Detecting impaired movements of stroke patients in bimanual training from motion sensor data

Roni Barak Ventura[a,b], Ligao Ruan[a,b], and Maurizio Porfiri*[a,b,c]

[a]Center for Urban Science and Progress, New York University Tandon School of Engineering, 370 Jay Street, Brooklyn, NY 11201, USA

[b]Department of Mechanical and Aerospace Engineering, New York University Tandon School of Engineering, 6 MetroTech Center, Brooklyn, NY 11201, USA

[c]Department of Biomedical Engineering, New York University Tandon School of Engineering, 6 MetroTech Center, Brooklyn, NY 11201, USA

ABSTRACT

Stroke-induced hemiparesis is associated with loss of mobility and independence, preventing survivors from participation in activities of daily living. Survivors can recover motor function of their paretic limbs by adhering to a rehabilitation regimen, consisting of repetitive, high-intensity exercises. In telerehabilitation, information and communication technologies are leveraged to deliver such physical therapy to patients' homes. However, monitoring motor performance remotely remains a challenging task, especially in light of high variability of motor impairments among patients. In order to evaluate motor performance, therapists require the aid of technicians, who would analyze sensor data and produce meaningful metrics. The therapists would then provide patients with feedback, after a few days at best. To automate this process and offer patients real-time feedback, we propose to train machine learning algorithms that detect impaired movements. We test this approach with ten healthy participants who interact with a low-cost telerehabilitation platform we have previously developed. The platform engages users in bimanual training, where movement of the affected arm is supported by the unaffected arm, and relies on a Microsoft Kinect sensor to record user movement. We report the accuracy of a classification algorithm in distinguishing movements of simulated of disability from normal ones. This effort constitutes a significant step toward programmed assessment of upper-limb movements in authentic telerehabilitation paradigms.

Keywords: Data science, Microsoft Kinect, motion analysis, stroke rehabilitation, telerehabilitation

1. INTRODUCTION

Stroke is a leading cause of adult disability in the United States, affecting 795,000 Americans every year.[1] Approximately 80% of stroke survivors experience muscle weakness on one side of the body, a condition known as Hemiparesis.[2] Hemiparesis can severely limit survivors' limb mobility, preventing them from engaging in activities of daily living independently and requiring them to seek costly caregiving.[1]

Stroke survivors can effectively recover muscle strength and regain their independence by adhering to a rehabilitation regimen consisting of frequent and repetitive exercises.[3] Telerehabilitation has emerged as a powerful means to relay such regimens to patients' homes. In telerehabilitation, patients are prescribed with home-based exercises involving an electronic device that measures their movements.[4] Data on their motion is then sent to clinicians, who remotely assess motor performance and provide patients with medical feedback. Through this process, patients are empowered to perform exercises without the need of scheduling appointments or traveling to a clinic, and readily receive professional feedback on their performance at a lower cost.[5]

While the telerehabilitation paradigm offers many advantages, remote analysis of sensor data remains a significant hurdle towards its attainment. In order to evaluate motor performance, a therapist would require the aid of a technician that synthesizes clinically meaningful metrics from measured trajectories. This undertaking

*Further author information: (Send correspondence to M.P.)
M.P.: Email:mporfiri@nyu.edu, Telephone: 1 646 997 3681

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could become especially laborious when the movement being evaluated is atypical due to motor impairment,[6] and the therapist might provide patients with medical feedback only a few weeks later. Thus, automatic identification of movements and scoring of their quality could significantly improve the feasibility and practicality of telerehabilitation.

Machine learning presents a viable means to automate classification of human movements in telerehabilitation. Scientific literature contains multiple examples where machine learning algorithms successfully detect and analyze different human behaviors with high accuracy, as well as deviations from those behaviors.[7–10] We propose to train machine learning algorithms for telerehabilitation that detect atypical movements using data from healthy participants simulating disability.

