Timo Kuhlgatz*, Matteo Antonino Caruso, Simona Ferrante, and Thomas Seel

Assessing sit-to-stand motion execution using 6D IMUs only - A proof of concept

https://doi.org/10.1515/cdbme-2025-0209

Abstract: In this paper, we propose a proof of concept for using 6D IMUs to assess the correctness of sit-to-stand (STS) motion, a critical task in post-stroke rehabilitation. Therefore, healthy individuals were instructed to mimic post-stroke movement patterns, providing a relevant model for post-stroke behavior. We demonstrate that using simple kinematic models for all articulated joints is a feasible approach to calculating joint angles and extracting relevant features. Using rule-based and learning-based classification models, we are able to distinguish between multiple error types in the STS motion, with average classification accuracies of 89.78% and 94.03%, respectively. In contrast to many state-of-the-art methods that only provide a binary classification of correct versus incorrect execution, our approach enables the differentiation between various error types. Additionally, it overcomes the limitations of complex, location-dependent camera systems and susceptibility to magnetic disturbances. This highlights the feasibility of this approach for evaluating STS motion, with potential applications in providing automated feedback for post-stroke rehabilitation and supporting the recovery of activities of daily living.

Keywords: STS assessment, joint angles, IMU, classification

1 Introduction

Stroke affects more than 15 million people annually [1] and often leads to significant motion impairments. The first twelve months are crucial for rehabilitation, as neuroplasticity is most active during this period, making it an ideal time for intensive therapy [2]. Repetitive task-specific exercises during this phase can improve mobilization and motor skills, reducing functional limitations and the need for long-term care [3]. A key goal of stroke rehabilitation is to restore activities of daily living, with sitting-to-stand (STS) movements being a crucial exercise to regain balance and mobility [4].

***Corresponding author: Timo Kuhlgatz,** Leibniz University Hannover, Institute of Mechatronic Systems, Hannover, Germany, e-mail: timo.kuhlgatz@imes.uni-hannover.de
Matteo Antonino Caruso, Simona Ferrante, Polytechnic University of Milan, Neuroengineering and Medical Robotics Laboratory, Milan, Italy
Thomas Seel, Leibniz University Hannover, Institute of Mechatronic Systems, Hannover, Germany

During physiotherapy sessions, physiotherapists provide essential feedback on the execution of specific motion tasks, helping patients refine their movements and improve overall motor function. However, limited access to supervised physiotherapy due to shortages of trained personnel, combined with non-compliance, i. e. not doing the prescribed exercises between supervised physiotherapy sessions, further hinders recovery. As early as 2001, Campbell et al. [5] found that the issue of non-compliance is primarily driven by patients' rational decision-making, as they fear performing the exercises incorrectly, but effective solutions are still missing.

To address these challenges, automatic feedback systems could support rehabilitation by complementing supervised therapy and encouraging adherence between supervised sessions. Such systems would ensure that patients engage correctly in prescribed exercises, optimizing recovery outcomes. Effective automated feedback requires automated assessment of movement correctness, achievable through motion tracking technologies.

Existing approaches for the automated assessment of STS movement correctness often use camera-based systems [6, 7], which have limitations such as privacy concerns, location dependence, and a strong dependence on maintaining the correct perspective. Alternatively, 9D inertial measurement units (IMUs) are frequently used [8, 9], though they are susceptible to disturbances in the magnetic field, such as those caused by ferromagnetic materials or electronic devices, which can negatively impact attitude estimation. Most importantly, most systems only provide binary classification [6–8], indicating whether an error occurred without specifying the nature of the error, making them unsuitable for providing detailed feedback.

To address these challenges, we propose and evaluate approaches for error classification in post-stroke STS execution. Using data from healthy individuals mimicking common post-stroke errors, we provide a proof of concept demonstrating that distinguishing between these errors is feasible with both learning-based and rule-based methods when relying solely on 6D IMUs and simple kinematic models for all articulated joints. By leveraging 6D IMUs, our approach bridges the gap between imprecise consumer devices and costly high-end systems [10]. Finally, we compare our proposed method to state-of-the-art approaches, highlighting its effectiveness and potential for further development.

2 Used dataset

This study involved only healthy participants who were instructed to mimic common post-stroke errors during sit-to-stand movements under the guidance of a physiotherapist specialized in post-stroke rehabilitation and based on [11]. The typical errors are: (1) Asymmetrical movement, where individuals leaned toward one side, mimicking hemiparesis; (2) Lack of control, where participants simulated an uncontrolled descent, mimicking the tendency of post-stroke patients to fall back into the chair due to insufficient motor control; and (3) Uneven weight distribution, where impaired balance led to uneven weight on both feet, sometimes requiring a corrective step for stability. For correct execution, participants were instructed to first shift their buttocks to the chair's edge, then lean forward to position their center of gravity over their feet before standing up without using momentum. This process resulted in six motion tasks (correct, plegia left/right, incorrect step left/right, and failure), but since left and right errors were treated equally, the data was ultimately categorized into four classes: correct, plegia, step, and failure.

