A Rehabilitation Leg Exoskeleton with Biomechanical Feedback

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Abstract

Approximately two-thirds of stroke patients initially experience impaired mobility, and stroke reduces mobility in more than half of survivors aged 65 years and older. Rehabilitation technologies must move beyond repetitive predefined assistance toward systems that can provide compact, efficient, and patient-responsive lower-limb support. This study proposes a deep learning-enhanced lower-limb exoskeleton that integrates a multicriteria-optimized mechanical design with EMG-based movement-intention classification. The mechanical subsystem is designed to improve foot-trajectory accuracy, step height, force transfer, and compatibility with human lower-limb anatomy while reducing structural bulk and actuator complexity. The control system acquires lower-limb EMG signals, extracts time–frequency features using Short-Time Fourier Transform, and classifies movement intentions using a deep learning model to generate corresponding motor assistance.

Multicriteria Optimization

Parameter space:

$$\vec{x} := (x_P, y_P, \xi_0, \eta_0, L)^T$$

$$\vec{P} := (\xi_D, \eta_D, \xi_G, \eta_G, r_{AB}, \varphi_0, \Phi, L_{BC}, L_{CD}, x_E, y_E, L_{EF}, L_{FG})$$

$\xi_{E_i}, \eta_{E_i}, i = 1, \ldots, N$ denote the actual absolute coordinates of the output

$$\xi^*_{P_i} := \xi_0 + \frac{i-1}{N-1}L, i = 1, \ldots, N; \quad \eta^*_{P_i} = \eta_0,$$

where L is the stride length, and $P^*_1(\xi_0, \eta_0)$ is the starting position

Criteria space:

$$c_1 := \max_i \left|\eta^0_P - \eta_{P_i}\right| \to \min, i = 1, \ldots, N.$$ Precision of foot path

$$\delta(\vec{P}) = \delta(\vec{P}, \vec{x}(\vec{P})) = \delta\left(\vec{P}, A^{-1}(\vec{P})\vec{b}(\vec{P})\right) \to \min.$$

$$c_2 := H = -x_4 \to min,$$ – Minimizing the chassis height

$$c_3 := \min_{0 \le \varphi \le 2\Pi}(\mu_{BCD}, \mu_{EFG})$$ To optimize force transfer efficiency, the minimum transmission angle must be maximized

$$c_4 := \frac{L_{FP}}{L_{FG}}$$ Anatomical accuracy

$$c_5 := \sum_{i=1}^{N} \max((\eta_0 - \eta_{P_i}), 0) \to \min$$ To prevent the foot center point P from moving below the reference ground level, a penalty term is implemented:

$$c_6 = \sum_{i=1}^{N} h_i$$ maximizing the step elevation

Solution:

$$A\vec{x} = \vec{b},$$

$$A = \begin{bmatrix} N & 0 & -K & -M & -K_1 \\ 0 & N & M & -K & K_2 \\ K & -M & -N & 0 & -\frac{1}{2}N \\ M & K & 0 & -N & 0 \\ K_1 & -K_2 & -\frac{1}{2}N & 0 & -N\frac{(2N-1)}{6(N-1)} \end{bmatrix}$$

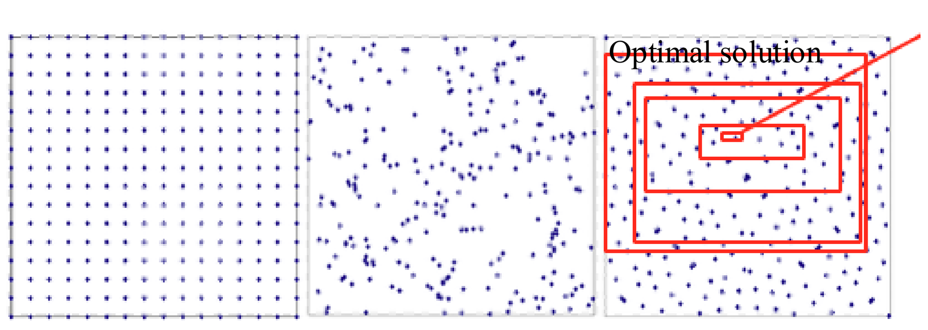
$$\vec{b} = \left[b_5\ b_6\ b_7\ b_8\ -K_3\right]^T,$$

