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DEEP LEARNING IN STROKE REHABILITATION COMPENSATORY MOVEMENT DETECTION: FROM LABORATORY BENCHMARKS TO CLINICAL REALITY

Xiao Xu[1], HaoNan Qin[2], LanShu Zhou[2*]
[1]*School of Health Science and Engineering, University of Shanghai for Science and Technology, Shanghai 200093, China.*
[2]*School of Nursing, Naval Medical University, Shanghai 200093, China.*
[*]*Corresponding Author: LanShu Zhou*

Abstract: Stroke rehabilitation is going through some pretty major changes right now. We're seeing a gradual move away from those subjective clinical scales toward more objective, automated assessments—though it's not happening as fast as some people hoped. Traditional methods like the Fugl-Meyer Assessment (FMA) are still considered the gold standard in clinics, but they've got some real problems. They're time-consuming, different raters often give different scores, and they tend to hit ceiling effects that miss subtle improvements patients are making.This review looks at important studies from 2016 to 2025. We trace how automated detection systems evolved from those lab-based depth sensors to RGB cameras you can use at home and wearable IMUs. We compare different sensing technologies and look at public datasets. There's also this "sim-to-real" gap issue - basically, models trained on healthy actors often don't work well with real patients, which is a big problem. The algorithms have changed a lot too, going from traditional machine learning to foundation models. Clinical metrics have also expanded beyond simple detection to things like severity grading.At the end, we talk about what this all means for tele-rehabilitation and why getting clinicians to actually adopt these technologies is still really challenging. We suggest a roadmap that focuses on privacy-preserving collaboration and long-term validation studies, though honestly implementing all of this won't be easy.
Keywords: Stroke rehabilitation; Compensatory movement; Deep learning; Multimodal fusion

1 INTRODUCTION

1.1 The Global Burden and Pathophysiology of Stroke

Stroke is one of the leading causes of adult disability around the world. While medical advances have helped reduce how many people die from strokes, the burden has kind of shifted toward chronic rehabilitation needs. Here's something sobering: up to 80% of stroke survivors develop acute upper limb hemiparesis, and about 50-60% still have persistent motor impairments six months after their stroke [1]. Those numbers are pretty concerning when you think about it.
There's this fundamental challenge in rehabilitation that involves trying to tell the difference between true motor recovery and compensatory strategies. Cirstea and Levin showed how stroke survivors frequently develop movement adaptations - like using excessive trunk flexion during reaching tasks when their elbow extension is limited[2]. These compensatory patterns let them complete the task right away, but the long-term effects aren't good. When people keep relying on compensation, it contributes to something called "learned non-use," which actually inhibits neuroplasticity. That's why contemporary rehabilitation approaches emphasize not just whether you can complete a task, but Quality of Movement (QoM) - basically how you're executing the movement matters.

1.2 Why Traditional Assessments Fall Short

Clinical practice still relies heavily on observational scales like the FMA, which are considered gold standards even though they have some inherent limitations. The scoring accuracy depends on what the therapist observes, which results in inter-rater variability. These scales also exhibit ceiling effects that fail to detect fine motor improvements and subtle compensatory deviations - Gladstone et al. talked about this[3].
A fundamental limitation of these assessments is their snapshot nature within clinical settings. They don't really capture how patients perform during daily activities at home, which is arguably what we should care most about.

1.3 The Move Toward Automation

To try and address these limitations, researchers have been developing automated systems. The past decade has seen substantial technological advances - we've gone from marker-based optical motion capture (OMC) to markerless tracking systems, and from laboratory equipment to portable sensors that work in different environments. This review takes a narrative approach, focusing on studies that introduced novel sensing technologies, algorithmic innovations, and validation with actual patient populations (not just healthy volunteers pretending to have impairments).

2 BUILDING BLOCKS: DATASETS AND THE SIM-TO-REAL PROBLEM

High-quality annotated data is critical for deep learning applications in stroke rehabilitation - you really can't do much without it. The KIMORE dataset is a key resource here, with recordings from 78 subjects and clinical assessment scores from trained clinicians[4]. The UI-PRMD dataset takes a different approach by explicitly including both correct and incorrect movements performed by healthy subjects, which helps with training binary classifiers[5].