A total of 11 participants completed the study, each performing every motion task five times, yielding 330 trials (6 tasks × 5 repetitions × 11 participants). Motion tracking was conducted using eight Xsens Awinda IMUs, sampling at 100 Hz, with only acceleration and angular velocity data being used. To account for sensor drift, a 20-second calibration measurement was taken before each participant's session with the IMUs at rest. The placement of the 8 sensors used followed the standard Xsens lower limb configuration and is illustrated in Fig. 1a.

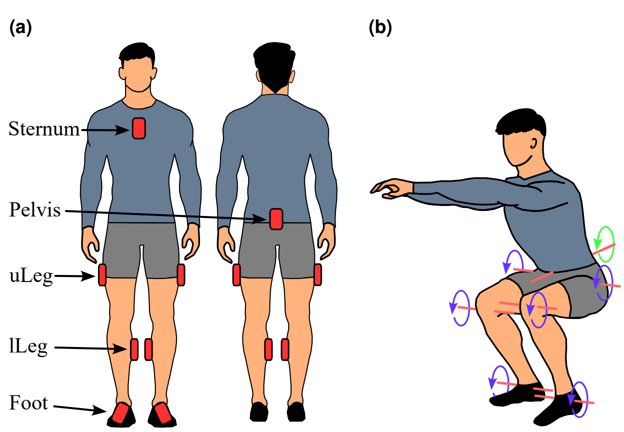

Fig. 1: a) Sensor placement used for this study following standard Xsens lower limb configuration involving eight IMUs. b) Joint axis assumptions applied for joint angle calculation. Violet rotation arrows indicate a rotation in the sagittal plane, while the green rotation arrow indicates a rotation in the frontal plane.

3 Data processing

The data processing aims to extract the changes in joint angles (JA) of the underlying motion. The pipeline began with the removal of turn-on bias, followed by gravity compensation using acceleration data. Next, attitude estimation for each sensor was performed using the versatile quaternion-based filter [12]. Since only 6D IMUs were used, absolute heading information was unavailable. Therefore, relative joint orientation was estimated under the assumption of 1 DoF joints with known sensor-to-segment orientation.

To determine joint axes between two adjacent IMUs, we employed the Olsson method [13] and computed the relative quaternion between adjacent segments. Heading offset correction was performed using the QMT library[1] and kinematic constraints for 1 DoF joint. The heading correction was applied following the kinematic chain from the foot to the pelvis sensor. While the hip joint is typically modeled with two or three DoFs, leg rotation is not essential in STS. Thus, we approximated the hip as a 2 DoF joint, which was further decomposed into two independent 1 DoF JAs—one in the sagittal and one in the frontal plane (see Fig. 1b). Finally, we decomposed the relative orientation quaternion between adjacent IMUs into Euler angles using the ZYX convention. Given the assumption of 1 DoF joints, this directly represented the change in JAs during the movement.

4 Classification methods

To provide accurate feedback on exercise performance, systems must effectively classify movements, distinguishing not only between correct and incorrect execution but also between different types of errors. This classification task can be approached using both learning-based and rule-based methods, each offering unique advantages.

Learning-based approaches, especially Machine Learning, use data-driven models to recognize patterns in performed movements. These models rely on training with labeled data and typically require large datasets to generalize effectively to unseen instances. However, they often lack interpretability, which can be particularly helpful, especially in medical applications.

In contrast, rule-based approaches, like Expert Decision Trees, use predefined rules derived from expert knowledge to make decisions. These models are transparent, easy to interpret, and ideal for scenarios with limited data, ensuring consistent and explainable outcomes. Yet, they can be rigid and struggle with nuanced variations.

1 https://qmt.readthedocs.io/en/stable/

4.1 Learning-based

A Random Forest classifier was chosen as they are known to perform well on limited data for multiclass classification. Based on [14], we extracted seven fundamental statistical features, and following [15], we extracted 13 dynamic features from the previously calculated JAs, using them as inputs for the Random Forest classifier.

We employed a nested 5-fold cross-validation strategy to ensure robust model evaluation and prevent data leakage. In each of the five outer folds, data from two participants were reserved as an unseen test set. The remaining data from nine participants underwent an inner 5-fold GroupKFold for hyperparameter tuning via grid search. Within each inner fold, data from two participants served as the validation set during training. The hyperparameter search space and the final selected hyperparameters for the Random Forest classifier are detailed in Table 1.