$$K_1 := \sum\left(\frac{i-1}{N-1}\cos\theta_i\right),$$

$$K_2 = \sum\left(\frac{i-1}{N-1}\sin\theta_i\right),$$

$$M := \sum_{i=1}^{N}\sin\theta_i$$

$$K_3 := \sum\left(\frac{i-1}{N-1}\xi_{P_i}\right).$$



Example of different parameter distribution in 2D

$$k := \sum_{i=1}^{N}\cos\theta_i$$

$$m := \sum_{i=1}^{N}\sin\theta_i$$

$$b_1 := \sum_{i=1}^{N}\left(-\xi_{E_i} + L\cdot\frac{i-1}{N-1}\right)\cos\theta_i - \sum_{i=1}^{N}\eta_{E_i}\sin\theta_i$$

$$b_2 := \sum_{i=1}^{N}\left(\xi_{E_i} - L\cdot\frac{i-1}{N-1}\right)\sin\theta_i - \sum_{i=1}^{N}\eta_{E_i}\cos\theta_i$$

$$b_3 := \sum_{i=1}^{N}\left(-\xi_{E_i} + L\cdot\frac{i-1}{N-1}\right)$$

$$b_4 := \sum_{i=1}^{N}(-\eta_{E_i}).$$

$$b_5 = \sum_{i=1}^{N}(-\xi_{P_i}\cdot\cos\theta_i - \eta_{P_i}\cdot\sin\theta_i);$$

$$b_6 = \sum_{i=1}^{N}(\xi_{P_i}\cdot\sin\theta_i - \eta_{P_i}\cdot\cos\theta_i);$$

$$b_7 = -\sum_{i=1}^{N}\xi_{P_i};$$

$$b_8 = -\sum_{i=1}^{N}\eta_{P_i}. = b_4.$$

Table 1: Compromising solutions

LPT	c_1	c_2	c_3 (°)	$\varphi_{support}$ (°)	c_4	c_5	c_6
732	0.015 92	−2.315 12	41.833 99	183.678 71	0.935 98	0.547 27	9.149 69
12432	0.009 65	−2.194 99	26.921 14	187.068 30	0.941 01	0.319 95	5.350 01