But here's where things get tricky. There's a critical limitation in relying on simulated data. Zhi et al. identified this "sim-to-real gap" in their Kinect-based monitoring study[6]. They compared classifiers (SVM and RNN) trained on simulated healthy subject data versus actual patient data. While the models showed high performance on simulated movements, accuracy dropped substantially with real stroke survivors. This happened because pathological movements are highly variable, there's frequent occlusion, and the complexity is just inherently different.

This finding really emphasizes that algorithms need to be validated on clinical populations, not just on healthy actors simulating impairments. It seems obvious in hindsight, but a lot of early work didn't do this properly.

3 SENSING TECHNOLOGIES: FROM LABS TO LIVING ROOMS

3.1 Making Vision Accessible

The period from 2021 to 2025 saw a decisive shift to RGB-only solutions using standard cameras without those specialized depth sensors. Lin et al. demonstrated that you could deploy compensatory detection on standard tablet devices, achieving 92% accuracy for shoulder elevation detection[8]. Yamamoto et al. established that single-camera RGB analysis could provide enough precision to actually guide clinical interventions - specifically for ankle-foot orthosis (AFO) adjustment in stroke patients, which was pretty impressive[9].

There have been some condition-specific innovations too. Zheng et al. addressed a practical challenge in cervical spondylotic myelopathy (CSM) assessment[11]. Clinicians manually count rapid hand movements during the "10-second grip and release" test, which is tedious. Their intelligent video system based on 3D-MobileNetV2 automated the test grading with 97.40% accuracy, giving clinicians an objective screening tool that actually saves time.

Novel camera placement strategies have helped with occlusion problems and limited viewing angles in home settings. Dousty and Zariffa developed an egocentric vision system for cervical spinal cord injury patients - the camera goes on the user to capture a first-person perspective[12]. By combining hand detection with RNN-based arm orientation estimation, they could detect "tenodesis grasp," which is a specific compensatory strategy. This represents a significant advance in monitoring daily activities outside the clinic.

For pediatric assessment, Sohn et al. designed something called the "MAGIC Table.[7]" It's a low-cost portable device using a standard camera to track objects like magnetic cups and rolling balls. The system quantifies upper-limb function in children with cerebral palsy through gamification, which kids respond well to. No expensive motion capture equipment or specialized lab facilities needed.

3.2 Wearable Sensors and Daily Function

While camera-based systems face line-of-sight limitations (someone has to be in view of the camera), wearable sensors enable continuous monitoring. Okita et al. demonstrated that a single wrist-worn IMU could distinguish impairment levels through sample entropy analysis of movements[13]. Just one sensor on the wrist - that's pretty remarkable.

Recent research has focused on specific functional impairments. Lu et al. used IMUs to assess frozen shoulder during daily activities like hair washing[14]. Movement smoothness metrics (SPARC) successfully distinguished patients from healthy controls, though they had to segment tasks into sub-tasks to reveal fine-grained dysfunctions. The sub-task segmentation adds complexity but seems necessary.

Fatigue-related compensation during home rehabilitation is another challenge that doesn't get enough attention. Chua et al. developed a flexible strain-sensor patch using carbon nanofibers for shoulder placement[15]. It detects skin deformation when patients elevate their shoulder to compensate during bicep curl exercises. The sensor output showed high correlation with EMG and optical motion capture while being much more comfortable for remote monitoring, which matters a lot for patient adherence.

For comprehensive analysis, multimodal sensor fusion is still the gold standard, though it's more complex to implement. S. Gao et al. introduced a "Physical Priori Network" that integrates surface EMG (sEMG) and pressure data with physical constraints incorporated into the loss function[16]. This enabled them to distinguish between active and passive movements with 94.7% accuracy, which is important for detecting learned non-use patterns.