Tab. 1: Hyperparameter search space and optimized values for the Random Forest classifier used for STS error classification.

Hyperparameter	Search Space	Optimized Value
`n_estimators`	$[100, 150, 200, 300]$	150
`max_depth`	$[None, 10, 20, 30]$	20
`min_samples_split`	$[2, 5, 10]$	5
`min_samples_leaf`	$[1, 2, 4]$	2
`max_features`	$['auto', 'sqrt', 'log2']$	'sqrt'
`bootstrap`	$[True, False]$	True

4.2 Rule-based

As this approach represents an expert decision tree, the rules have been defined based on expert knowledge without knowing the underlying data distribution. Therefore, we defined the following rules for general asymmetry and the range of motion (ROM):

$$\text{Asymmetry}_j := \max_{i \in T} \left(|\text{JA}_i^L - \text{JA}_i^R| \right) > 15°, \quad \forall j \tag{1}$$

$$\text{ROM}_j := \max_{i \in T}(\text{JA}_i^S) - \min_{i \in T}(\text{JA}_i^S), \quad \forall j, \quad S \in \{L, R\} \tag{2}$$

where S represents the side with L for the left side and R for the right side, j denotes the joint being analyzed and i is a timestep within the time period T of a complete trial. A **correct STS movement** is characterized by synchronized flexion and extension of the hip and knee joints. However, in cases where deviations occur, certain compensatory strategies can be considered tolerable [11]. Specifically, if the knee joint angle exceeds 75°, the hip joint must compensate by maintaining an angle of less than 30°. Conversely, if the hip joint angle exceeds 90°, the knee joint must compensate by maintaining an angle of less than 45°. Additionally, no asymmetry as defined in equation 1, occurs in either the hip or the knee JA.

The class of **failed movement** is characterized by a restricted knee movement, with a limited ROM (see equation 2) of less than 40° [16]. In contrast, a full range of motion for the knee would be approximately 90°. The class of **bending movements**, mimicking the **plegie**, is characterized by a consistent asymmetry of the torso in the frontal plane [17], a characteristic pattern seen in plegic movements, where one side is affected and moves with less flexibility. A movement is considered asymmetric if the absolute difference between left and right hip angles remains above a threshold of 15° for at least 50% of the movement duration. The last class, a **corrective step**, is characterized by an asymmetry bigger than 10° of the knee angles between one and 2.5 seconds of the motion trial. In addition, the knee angle of one knee must decrease after reaching full extension.

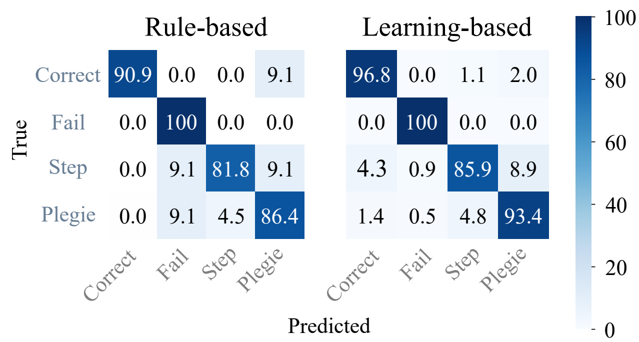

Fig. 2: Confusion matrices showing the mean classification results of STS movement and common error types for the rule-based (left) and learning-based (right) approach.

5 Results

With the rule-based approach, we were able to achieve a mean classification accuracy of 89.78% across all participants, whereas with the learning-based method, we were able to achieve a mean classification accuracy of 94.03% on the five folds of unseen test data. This shows that, although our approach not only distinguishes between correct and incorrect execution, but also between different error types, these results are comparable to state-of-the-art results (see Table 2). The average confusion matrix of the rule-based approach across all participants is shown in Fig 2 (left) and the average confusion matrix across all test sets of the nested 5-fold cross validation of unseen test data for the random forest classifier is shown in Fig 2 (right). It can be seen that both the rule-based and the learning-based approach recognize the failed execution in all cases. This is expected as this movement differs significantly from all other movements.

Tab. 2: Comparison of the proposed rule-based (Res.I) and learning-based (Res.II) approach with state-of-the-art STS classification approaches.