Control System

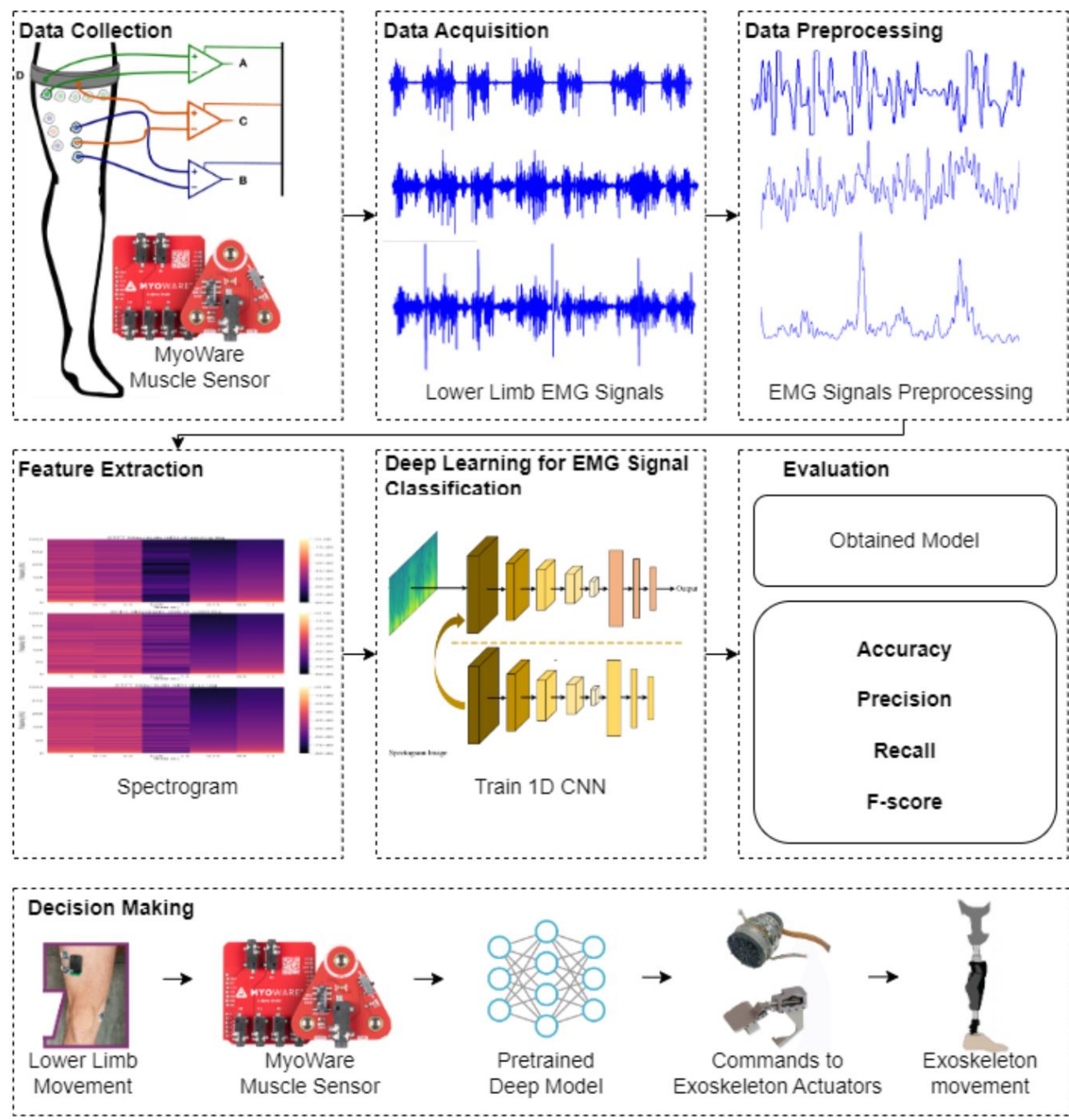
