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Application of Computer Vision Technology in Sports and Rehabilitation Auxiliary Assessment

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Abstract. Computer vision (CV) has shown to have tremendous capabilities of providing motor functions assessment in rehabilitation. Nevertheless, the current research is still disjointed, and the particular uses and aims of CV-based rehabilitation evaluation approaches have not been fully revealed. To address this gap, the study will use the method of an exploratory review to give a summary of the current research on the topic of CV based rehabilitation motor function assessment. The findings of the 15 articles used show that CV technology use in the rehabilitation assessment is mostly revealed in estimating the posture and measuring joint kinematics, gait and evaluating spatiotemporal parameters, motion recognition and continuous functional movement, and motion data synthesis and further development. The applications are designed to enhance the scaleability and availability of assessments, attain objective and automated assessments, enable longitudinal follow-ups, as well as feedback and exploration system building. The paper highlights the importance of using more goal-focused and clinically-based CV technologies in the rehabilitation assessment and offers an overall viewpoint to inform further studies and system design.

Keywords: Computer vision, motor rehabilitation, assisted assessment, motion analysis, system review

1. Introduction

Motor dysfunction is considered one of the leading causes of the disability all over the world, and its rehabilitation evaluation plays an important role in developing treatment programs, as well as establishing the therapeutic influence. Conventional rehabilitation evaluation is primarily based on subjective observation of the therapists, and few standardized scales. The limitations of these methods include; low consistency in assessment, labor-intensive and time consuming and they are unable to provide a high frequency of continuous monitoring [1] This lack of professionals in particular cases with community and home rehabilitation has acted as a barrier to timely and proper assessment and feedback of many patients, thereby delaying the optimal rehabilitation opportunity, thereby putting pressure on the medical system [2].

The visual data produced during the rehabilitation practice, such as motion videos made using the usual cameras, depth cameras, wearable gadgets, etc. have abundant information regarding the motor functions [4]. Research indicates that a patient with given movements disorder has characteristic movements. These motor biomarkers which are visually different will form the basis

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of perception-based automatic evaluation [3]. The Computer vision (CV) technology has been a breakthrough development over the last few years and has experienced some of the main development phases [4]. The CV technology has provided a qualitative breakthrough in the capabilities of understanding and analysis capabilities of images and video. The pose estimation algorithms and time motion localization technology have also significantly advanced the computer to learn sophisticated moves in a human being [5]. CV technology can well extract quantitative information (coordinates of joints, trajectory, angle and speed) with videos, offering excellent technical assistance to the motion function analysis [6]. Models that are optimized with a medical scenario have been excellent in processing clinical motion videos in the field of rehabilitation. Some sensors have also been combined with computer vision technology to create multimodal detection as sensor fusion and wearable to detect activities and biomechanical signals, and to detect movement and load using physiological signals [7,8].

Despite the immense potential of CV in motor rehabilitation assessment, existing research has several limitations. The applications and objectives of these studies remain unclear. Therefore, this study aims to provide a snapshot to answer the following research questions:

(1) How can computer vision technology be applied to different types of motor function assessment?

(2) What are the purposes of applying computer vision technology in these rehabilitation assessment areas?

This study aims to elucidate the crucial role of CV in motor and rehabilitation services, providing a new methodological perspective for cross-cultural rehabilitation research. At the clinical level, this study promotes the integration of traditional rehabilitation assessment with AI technology, laying a scientific foundation for building a more precise and efficient rehabilitation medical service system.

2. Methods

2.1. Review design

This study adopted a review-based methodological approach with the aim of rapidly and exploratorily examining existing research on computer vision–based approaches for assisted motor function assessment in rehabilitation contexts. Particular attention was paid to how computer vision techniques are applied in practice and the specific assessment purposes they serve.

2.2. Literature search strategy

Relevant studies were identified through a systematic search of the Web of Science database. The search strategy was designed to capture literature related to computer vision, pose estimation, movement analysis, gait analysis, and rehabilitation assessment. The selected search terms included “computer vision”, “pose estimation”, “sports rehabilitation”, “motion analysis”, “gait analysis”, and “rehabilitation assessment”. An overview of the database and search query is presented in Table 1.

