

Refining movement quantitation in stroke

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Background.

Training functional movements is an essential clinical intervention to improve motor recovery after stroke, but a tool to measure training dose in the upper extremities (UE) does not currently exist. To bridge this gap, we previously developed an approach to classify movement primitives, the building blocks of functional movements. This approach combined wearable sensors and a machine learning (ML) algorithm, and achieved encouraging classification performance (positive predictive value (PPV) 79%). However, the approach had computational and practical limitations, such as ML training time and sensor cost and drift. In this study, we sought to refine this approach to facilitate real-world implementation. We determined the ML algorithm, sensor configurations, and data types needed to maximize computational and practical performance in the classification of movement primitives.

Methods.

Motion data were collected from 6 mild-to-moderately impaired stroke patients (2F/4M, mean age 61 years, all right paretic, Fugl-Meyer assessment score 52). Patients wore 11 IMUs on their upper body (hands, forearms, arms, scapulae, sternum, head, and pelvis) and were videotaped while moving objects on a horizontal target array. Trained coders labeled the functional primitives (*reach*, *transport*, *reposition*, and *idle*) using the video data, which simultaneously labeled the IMU data. To identify optimal ML performance, we evaluated four off-the-shelf algorithms that are commonly used in activity recognition (linear discriminant analysis (LDA), naïve Bayes classifier, support vector machine, and k-nearest neighbors). We compared their classification accuracy, computational complexity, and tuning requirements. To identify optimal sensor configuration, we progressively sampled fewer sensors and compared classification accuracy on reduced datasets. To identify optimal data type, we compared classification accuracy using data from IMUs versus accelerometers.

Results.

We found that LDA had the highest classification accuracy (positive predictive value (PPV) 92%) of the ML algorithms tested. It also was the most pragmatic, with low training (26 s) and testing times (0.04 ms) and modest tuning requirements (prior probability, optimizer, amount of regularization). We found that 7 sensors affixed to the paretic hand, forearm, arm, scapula, sternum, pelvis, and head resulted in the best accuracy (PPV 92%). Regardless of sensor number or configuration, accelerometry consistently underperformed relative to IMUs. Using the optimal array of 7 sensors, accelerometry data produced a lower accuracy (PPV 84%) than IMU data. Finally, we found that if only one sensor was available, the forearm location was the most informative, although classification performance was modest (PPV 71% for an IMU).

Conclusion.

Overall, we refined strategies to accurately and pragmatically quantify movement primitives in stroke patients. Of four ML algorithms, LDA represented the best combination of accuracy and practicality. We also found that seven sensors on the paretic UE and trunk optimized classification, while more or fewer sensors worsened classification. The reduction in accuracy with the increased sensor count is likely due to increased dimensionality causing the ML algorithm to overfit the training data. Finally, accelerometry led to poorer classification accuracy than IMU data, likely due to reduced dimensionality of the data. Despite their lesser expense and robustness in a magnetically noisy environment, accelerometers may be inadequate for UE primitive identification. We propose that this optimized ML-IMU approach may support the quantitation of rehabilitation after stroke.