	[6]	[8]	[9]	Res.I	Res.II
Stationary/ Wearable	Stationary	Wearable	Wearable	Wearable	Wearable
Sensors	*Camera*	*9D IMUs & EMG*	*9D IMUs*	*6D IMUs*	*6D IMUs*
Error Types	0	0	2	3	3
Approach	*AI-based*	*AI-based*	*AI-based*	*Rule-based*	*AI-based*
Accuracy	91.25%	98.80%	88.65%	89.78%	94.03%

In order to further improve the classification of the other classes, the defined rules could be completed by additional rules, for example, by using not only the calculated JAs but also the raw IMU data. If, for example, the acceleration of a foot-mounted sensor exceeds a certain threshold in the later phase, it could suggest a step and, therefore, improve the classification of this error class. Additionally, a linear relationship between the knee and hip JA could be implemented to better account for the tolerable compensatory strategy.

6 Conclusion

Our results demonstrate that both rule-based and learning-based methods are suitable for the task of assessing sit-to-stand (STS) motion based on extracted features from joint angles. Using 6D IMUs and simple kinematic models for all articulated joints keeps the setup simple and location-independent, as no complex camera system is needed and magnetic disturbances have no influence on the underlying data. This simplicity ensures that the approach can be easily integrated into rehabilitation assistance systems. Although this is still a proof of concept, we achieved results comparable to state-of-the-art methods while offering the benefit of distinguishing between different error types instead of just binary classifying correct and incorrect execution. This highlights the feasibility of the proposed approach and shows the potential to be used to provide helpful feedback on the STS execution, for example, in post-stroke rehabilitation. By enabling more patients to receive personalized, real-time feedback, this approach could support better recovery outcomes and help combat the issue of non-compliance in rehabilitation programs. Future work focused on improving classification accuracy and enabling online inference could provide automated feedback for STS movements, thereby assisting individuals in regaining the ability to perform activities of daily living.

Author Statement

Research funding: The authors state that no funding was involved. Conflict of interest: Authors state no conflict of interest. Informed consent: Informed consent has been obtained from all individuals included in this study.

References

[1] Wolfes, C. and Rudd, T.: The burden of stroke in europe: Key findings and recommendations; 2016 https://safestroke.eu/wp-content/uploads/2016/07/FINAL_Burden_of_Stroke.pdf
[2] Li, S. et al.: A new definition of poststroke spasticity and the interference of spasticity with motor recovery from acute to chronic stages; Neurorehabilitation and Neural Repair; 2021;35; 601–610
[3] Dewey, H. M. et al.: Stroke rehabilitation 2007: What should it be?; International Journal of Stroke; 2007;2; 191–200. pMID: 18705943
[4] Janssen, W. et al.: Determinants of the sit-to-stand movement: A review; Physical therapy; 2002;
[5] Campbell, R. et al.: Why don't patients do their exercises? understanding non-compliance with physiotherapy in patients with osteoarthritis of the knee; J Epidemiol Community Health; 2001;
[6] Xie, S. Q. and Sheng, B.: Rehabilitation assessment system for stroke patients based on fusion-type optoelectronic plethysmography device and multi-modality fusion model; Sensors; 2024;
[7] Zhao, W. et al.: Rule-based human motion tracking for rehabilitation exercises: Realtime assessment, feedback, and guidance; IEEE Access; 2017;5; 21382–21394
[8] M., J. and J., S.: Automated error detection in physiotherapy training; Health Informatics Meets eHealth; 2018;
[9] Yurtman, A. and Barshan, B.: Automated evaluation of physical therapy exercises using multi-template dynamic time warping on wearable sensor signals; Comput Methods Programs Biomed.; 2014;
[10] Hribernik, M. et al.: Review of real-time biomechanical feedback systems in sport and rehabilitation.; Sensors 2022;
[11] Mao, Y. R. et al.: The crucial changes of sit-to-stand phases in subacute stroke survivors identified by movement decomposition analysis; Frontiers in Neurology; 2018;9
[12] Laidig, D. and Seel, T.: Vqf: Highly accurate imu orientation estimation with bias estimation and magnetic disturbance rejection; Information Fusion; 2023;
[13] Olsson, F. et al.: Robust plug-and-play joint axis estimation using inertial sensors; Sensors (Switzerland); 2020;20; 1
[14] Karunarathna, I. et al.: Statistical Methods in Research: A Comprehensive Overview; 2016
[15] Aresta, S. et al.: Combining biomechanical features and machine learning approaches to identify fencers' levels for training support; Applied Sciences; 2022;
[16] Riley, P. O. et al.: Biomechanical analysis of failed sit-to-stand; IEEE Trans Rehabil Eng.; 1997;
[17] A, B. and F, P.: Determinants of sit-to-stand tasks in individuals with hemiparesis post stroke: A review; Ann Phys Rehabil Med.; 2015;