Table 1. Databases and search strategy

Database	Search Query
Web of Science	TS = ("computer vision") AND TS = ("sports rehabilitation") AND TS = ("application") AND (Document Types: Article) AND (Languages: English)

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2.3. Inclusion and exclusion criteria

In this review, the researchers have considered the studies, which use computer or machine vision models, both traditional computer vision techniques and deep learning, based techniques, on visual data to native motor functional measurements. The thicknesses of the intended studies involving multimodal studies involving visual cues as well as inertia sensors or any other modalities that complement those were also enrolled. Studies which were based on non-visual data only were not counted though.

Peer reviewed journal articles were the only ones that were accepted as eligible. Other non-peer-reviewed papers (including conference papers, posters etc.) have been excluded to guarantee methodological rigor, reliability and transparency. Conference publications tend to include little information about experimental design, data properties, and reproducibility and can be preliminary results, thus not so much would be synthesized in a review that focuses on rehabilitation, especially in cases of clinical data. In Table 2, the inclusion and exclusion criteria are given.

Table 2. Inclusion and exclusion criteria

Inclusion Criteria	Exclusion Criteria
Studies applying computer vision or deep learning models to visual data	Studies not using computer vision methods
Focus on motor function assessment or monitoring	Non-assessment purposes (e.g., game interaction only, generic action recognition)
Use of rehabilitation- or clinical-related visual data (e.g., clinical recordings, home-based monitoring videos, rehabilitation training videos)	Non-rehabilitation datasets (e.g., sports performance analysis, animation or film data)
Peer-reviewed research articles	Non-academic publications
Full-text articles in English	Non-English publications

2.4. Study selection process

Two stages were involved in the study selection process. During the first step, two reviewers independently sifted through the titles and abstracts of all the records retrieved based on the set inclusivity criteria. Both reviewers graded each record separately. Where there was disagreement, the third reviewer was involved and his decision was arrived at. The level of inter-rater reliability was also evaluated with the use of the Cohen kappa coefficient with the result of a great degree of agreement ($\kappa = 0.84$). EndNote 21 software was used to manage references, facilitate the screening process, and ensure reviewer blinding.

During the second step, the full texts of all potentially eligible studies were retrieved and rated by the two reviewers (the same people who made the initial screening) independently. The formal screening was preceded by pilot-test of the standardized form of screening in a sample of ten articles. The causes of exclusion at the full-text stage were recorded. Differences were observed to be settled by the discussion and this led to a final rate of 96 percent of agreement. The final reference list has been presented in Table.

Table 3. Literature summary

No.	Authors	Article Title	Category	Core Research Objective	Key Technologies	Primary Application Scenarios

DOI: 10.54254/2755-2721/2026.CH31473

1	Cao, J; Zhao, G; et al. [9]	Augmented Motion Representation Learning Based on Virtual Reality Sports Game Review Data	VR/AR in Sports & Rehabilitation	Construct augmented motion representation learning framework to optimize UX in VR sports games	DeepCoNN, User review big data, Motion glossary	VR game UX analysis, Personalized recommendation
2	Tarekegn, AN; Ullah, M; et al. [10]	Enhancing Human Activity Recognition Through Sensor Fusion and Hybrid Deep Learning Model	Sensor Fusion & Activity Recognition	Improve ADL recognition accuracy using multi-sensor fusion and hybrid deep learning	CNN-BiLSTM, Accelerometer, Gyroscope	Health monitoring, Activity recognition
3	Toyoshima, K; Alemayoh, TT; et al. [11]	Development of an Insole Pressure Measurement System for a Deep Learning-based Human Leg Joint Angle Estimation During Gait	Gait Analysis & Joint Angle Estimation	Develop low-cost insole pressure system for gait joint angle estimation	1D-CNN/LSTM, Insole pressure sensors, Motion capture	Clinical gait assessment, Mobile analysis
4	Lin, R; Wang, F; et al. [12]	Reducing the Influence of Individual Variability in sEMG-Based Fatigue Detection Using Transfer Learning	Physiological Signal Recognition	Reduce individual variability in sEMG fatigue detection via transfer learning	Transfer learning, sEMG signals	Muscle fatigue monitoring, Rehabilitation
5	Jiang, YY; Zhang, XD; et al. [13]	Deep Learning Based Recognition of Hand Movement Intention EEG in Patients with Spinal Cord Injury	Physiological Signal Recognition	Improve EEG-based hand movement intention recognition for SCI patients	CNN, CSP, EEG	BCI, Prosthetic control
6	Deniz, SM; Javaheri, H; et al. [14]	Prediction of Lifted Weight Category Using EEG Equipped Headgear	Physiological Signal Recognition	Classify lifted weight category using EEG signals	Feature-based & DL models, EEG	Exercise load monitoring, Rehabilitation
7	Shi, RL; Wang, S; et al. [15]	mmHAT: 3D Human Arm Tracking with Joint Learning using Dynamic mmWave Point Cloud	Deep Learning & Pose Estimation	Accurate non-invasive 3D arm trajectory tracking using mmWave radar	Multi-task learning, mmWave point clouds	Rehabilitation, Sports analysis, HCI
8	Tang, FC; Chen, Z [16]	Dangerous Action Recognition Algorithm Based on Motion Capture	Computer Vision & Motion Capture	Automatic identification of high-risk actions	Improved MN-SIFT, NTU RGB+D	Industrial safety, Security monitoring