In this study, we test this approach with a camera sensor-based telerehabilitation platform we have previously developed,[11] consisting of a Microsoft Kinect sensor (Microsoft Corporation, Redmond, Washington), Unity game engine-based software (Unity Technologies SF, San Francisco, CA, USA), and a wooden dowel (Figure 1a). The platform is dedicated to bimanual training such that voluntary movements of the intact limb facilitate voluntary movement of the paretic limb.[12] Specifically, users interact with the interface by performing coordinated movements with both hands holding the dowel. The users could move the cursor and select objects on the screen by performing horizontal shoulder abduction/adduction, shoulder flexion/extension, elbow flexion/extension, and clockwise/counterclockwise rotation of the dowel while perpendicular to the ground.[11]

Herein, we implement a classification algorithm to distinguish atypical movements from normal ones. We collect data on ten healthy people who interact with the telerehabilitation platform twice, once when behaving normally, and again when simulating stroke disability. For proof of concept, we focus on a single movement from the platform's repertoire of eight possible movements: horizontal shoulder abduction/adduction to the right side of the body (Figure 1b). We demonstrate that machine learning could distinguish movement from lack of movement and whether disability was simulated or not with exceptionally high accuracy.

Figure 1. Experimental set-up of the telerehabilitation platform. The user holds a dowel and manipulates it with both hands to control an application that is launched on a monitor (a). A Kinect sensor is positioned below the monitor to record the user's movements. The present study focuses on machine learning of horizontal shoulder abduction/adduction (b).

2. METHODS

2.1 Data collection

The study protocol was reviewed and approved by New York University's institutional review board, the University Committee on Activities Involving Human participants (IRB FY2019-2828). We collected data on ten healthy participants who interacted with our telerehabilitation platform. Each participant was recruited and escorted to a private room where they were briefed on the experimental set-up, simulation of disability, and experimental procedure. Upon granting informed consent, the experiment began.

A calibration phase was initiated by the telerehabilitation platform, aiming to measure the user's range of motion and adjust the software's sensitivity to their movements. During calibration, the participant stood in front of the Kinect sensor and held a dowel with both hands. Starting from a baseline pose with their arms held straight and parallel to the ground, the participant performed horizontal shoulder abduction toward the right side of their body and returned to the center, repeating this movement five times.

Each participant carried out the set of five horizontal shoulder abduction movements twice: once while behaving normally (designated as the control condition; Figure 2a), and once while simulating physical disability (designated as the experimental condition; Figure 2b). Simulation of disability involved standard techniques borrowed from disability awareness training programs.[13–15] The participant wore a cold protection glove (Memphis Flex-Therm, MCR Safety, Collierville, Tennessee) and a wrist brace (ProFlex 675, Ergodyne Corporation, Saint Paul, Minnesota) on one arm. The participant also wore an elastic resistance band (Physix Gear Sport, Miami, Florida) around their torso and the same arm to limit shoulder movement. Five participants simulated disability on their left arm and the other five simulated it on their right arm. The order in which participants performed the control and experimental conditions was counterbalanced.

Throughout the experiment, the Kinect logged the participant's joint positions in three dimensions at a sampling rate of 60 measurements per second.