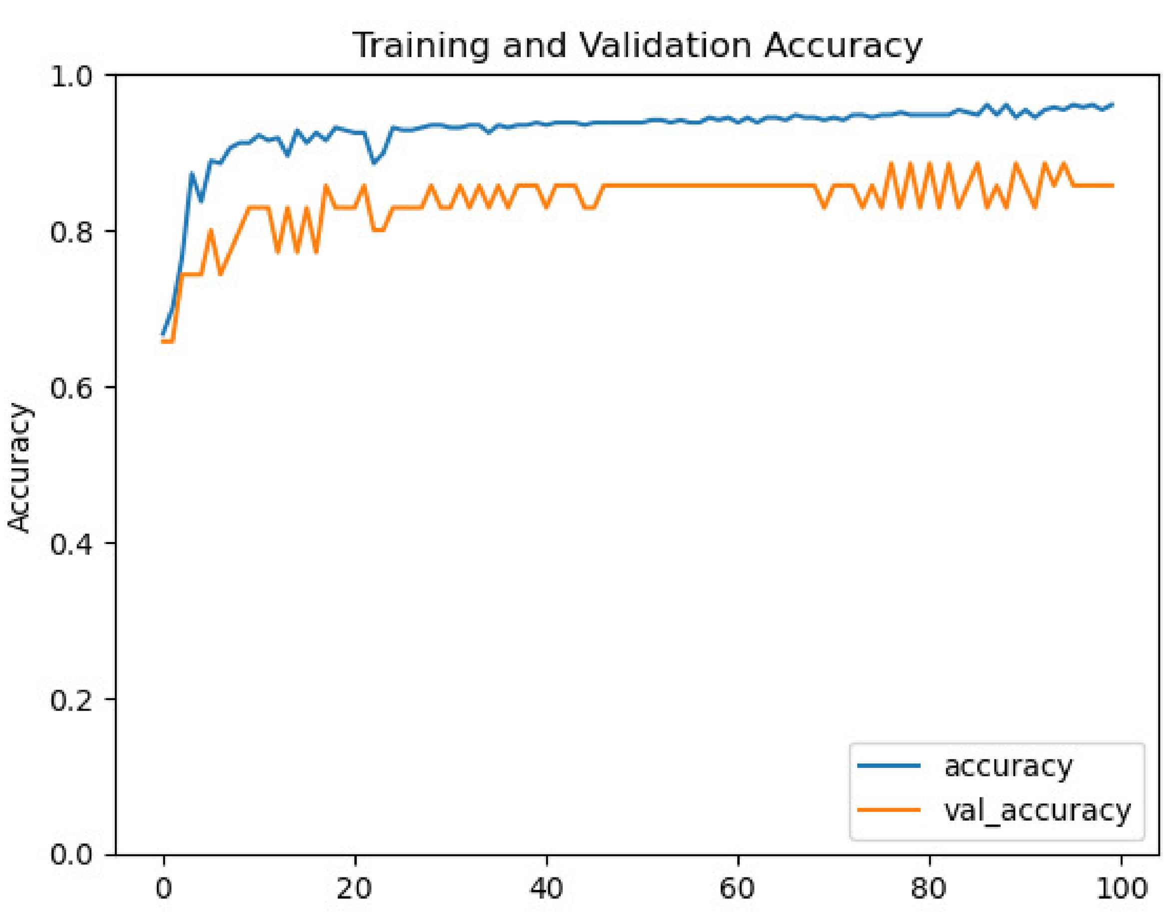
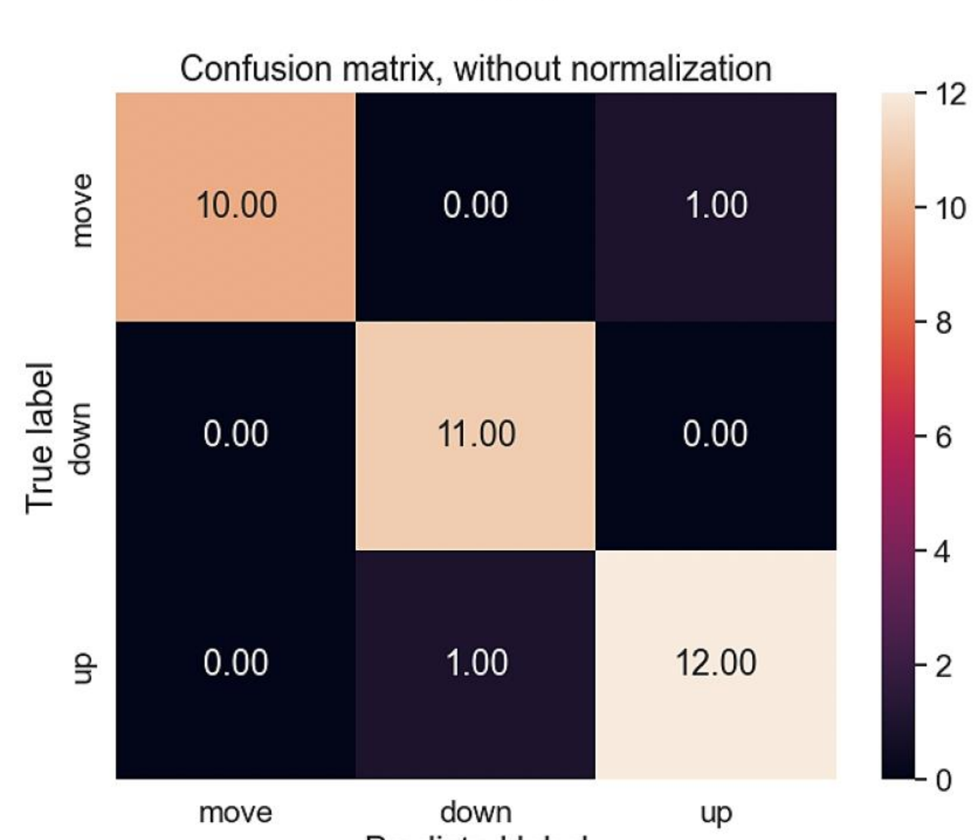