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Table 3. (continued)

9	Hakim, IM; Zakaria, H; et al. [17]	3D Human Pose Estimation Using Blazepose and Direct Linear Transform (DLT) for Joint Angle Measurement	Computer Vision & Motion Capture	Low-cost markerless 3D pose estimation for joint angle measurement	BlazePose, DLT	Exercise posture assessment, Rehabilitation
10	Segal, Y; Hadar, O; et al. [18]	Assessing Human Mobility by Constructing a Skeletal Database and Augmenting it Using a GAN Simulator	Deep Learning & Pose Estimation	Augment scarce motion datasets using GAN-generated skeletons	GANs, OpenPose skeletons	Physiotherapy databases, Training data generation
11	Wicaksono, I; Hwang, PG; et al. [19]	3DKnITS: Three-dimensional Digital Knitting of Intelligent Textile Sensor for Activity Recognition and Biomechanical Monitoring	Smart Textiles & Novel Sensing	Develop intelligent textile sensors for activity and biomechanical monitoring	Digital knitting, Piezoresistive fabric, CNN	Wearables, Exercise monitoring
12	Fürst-Walter, I; Nappi, A; et al. [20]	Design Space Exploration on Efficient and Accurate Human Pose Estimation from Sparse IMU-Sensing	Sensor Fusion & Activity Recognition	Optimize IMU sensor configurations for efficient pose estimation	Sparse IMUs, Design space exploration, DL	Privacy-sensitive & resource-constrained systems
13	Qin, RZ [21]	Research on Application of Virtual Reality Technology in Sports Rehabilitation	VR/AR in Sports & Rehabilitation	Review VR applications and future directions in sports rehabilitation	Literature review	Rehabilitation training, Therapy
14	Irfan, M; Suryadevara, NK; et al. [22]	Comparative Analysis of Computer Vision and IMU Sensing Systems for Accurate Determination of Gait Parameters	Gait Analysis & Joint Angle Estimation	Compare CV and IMU-based gait analysis systems	BlazePose, MPU6050 IMU	Gait analysis, System selection
15	Arellano-González, JC; Medellín-Castillo, HI; et al. [23]	Reconstruction and analysis of human walking patterns using a computer 3D vision system	Gait Analysis & Joint Angle Estimation	Reconstruct and analyze 3D walking trajectories	3D computer vision	Biomechanics, Prosthetic design

3. Analysis and discussion

Although there is growing interest in applying CV technology to movement assessment in the field of rehabilitation, existing research remains rather scattered in terms of application areas and potential goals. Current research does not tend towards a unified evaluation framework but rather presents a variety of exploratory practices. For this reason, this study summarizes the current

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application of computer vision technology in the assessment of different types of motor functions and clarifies the main purposes of these applications.

3.1. Research question 1: how can computer vision technology be applied to the assessment of different types of motor functions

Review studies have shown that computer vision technology is applied to the assessment of motor function in several distinct yet overlapping ways, mainly depending on the type of motion being evaluated and the assessment environment.

Firstly, computer vision is widely used in pose estimation and joint Angle measurement in rehabilitation-oriented motor assessment. Unlabeled pose estimation models such as BlazePose and OpenPose can extract skeletal key points from monocular or multi-view video streams. These methods are usually applied to structured repetitive movements, where joint kinematics can serve as an indicator of the quality of motor function. Compared with traditional motion capture systems, the CV-based method has higher accessibility and lower deployment costs, making it suitable for home or community rehabilitation monitoring.