4 ALGORITHM EVOLUTION

4.1 When Simple Works Better

Traditional machine learning approaches continue to be useful in specific scenarios - deep learning isn't always the answer. Ding et al. found that K-Nearest Neighbors (KNN) with engineered features actually outperformed deep learning models for severity grading using limited IMU data, achieving an F1-score of 96.8%[17]. Sometimes the simpler approach works better, especially with limited data.

The scope of algorithms has expanded beyond just detection. Wu et al. developed an adaptive control strategy for a soft elbow exoskeleton[18]. They feed sEMG signals into a neural network that compensates for the non-linear behavior of soft materials. The system automatically switches between passive, active, and assist-as-needed modes based on patient intent and impairment level. This enables real-time coupling of detection and intervention, which is where the field needs to go.

4.2 Advanced Architectures and Annotation-Efficient Learning

Recurrent Neural Networks (RNNs) are effective at handling complex temporal patterns. Zhu et al. designed an Encoder-Decoder GRU to reconstruct missing frames during wireless data transmission loss[19]. This ensures system robustness during real-time operation, which is critical when you're dealing with wireless sensors that might drop packets.

A significant trend in 2025 addresses the annotation costs associated with frame-by-frame labeling, which is extremely expensive and time-consuming. Cóias et al. proposed a weakly supervised learning (WSL) framework that learns from video-level labels rather than frame-level annotations[21]. They use saliency maps to generate frame-level pseudo-labels. Validation on the SERE dataset showed effective real-time detection of trunk and shoulder compensations with good generalization across patients, without requiring dense manual annotation. This could really help with scalability.

Foundation models are beginning to emerge in this domain too. Mesquita et al. adapted MOMENT, a time-series foundation model, and demonstrated superior zero-shot generalization compared to task-specific models when tested on previously unseen patients[20]. Foundation models might be the future here, though they require substantial computational resources.

5 VISUAL OVERVIEW AND COMPARISON

Figure 1 (conceptual) shows the timeline. We start with Kinect-based benchmarks in 2016. By 2024-2025, we see egocentric vision and weakly supervised learning becoming mainstream.

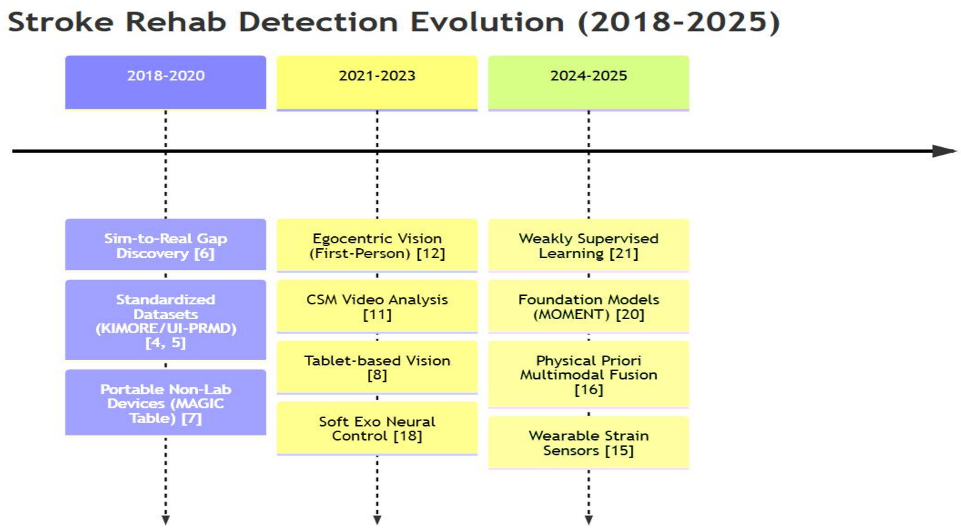

Figure 1 Technology Evolution Timeline

Table 1 provides a systematic comparison of the representative studies we've discussed, including the newly integrated literature.