Table 1. Architecture of the proposed model for EMG signal classification.

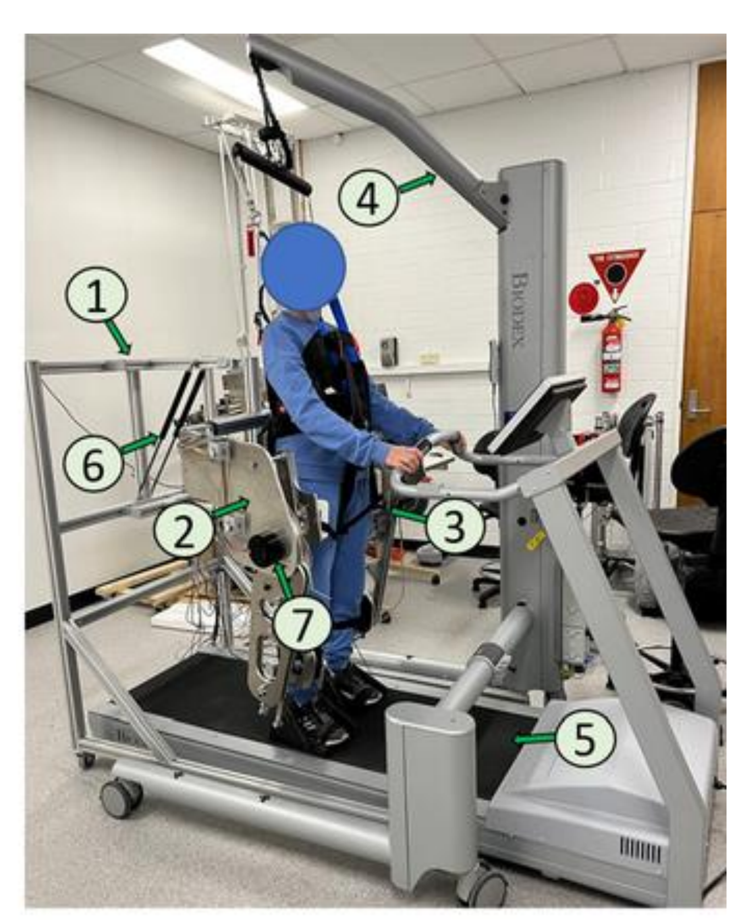
Layer (type)	Output Shape	Param #
Conv1d_32 (Conv1D)	(None, 1023, 32)	512
Max_pooling1d_32 (MaxPooling1D)	(None, 511, 32)	0
Conv1d_33 (Conv1D)	(None, 509, 64)	6208
Max_pooling1d_33 (MaxPooling1D)	(None, 254, 64)	0
Flatten_16 (Flatten)	(None, 16256)	0
Dense_48 (Dense)	(None, 128)	2080896
Dropout_16 (Dropout)	(None, 128)	0
Dense_49 (Dense)	(None, 64)	8256
Dense_50 (Dense)	(None, 3)	195





Conclusion

Multi-criteria optimization delivers an efficient mechanical design (76% trajectory improvement, 1.018 m step height) whose simplified control system is driven in real time by the patient's decoded EMG intent replacing passive trajectory playback with the active engagement that drives neuroplasticity and recovery.



Ref erences

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