limited to scenarios with silhouettes	Single/Multiple Person	2D/3D

METHODS SPECIFIC TO VARIOUS ACTIVITIES:

Normal Activities of day-to-day life includes sitting, standing and walking or motion. However, in few scenarios sleeping or laying down pose can be seen in hospital of garages. Although different methods are useful for mentioned classification depicted above. So far as main concern about occlusion plays an important role in such cases as sitting and standing often differentiate upper limb and lower limb, in ergonomics it is scored under rapid upper limb assessment and rapid entire body assessment, the key aspect is to which activity needs to be monitored under which condition day or light, and number of persons along with 2D or 3D as mentioned in the table above.

Sitting	Standing	Walking or Motion Assessment
DensePose	DensePose	DensePose
OpenPose	DenseReg	GraphCMR
HRNet (Lite)	HRNet(Lite)	DenseReg
GraphCMR	Pose2DHRNet(Lite)	Pose2DHRNet(Lite)
DenseReg	MediaPipe	MediaPipe
Pose2DHRNet(Lite)	EfficientPose	EfficientPose
MediaPipe	3d UPose	3d UPose
EfficientPose	PifPaf	PifPaf
3d UPose	Monocular Total Capture	Monocular Total Capture
PifPaf	Pose Uncertainty Estimation	Pose Uncertainty Estimation
Monocular Total Capture	Temporal Pose Machines	Temporal Pose Machines
Pose Uncertainty Estimation	SimpleBaseline	JTA
Temporal Pose Machines	V2V-PoseNet	VideoPose3D
JTA	Graph CMR	Spatio-Temporal Pose
	Openpose	Vision + IMU Integration
	JTA	OpenPose
		AlphaPose
		HRNet(Lite)

It can be seen that methods which can be used in sitting posture assessment can be used in standing posture and walking posture assessment as the occlusions can be discarded in pose estimation. However, in only walking and standing few methods work well as depicted. These methods have the potential to be applied to various postures, including sitting, standing, walking, and motion. They are versatile in their ability to estimate human pose in different scenarios. However, it's important to note that the effectiveness of these methods may still depend on specific use cases, dataset quality, and the level of accuracy required for posture assessment. Testing and evaluation with your specific dataset and application scenario may be necessary to determine the most suitable method.

CONCLUSION

In conclusion, this research paper has delved into the fascinating realm of posture assessment through the lens of camera technology. Through a comprehensive exploration of various methods and advancements, we have witnessed how this marriage of art and science has evolved over time. Paper began with an examination of the importance of posture assessment in the context of health, ergonomics, and rehabilitation. Then proceeded to investigate the traditional methods used for posture assessment and the limitations they present. In response to these limitations, we ventured into the world of computer vision and machine learning, highlighting how these technologies have ushered in a new era of accurate and non-invasive posture assessment. Furthermore, the potential applications of camera-based posture assessment are in fields such as healthcare, sports performance analysis, and workplace ergonomics. We have seen how these applications have the potential to enhance the quality of life for individuals and contribute to the prevention and treatment of various musculoskeletal disorders. In the ever-evolving landscape of technology, we acknowledge that there are still challenges and areas for further research. These include refining algorithms for greater accuracy, addressing privacy concerns, and making these systems more accessible to a wider range of users.

FUTURE SCOPE

The art and science of posture assessment using cameras continue to evolve, offering exciting possibilities for both research and practical applications. As technology continues to advance, the world will look forward to even more sophisticated physics based methods and user-friendly solutions that will have a positive impact on our health and well-being. In this light, it is imperative that researchers, practitioners, and innovators collaborate to harness the full potential of camera-based posture assessment, as it holds the promise of revolutionizing how we understand and optimize the way we carry ourselves in our daily lives.

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