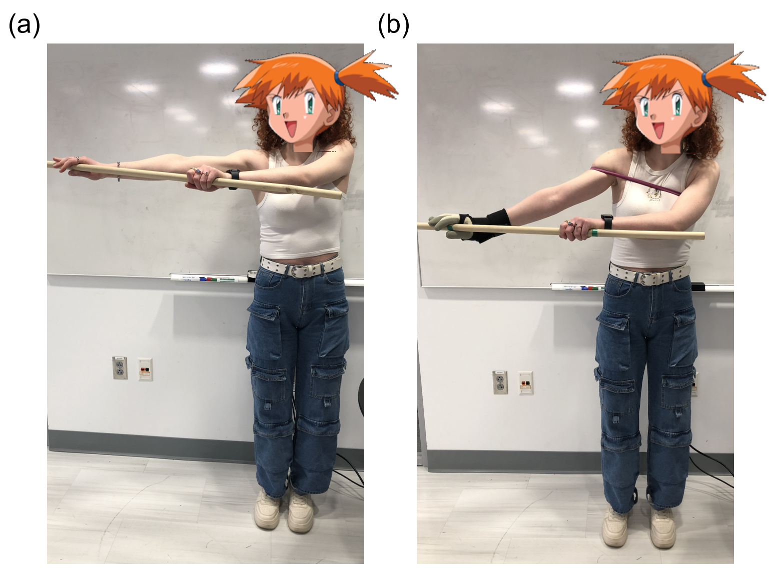

Figure 2. Illustration of the control (a) and experimental (b) conditions. During the experimental condition, participants wore a glove and a wrist brace on one hand, and had their arm tied to their torso using an elastic resistance band.

2.2 Data processing

Data were processed in MATLAB (MATLAB R2022b, The MathWorks, Inc., Natick, Massachusetts, United States). A skeleton model of the user's body was reconstructed from the three-dimensional positions of each joint recorded by the Kinect. The reference frame was defined with its origin fixed at the shoulder-center joint[16,17] (Figure 3). The reference frame was oriented with the X-axis parallel to the ground, the Y-axis perpendicular to the ground, and the Z-axis was orthogonal to the plane produced by the X- and Y-axes, following the right-hand rule. Within this framework, the X-Y, X-Z, and Y-Z planes correspond to the coronal, transverse, and sagittal planes, respectively.

Once the skeleton model was reconstructed, a ninth-order median filter was applied on joint positions to remove noise. Then, for each time step, vectors that corresponded to upper limb segments were computed by

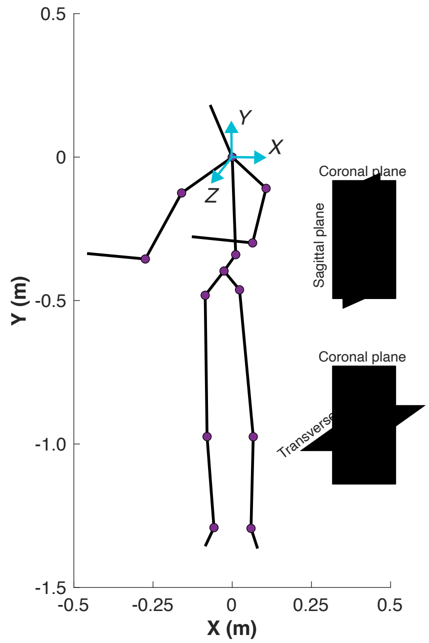

Figure 3. A skeleton model reconstructed from Kinect data, while the participant performed shoulder abduction to the right side of their body. The black lines represent limb segments and the purple circles represent articular joints between them. The reference frame is placed with its origin at the neck, colored in blue.

subtraction of the coordinates of a joint at one end of the segment from the coordinates of the joint at the other end of the segment. Three instantaneous joint angles were subsequently computed for each arm: shoulder horizontal abduction ($\theta_{\mathrm{SA,L}}$ and $\theta_{\mathrm{SA,R}}$), shoulder flexion ($\theta_{\mathrm{SF,L}}$ and $\theta_{\mathrm{SF,R}}$), and elbow flexion ($\theta_{\mathrm{EF,L}}$ and $\theta_{\mathrm{EF,R}}$), where L and R denote the left and right arms, respectively. Shoulder abduction angles were computed by projecting the arm vector onto the transverse plane and computing the angle it formed relative to the ground. Shoulder flexion angles were computed by projecting the arm vector onto the sagittal plane and computing the angle it formed relative to the ground. Elbow angles were computed using the scalar product between the arm and forearm vectors.