Secondly, CV technology is applied to gait analysis and spatio-temporal parameter estimation, including step length, step frequency and walking symmetry. In these studies, CV serves as a non-contact alternative based on inertial measurement units (IMUs) or force platform systems. Comparative studies have shown that although the accuracy of gait assessment based on CV may decrease under unconstrained conditions, it is sufficient to meet the requirements of screening, trend analysis and longitudinal monitoring, especially when clinical-grade instruments are not available.

Third, CV is also used in more motion recognition and motion quality classification. It is not aimed at determination of correct (fine) biomechanical parameters, but it is intended to reveal functioning movement patterns or harmful behaviors. The applications are usually based on deep learning classifiers that are trained on skeletal trajectories or RGB-D video footage to determine normal and abnormal actions. They can mainly be applied to industrial rehabilitation as well as the detection of fall risks and compliance with exercises.

However, also some of the studies have broadened the use of computer vision to the creation of data and its enhancement, including the creation of skeletal databases or generative models of motion data syntheses. Computer vision as used in these is an assistant technology to the downstream learning tasks (as opposed to being an evaluation instrument). This research also occupies the first steps of exploration, but it is important to mark that computer vision is used to cope with the problem of the lack of data in rehabilitation studies.

To sum up, these results show that the use of computer vision in the rehabilitation assessment tasks is also not homogenous. Instead, the scope of its application is of quantitative measurement of kinematic quantities to qualitative identification of functions, based on the subject of assessment and limitations.

3.2. Research question 2: what is the purpose of applying computer vision in rehabilitation assessment

Besides technical implementation, literature review portrays that there exist a good number of purposes that are commonly applied to computer vision use in rehabilitation assessment that both represent practical motivation and conceptual motivation. Enhance capacity of accessibility and scalability is one of the primary ones. Numerous papers have placed computer vision-based systems squarely as low-cost and label-free to lab motion capture with the aim of taking the evaluation of

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rehabilitation out of the clinical laboratory. Such an objective is especially noticeable in situations where rehabilitation is carried out at home, via the internet, as convenience on deployment and the burden on users pose vital considerations in this context. The second aims at assisting objective and automated evaluation. Motion features can be computed automatically by computer vision as opposed to subjective judgment of clinicians or even self-reported performance. In the same way, computer vision is typically conceptualized as a standardized instrument that could be used to generate more consistent patterns of assessment over time, setting and assessors.

Thirdly, computer vision is used to achieve continuous and longitudinal monitoring rather than one-off diagnostic measurements. By analyzing the video streams during repetitive training processes, CV-based systems can capture trends in motion recovery, fatigue or motion adaptation. This perspective of the time dimension is highly consistent with the rehabilitation goals. Another important use is to provide feedback and decision support. In some studies, the output of CV has been integrated into the feedback system of patients or clinicians to support corrective guidance, exercise guidance or rehabilitation programs. Although real-time feedback remains technically challenging, especially in unrestricted environments, its potential role in motor learning and participation is often emphasized [24].

Even as real-time feedback is technically difficult to implement, particularly in the field where the limitation is not applied, its potential in motor learning and involving participation has been highlighted [22]. And lastly, many few studies apply CV to exploratory or developmental applications like creating motion data or checking new sensing paradigms or comparing CV to wearable sensors. Such studies need not necessarily be meant to apply in clinical practice immediately, but as a methodological basis of future rehabilitation uses.

4. Implications for future research

Various directions are named in the literature review as of the future research. To begin with, one has to come out of the isolated technological optimization and into human-oriented integrated systems which are holistically responsive to perceptual accuracy, user experience, cognitive load, and contextual adaptability. This is especially critical in rehabilitation programs built up using virtual reality and smart tutoring settings. Second, the future studies are supposed to pay more attention to the cross-modal learning and optimization mechanisms [25-27], in order to make the system adapt dynamically to the physiological condition, proficiency and learning or recovery course of the user.

5. Conclusion

This study provides an exploratory snapshot of how computer vision technologies are currently applied in movement function assessment within rehabilitation contexts. By systematically examining existing studies, we address two guiding questions concerning the application forms of computer vision and the underlying purposes motivating its adoption. The findings indicate that computer vision is mainly used for pose estimation, gait analysis, action recognition, and motion data construction, supporting both quantitative kinematic measurement and qualitative functional evaluation. At the same time, these applications serve multiple purposes, including improving assessment accessibility, enabling automated and objective evaluation, supporting longitudinal monitoring, and facilitating feedback and exploratory system development. This article lays the groundwork for more coherent, purpose-driven applications of computer vision in movement rehabilitation assessment.

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