siam news

SIAM News Blog **RESEARCH**

Robotics and Machine Learning Techniques Enable At-home Stroke Rehabilitation

January 31, 2025

By Russell Jeter, Raymond Greenfield, Steven N. Housley, and Igor Belykh

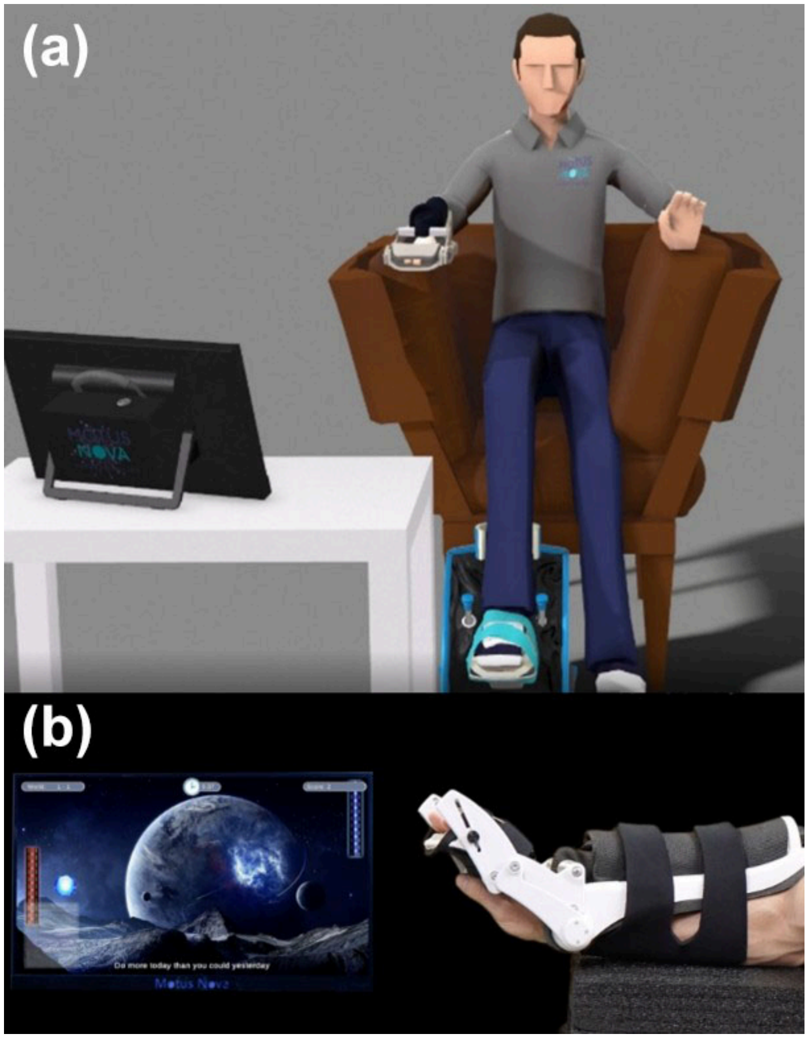


Figure 1. The Motus Hand and Motus Foot serve as at-home rehabilitation options for stroke survivors. **1a.** The apparatuses include a pneumatically driven exogenous robotic device that patients wear on the affected hand, arm, or foot during therapy sessions. **1b.** The Motus Hand peripheral acts as a game controller through an angle sensor that is embedded in the wrist joint, which allows users to play therapeutic video games that dynamically adapt to their needs and provide the requisite assistance or resistance. Figure courtesy of [3].

Stroke is a leading cause of mortality and disability worldwide, and its treatment imposes significant economic costs. In 2019, there were 12.2 million recorded incident cases of stroke and 6.55 million stroke deaths across the globe [2]. Strokes can range from mild to severe, and severe occurrences often lead to long-term disability or death. Neuromotor stroke recovery has traditionally taken place at inpatient and outpatient rehabilitation facilities, where patients work directly with trained physical and occupational therapists to improve their motor and cognitive function.

Recently, increasing efforts have sought to move the rehabilitation process from these facilities to the home by integrating technology-based interventions. For instance, Motus Nova's Motus Hand and Motus Foot are robotic therapeutic devices that stroke survivors with residual upper and lower extremity impairments can use at home, without the help of a clinician or caregiver [1]. The apparatuses engage the user's affected wrist or ankle, guiding them through various therapeutic exercises that target functional tasks such as gross and fine motor control and precision tracking (see Figure 1a).

Each device consists of two major components: (i) a peripheral that the patient attaches to their affected limb (see Figure 1b) and (ii) an interactive console that guides their therapy routine and assessment with a video game interface. The peripherals include a pneumatic actuator that dynamically provides assistance or resistance by filling an air muscle that moves the wrist or ankle joint. The joint also incorporates an embedded angle and pressure sensor that transmits live data to the console, allowing the console to offer immediate visual feedback of the user's movement via a video game avatar.