For a complete kinematic analysis, instantaneous angular velocities ($\dot{\theta}_{\mathrm{SA,L}}$, $\dot{\theta}_{\mathrm{SA,R}}$, $\dot{\theta}_{\mathrm{SF,L}}$, $\dot{\theta}_{\mathrm{SF,R}}$, $\dot{\theta}_{\mathrm{EF,L}}$, and $\dot{\theta}_{\mathrm{EF,R}}$) and accelerations ($\ddot{\theta}_{\mathrm{SA,L}}$, $\ddot{\theta}_{\mathrm{SA,R}}$, $\ddot{\theta}_{\mathrm{SF,L}}$, $\ddot{\theta}_{\mathrm{SF,R}}$, $\ddot{\theta}_{\mathrm{EF,L}}$, and $\ddot{\theta}_{\mathrm{EF,R}}$) were computed at each time step for each joint by applying a central difference scheme on angle measurements. We also developed features that could inform the type of movement being performed. We applied a moving window algorithm centered about each time step, such that movements are evaluated over several time steps before and after the time step under consideration.[11] The length of the moving window was set to 41 time steps, equivalent to 0.68 seconds. During this time frame, the ranges and variances of elbow and wrist joints positions, velocities, and accelerations along the X-, Y-, and Z-axes were computed. Also, every possible pair of joint position along the X-axis and each joint angular velocity was related by calculating their correlation coefficients. In total, we computed 36 ranges, 36 variances, and 42 correlation coefficients.

Finally, since we attempted to distinguish between the control and experimental conditions during movement, we had to determine whether the participant was moving or unmoving at every measurement. Given joints' angular velocities at each time step t, we identified instances where the participant moved by computing the sum of squared instantaneous angular velocities[18] as

$$\Omega_t = (\dot{\theta}_{\mathrm{SA,L},t})^2 + (\dot{\theta}_{\mathrm{SA,R},t})^2 + (\dot{\theta}_{\mathrm{SF,L},t})^2 + (\dot{\theta}_{\mathrm{SF,R},t})^2 + (\dot{\theta}_{\mathrm{EF,L},t})^2 + (\dot{\theta}_{\mathrm{EF,R},t})^2. \tag{1}$$

Whenever Ω_t was greater than a threshold, we determined the participant was moving in the specified time step. A participant-specific threshold was derived empirically by visual inspection of the time series. We assigned the true class of each measurement based on the condition and the state of moving or unmoving: control/no movement, control/movement, experimental/no movement, and experimental movement.

2.3 Training a machine learning algorithm

We used the Classification Learner app on MATLAB to train an algorithm. In particular, we entered measurements' true classes and the features associated with them as the training data set for all ten users. We applied the Minimum Redundancy Maximum Relevance (MRMR) algorithm[19] to reduce data dimensionality and selected the ten top-ranked features for training. We opted for K-fold cross-validation specifying $K = 5$, and selected ensemble classifier Bagged Trees for the model type. The importance of each feature in the classification process was estimated through "out-of-bag" error.

3. RESULTS

3.1 Data collection and processing

Data were collected on all ten participants with no missing data points. Visual inspection of trajectories showed that participants' range of motion was generally narrower under the experimental condition, relative to the control condition (Figure 4). In total, 41,748 observations were recorded, each containing 168 potential features. The majority of observations belonged to non-movement whereby 16,330 instances of control/no movement and 16,316 instances of experimental/no movement were recorded. In contrast, 4,411 and 4,691 instances of movement were recorded for the control and experimental conditions, respectively.

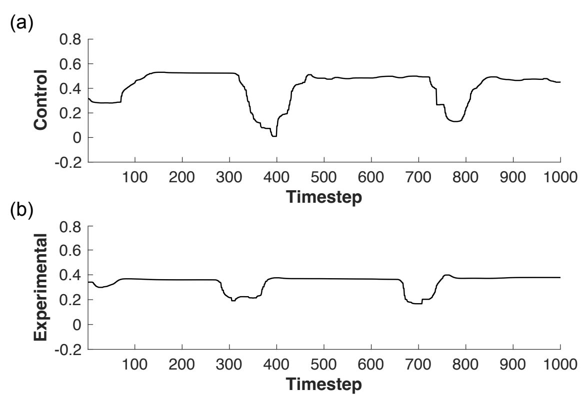

Figure 4. Exemplary trajectories of the right wrist along the X-axis for a user performing horizontal shoulder abduction to the right side of their body when subjected to the (a) control condition and (b) experimental condition.