Table 1 Comparison of Representative Studies

Study	Sensors Used	Method	What They Measured	Key Results
Wu [18]	sEMG + Soft Exoskeleton	Neural Network Control	Exoskeleton control modes	Smart switching between active/passive/assist modes; better tracking
Zheng [11]	RGB video	3D-MobileNetV2	CSM severity assessment	97.40% accuracy automating the "grip and release" counting test
Chua [15]	Flexible strain sensor	Statistical correlation	Fatigue-induced compensation	Detected shoulder lift via skin stretch; matched gold-standard EMG
Dousty [12]	First-person camera	Hand detection + RNN	Tenodesis grasp	First system to catch this compensatory grasp from user's viewpoint
Cóias [21]	RGB video	Weakly supervised learning	Stroke rehab exercises	F1: 80.5%; trained on video labels, not expensive frame-by-frame annotations
Zhi [6]	Kinect depth sensor	SVM / RNN	Robot-assisted rehab	Exposed the sim-to-real problem: models fail on real patients
Sohn [7]	RGB (MAGIC Table)	Computer vision	Cerebral palsy assessment	Low-cost portable system using tracked objects and games
Lu [14]	IMU	Movement smoothness (SPARC)	Frozen shoulder	Detected dysfunction in daily tasks when broken into sub-movements
Mesquita [20]	Body keypoints	MOMENT foundation model	Cross-patient generalization	AUC: 0.73; worked on patients it never saw during training
Yamamoto [9]	Single RGB camera	OpenPose	Gait analysis for AFO tuning	Precise enough to guide orthosis adjustments
Pilla-Barroso [10]	RGB-D hybrid	Curvature-based switching	Joint angle estimation	Error < 6.8°; automatically switches between RGB/depth when occluded
Ding [17]	3 IMUs	KNN with PCA features	Severity grading	F1: 96.8%; simple approach beat deep learning on limited data
Zhu [19]	IMU	Encoder-decoder GRU	Handling data loss	51.5% error reduction even with 50% packet loss
S. Gao [16]	sEMG + pressure sensors	Physics-informed network	Active vs. passive movement	94.7% accuracy distinguishing learned non-use patterns
Okita [13]	Single wrist IMU	Movement entropy	Movement quality	Strong effect size (Cohen's D: 0.99) separating impairment levels
Lin [8]	Tablet camera	XGBoost	Home-based detection	92% accuracy on consumer tablets - no special hardware needed

6 WHAT THIS MEANS CLINICALLY

6.1 Beyond Binary Detection

Algorithmic advances have enabled a transition from simple binary classification (compensating or not) to more granular quantification. Modern systems can provide severity grading and assess specific conditions like CSM and frozen shoulder [11, 14, 17]. The integration of control algorithms suggests future systems might simultaneously detect compensation and adjust robotic assistance levels - basically concurrent assessment and intervention, which would be a big step forward[18].

6.2 Design Considerations for Clinical Implementation

Single-tablet solutions and wearable patches demonstrate that simplicity really does promote adherence in home settings[8, 15]. The MAGIC Table shows that rehabilitation can be gamified and made portable, which reduces barriers especially for pediatric patients who need extra motivation[7].

However, complex multi-sensor setups with multiple electrodes continue to see high abandonment rates. Patients get frustrated, caregivers have difficulties with system setup, and people just stop using them. Technology usability directly impacts clinical adoption - this can't be overstated.

6.3 Barriers to Clinical Adoption

Technical success doesn't guarantee clinical implementation, which is frustrating for researchers. The sim-to-real gap that Zhi et al. identified remains a significant obstacle[6]. Algorithms trained on healthy actors performing simulated impaired movements just don't generalize well to actual patients. Future research really needs to prioritize collecting data from authentic patient populations, like the recent work on CSM and stroke datasets has done[11, 21]. But this requires interdisciplinary collaboration between engineers and clinicians, which isn't always easy to coordinate.

Regulatory and liability frameworks present additional challenges that often get overlooked. Who's responsible when an AI system guides a clinical decision that turns out badly? These questions need answers before widespread adoption can happen.

COMPETINGINTERESTS

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