An at-home therapy session with the Motus Hand or Foot can involve different activities—including stretching and exercises that target gross motor control, fine motor control, and endurance—depending on the patient's needs. For instance, the individual in Figure 1b is playing "Cosmic Tennis" — a gross motor control exercise that is similar to the classic arcade game Pong. The user's wrist movements correspond to the movement of the paddle on the screen, with the goal of hitting the ball back and forth to score on the automated opponent.

The sensors in the wrist/ankle joint and corresponding pressure management system collect high-resolution angle and pressure data at a frequency of 30 hertz and store it in a time series database. In our study, we used anonymous data from 33 stroke patients who performed a total of 32,902 therapeutic activities (see Figure 2). Our goal was to autonomously classify a patient's residual stroke severity based on these data.

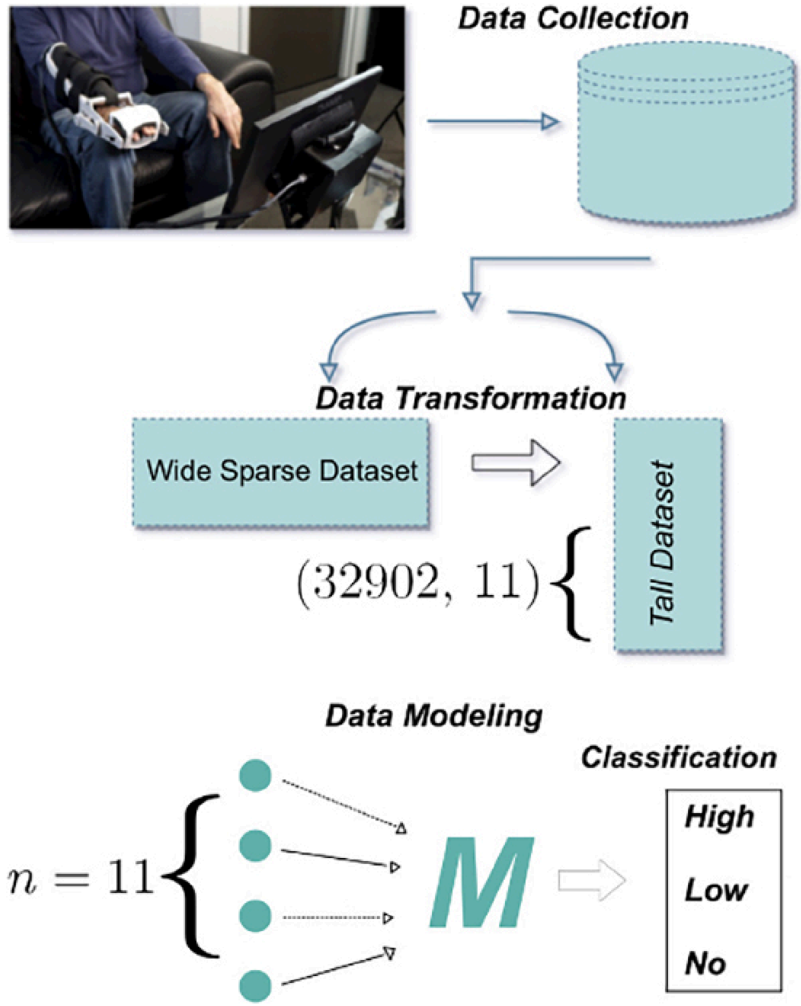


Figure 2. Our study analyzed data from 33 patients who performed at-home therapy with the Motus Hand and Motus Foot rehabilitation devices. Sensors in the devices capture live angle and pressure data, which is processed and summarized to provide statistics for a total of 32,902 therapeutic activities. A total of 11 features (i.e., therapeutic summary statistics such as maximum, minimum, and mean pressure in the pneumatic system) and 32,902 points comprise the base dataset for our analysis. After splitting the data, we used it to train a supervised machine learning model that classifies stroke severity for each patient. Figure courtesy of [3].

To begin, each patient completed a guided assessment with a clinician to classify their range of motion as *high*, *low*, or *none*. These classification levels were intentionally coarse to mimic the environment of an inpatient or outpatient rehabilitation therapy session. Using Motus Nova's self-guided rehabilitation robotics, we generated a model that autonomously classifies stroke survivors into these three broad motor function categories based on low-resolution data that are collected on the time scale of a therapeutic activity. This restrictive approach (without the high-resolution sensor data) allowed us to develop an autonomous classifier that could feasibly assist and potentially free up time for overworked clinicians in an inpatient or outpatient rehabilitation facility.