Variable	Observation	Notation
u_1	right elbow position along the Y-axis	$Y_{\mathrm{E,R}}$
u_2	right shoulder abduction angle	$\theta_{\mathrm{SA,R}}$
u_3	left elbow acceleration along the Z-axis	$\ddot{Z}_{\mathrm{E,L}}$
u_4	variance of the right wrist position along the X-axis	$\mathrm{var}(X_{\mathrm{W,R}})$
u_5	angular acceleration of right shoulder abduction	$\ddot{\theta}_{\mathrm{SA,R}}$
u_6	variance of the left elbow position along the X-axis	$\mathrm{var}(X_{\mathrm{E,L}})$
u_7	left wrist acceleration along the Z-axis	$\ddot{Z}_{\mathrm{W,L}}$
u_8	variance of the right elbow position along the X-axis	$\mathrm{var}(X_{\mathrm{E,R}})$
u_9	left shoulder flexion angle	$\theta_{\mathrm{SF,L}}$
u_{10}	variance of the right wrist position along the Z-axis	$\mathrm{var}(Z_{\mathrm{W,R}})$

Table 1. Summary of the variables used in algorithm training.

True class \ Predicted class	Control, no movement	Control, movement	Experimental, no movement	Experimental, movement
Control, no movement	16196 (99.2%)	105 (0.6%)	28 (0.2%)	1 (0.0%)
Control, movement	112 (2.6%)	4290 (97.3%)	1 (0.0%)	8 (0.1%)
Experimental, no movement	25 (0.2%)	7 (0.0%)	16203 (99.3%)	81 (0.5%)
Experimental, movement	5 (0.1%)	8 (0.2%)	134 (2.8%)	4544 (96.9%)

Table 2. A confusion matrix summarizing the accuracy of the classification algorithm. Each row presents classification of instances in a true class into predicted classes. For example, Control movement was accurately identified as such in 4,290 of 4,411 instances. Thus, the TPR with respect to this class is 97.3%. Across all movements, 41,233 out of 41,748 instances were classified correctly, resulting in a TPR of 98.8%.

3.2 Machine learning algorithm

MRMR reduced the training data set to the ten features summarized in Table 1. Six features contained kinematic metrics, and the remaining four reflected the variance of kinematic metrics. Ranges and correlation coefficients were not selected for the final set of ten features.

Upon training with bagged trees, our model reached an accuracy of 98.8%. The true positive rate (TPR) was highest for experimental/no movement, reaching 99.3% success in classification (Table 1). Classification of experimental/movement was least favored by the algorithm where TPR reached 96.9%. The majority of misclassifications (433 out of 515 falsely classified instances) stemmed from incorrect identification of the state of movement within a condition, rather than across conditions. False negatives across conditions primarily resulted from misclassification of control/no-movement as experimental/no-movement (28 instances) and experimental/no-movement as control/no-movement (25 instances).

Out-of-bag analysis showed that kinematic measurements were most critical in the classification of movements (Figure 5). In particular, $Y_{\mathrm{E,R}}$ and $\theta_{\mathrm{SA,R}}$ were most important, followed by $\ddot{Z}_{\mathrm{E,L}}$ and $\theta_{\mathrm{SF,L}}$. Among the variances, $\mathrm{var}(X_{\mathrm{E,L}})$ was the least important whereas $\mathrm{var}(X_{\mathrm{E,R}})$ was most important for classification.

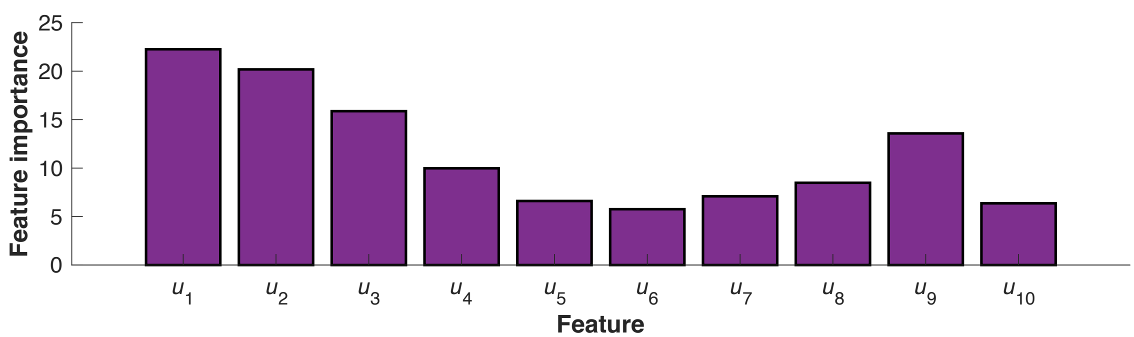

Figure 5. Feature importance based on "out-of-bag" error estimation.

4. DISCUSSION

Automatic identification of movements and their quality has the potential to transform state-of-the-art telerehabilitation regimens. Easing remote assessment of motor performance from sensor data could offer patients frequent feedback on their recovery, and enable the implementation of real-time intervention systems. We propose to advance such remote assessment by introducing a machine learning algorithm that classifies human movements as typical or atypical.

As a first step to attain this goal, we demonstrated the possibility of training a machine learning algorithm that distinguishes movements of simulated of disability from normal ones. We trained a bagged tree algorithm on skeletal data derived from a Kinect sensor. Cross-validation indicated that the algorithm reaches an exceptionally high accuracy of 98.8%. Furthermore, the majority of errors results from misclassifications of instances of movement as instances of stationarity (and vice versa) rather than misclassifications across the control and experimental conditions. This finding suggests that our approach could successfully distinguish atypical movements from typical ones too.

These preliminary results show great promise, yet, they warrant additional analyses. First, the sample of healthy participants must be expanded to account for physical and kinematic variability. Second, the classification algorithm should be trained on the other movements tailored to our telerehabilitation platform, namely shoulder abduction to the left, shoulder flexion (raising the dowel with both arms), shoulder extension (lowering the dowel with both arms), elbow flexion and extension (pushing the dowel forward and back), and composite movements (clockwise and counterclockwise rotation of the dowel while perpendicular to the ground).

Once all movements have been characterized by features, we will train the algorithm to distinguish between all possible movements, when disability is simulated and when it is not. To achieve comparably high accuracy, we may need to develop additional features[20] and compare the performance of alternative classifiers.[21] We will perform out-of-sample generalization with participants whose data was not used in training. These effort will promote programmed assessment of upper-limb movements towards a genuine telerehabilitation paradigm.

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REFERENCES

[1] Virani, S. S., Alonso, A., Benjamin, E. J., Bittencourt, M. S., Callaway, C. W., Carson, A. P., Chamberlain, A. M., Chang, A. R., Cheng, S., Delling, F. N., et al., "Heart disease and stroke statistics—2020 update: A report from the american heart association," *Circulation* **141**(9), e139–e596 (2020).

[2] Dobkin, B. H., "Strategies for stroke rehabilitation," *The Lancet Neurology* **3**(9), 528–536 (2004).

[3] Langhorne, P., Coupar, F., and Pollock, A., "Motor recovery after stroke: a systematic review," *The Lancet Neurology* **8**(8), 741–754 (2009).

[4] McCue, M., Fairman, A., and Pramuka, M., "Enhancing quality of life through telerehabilitation," *Physical Medicine and Rehabilitation Clinics* **21**(1), 195–205 (2010).

[5] Cherry, C. O., Chumbler, N. R., Richards, K., Huff, A., Wu, D., Tilghman, L. M., and Butler, A., "Expanding stroke telerehabilitation services to rural veterans: A qualitative study on patient experiences using the robotic stroke therapy delivery and monitoring system program," *Disability and Rehabilitation: Assistive Technology* **12**(1), 21–27 (2017).