To efficiently train the classifier, the high-resolution sensor data must be processed and summarized to create a dataset of summary statistics for each therapeutic activity — similar to what would be collected during a traditional rehabilitation facility visit. We smooth the time series via a Gaussian filter to suppress high-frequency oscillations; compute the maximum and minimum angle and pressure for each therapeutic activity; and record the score, activity type, and number of movements. These data summarize each therapeutic activity and the clinician-assigned stroke severity classification for every patient, thus providing the perfect setup to train a classification model.

We compared numerous classification models based on their F1 scores—an evaluative metric that incorporates both precision and recall of a classifier—and presented our results in a recent paper [3]. The top performing model was a type of gradient boosting decision tree known as the Light Gradient-Boosting Machine (LightGBM) [4]. Gradient boosting decision trees are quite popular for their efficiency, accuracy, and interpretability, and LightGBM is an ensemble technique that selectively utilizes the provided dataset to improve training time without impacting accuracy. We found that for all three classification levels, the trained LGBM model had a weighted F1 score of 96.70 percent. This score is more favorable than those of classical methods like logistic regression (55.82 percent) and computationally intensive methods like deep feedforward neural networks (70.11 percent).

Because the model only relies on therapy session summary statistics, we expect our proposed method to perform successfully on comparable rehabilitation datasets. Our trained model is highly portable and can be integrated into other rehabilitation settings—such as outpatient facilities with appropriate technological resources—to provide autonomous, real-time classification of stroke residual severity.

This article is based on a study that was published in late 2024 [3]. Russell Jeter delivered a minisymposium presentation on this research [5] at the 2024 SIAM Conference on Mathematics of Data Science, which took place in Atlanta, Ga., last October.

Acknowledgments: The authors would like to thank Motus Nova, LLC, for providing the raw sensor data that was used in this study. This work was supported by the U.S. National Science Foundation through grant CMMI-1953135.

References
[1] Butler, A., Housley, S.N., Chen, Y.-A., & Wolf, S. (2017). Increasing access to cost effective home-based robotic telerehabilitation for stroke survivors. In *2017 international symposium on wearable robotics and rehabilitation (WeRob)*. Houston, TX: Institute of Electrical and Electronics Engineers.
[2] GBD 2019 Stroke Collaborators. (2021). Global, regional, and national burden of stroke and its risk factors, 1990-2019: A systematic analysis for the Global Burden of Disease Study 2019. *Lancet Neurol.*, *20*(10), 795-820.
[3] Jeter, R., Greenfield, R., Housley, S.N., & Belykh, I. (2024). Classifying residual stroke severity using robotics-assisted stroke rehabilitation: Machine learning approach. *JMIR Biomed. Eng.*, *9*, e56980.
[4] Ke, G., Meng, Q., Finely, T., Wang, T., Chen, W., Ma, W., ... Liu, T.-Y. (2017). LightGBM: A highly efficient gradient boosting decision tree. In *NIPS'17: Proceedings of the 31st international conference on neural information processing systems*. Long Beach, CA: Curran Associates, Inc.
[5] Sorg, L. (2024, October 24). Robotics-assisted stroke rehabilitation device uses machine learning to classify residual severity. *SIAM News Online*. Retrieved from https://www.siam.org/publications/siam-news/articles/robotics-assisted-stroke-rehabilitation-device-uses-machine-learning-to-classify-residual-severity.

MDS24

About the Authors

Russell Jeter

Assistant professor, Georgia State University

Russell Jeter is an assistant professor of mathematics and statistics at Georgia State University.

Raymond Greenfield

Georgia State University

Raymond Greenfield holds a Master of Science in mathematics from Georgia State University.

Steven N. Housley

Assistant professor, Georgia Institute of Technology

Steven N. Housley is an assistant professor of neuroscience at the Georgia Institute of Technology.

Igor Belykh

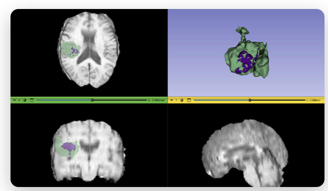
Distinguished University Professor, Georgia State University

Igor Belykh is a Distinguished University Professor of Applied Mathematics at Georgia State University.

Related Reading

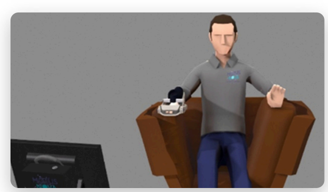
Persistent Homology Identifies Tumor Shapes to Enhance Prognostic Precision

January 29, 2025



Robotics-assisted Stroke Rehabilitation Device Uses Machine Learning to Classify Residual Severity

October 24, 2024



Virtual Heart Simulator Revolutionizes Cardiovascular Science and Healthcare

July 29, 2024