[6] Beckerle, P., Salvietti, G., Unal, R., Prattichizzo, D., Rossi, S., Castellini, C., Hirche, S., Endo, S., Amor, H. B., Ciocarlie, M., et al., "A human–robot interaction perspective on assistive and rehabilitation robotics," *Frontiers in Neurorobotics* **11**, 24 (2017).

[7] Begg, R. and Kamruzzaman, J., "A machine learning approach for automated recognition of movement patterns using basic, kinetic and kinematic gait data," *Journal of Biomechanics* **38**(3), 401–408 (2005).

[8] Novak, D., Reberšek, P., De Rossi, S. M. M., Donati, M., Podobnik, J., Beravs, T., Lenzi, T., Vitiello, N., Carrozza, M. C., and Munih, M., "Automated detection of gait initiation and termination using wearable sensors," *Medical Engineering and Physics* **35**(12), 1713–1720 (2013).

[9] Semwal, V. B., Raj, M., and Nandi, G. C., "Biometric gait identification based on a multilayer perceptron," *Robotics and Autonomous Systems* **65**, 65–75 (2015).

[10] Martinelli, F., Mercaldo, F., Orlando, A., Nardone, V., Santone, A., and Sangaiah, A. K., "Human behavior characterization for driving style recognition in vehicle system," *Computers and Electrical Engineering* **83**, 102504 (2020).

[11] Barak-Ventura, R., Ruiz-Marín, M., Nov, O., Raghavan, P., and Porfiri, M., "A low-cost telerehabilitation paradigm for bimanual training," *IEEE/ASME Transactions on Mechatronics* **27**(1), 395–406 (2021).

[12] Wu, C.-y., Yang, C.-l., Lin, K.-c., Wu, L.-l., et al., "Unilateral versus bilateral robot-assisted rehabilitation on arm-trunk control and functions post stroke: a randomized controlled trial," *Journal of NeuroEngineering and Rehabilitation* **10**(1), 35 (2013).

[13] Clark, M. C., Foos, P. W., and Faucher, M. H., "You can touch this: Simulation exercises for aging and disability," *Educational Gerontology* **21**(7), 643–651 (1995).

[14] Loovis, E. M. and Loovis, C. L., "A disability awareness unit in physical education and attitudes of elementary school students," *Perceptual and Motor Skills* **84**(3), 768–770 (1997).

[15] Wurst, S. A. and Wolford, K., "Integrating disability awareness into psychology courses: Applications in abnormal psychology and perception," *Teaching of Psychology* **21**(4), 233–235 (1994).

[16] Palermo, E., Laut, J., Nov, O., Cappa, P., and Porfiri, M., "A natural user interface to integrate citizen science and physical exercise," *PLoS One* **12**(2), e0172587 (2017).

[17] Pacilli, A., Germanotta, M., Rossi, S., and Cappa, P., "Quantification of age-related differences in reaching and circle-drawing using a robotic rehabilitation device," *Applied Bionics and Biomechanics* **11**(3), 91–104 (2014).

[18] Fod, A., Matarić, M. J., and Jenkins, O. C., "Automated derivation of primitives for movement classification," *Autonomous Robots* **12**(1), 39–54 (2002).

[19] Ding, C. and Peng, H., "Minimum redundancy feature selection from microarray gene expression data," *Journal of Bioinformatics and Computational Biology* **3**(02), 185–205 (2005).

[20] Chang, X., Ma, Z., Lin, M., Yang, Y., and Hauptmann, A. G., "Feature interaction augmented sparse learning for fast kinect motion detection," *IEEE transactions on image processing* **26**(8), 3911–3920 (2017).

[21] Seiffert, C., Khoshgoftaar, T. M., Van Hulse, J., and Napolitano, A., "Rusboost: A hybrid approach to alleviating class imbalance," *IEEE Transactions on Systems, Man, and Cybernetics-Part A: Systems and Humans* **40**(1), 185–197 (2009).