could be obtained by counting the number of maxima. Since capabilities between trainees vary a small initial peak threshold θ_{in} was fixed per exercise to detect small motion, while avoiding capturing vibration and noise. Table II provides an overview on the exercises and parameters.

Table II Overview on the rehabilitation exercises and parameter ranges estimated in this work. All parameters were dynamically fitted during system runtime to personalize the training.

Exercise	Motion feature	θ_{in} [degree]	[θ_{min} - θ_{max}] [degree]	[d_{min} - d_{max}] [samples]	[r_{min} - r_{max}] [degree]
Ex1: Arm abductions	Pitch O_y	25	[22.5-22.5]	[3.1-4.6]	[70.4-82.8]
Ex2: Elbow circle	Pitch O_y	15	[13.5-18.9]	[1.5-2.6]	[24.0-42.6]
Ex3: Elbow breathing	Azimuth O_x	15	[13.5-13.5]	[2.5-3.2]	[40.1-68.1]
Ex4: Knee extensions	Pitch O_y	15	[13.5-13.5]	[2.6-3.5]	[58.3-87.0]
Ex5: Leg lifts	Pitch O_y	10	[3.1-9.0]	[2.5-3.3]	[7.6-21.9]
Ex6: Steps up	Pitch O_y	6	[3.1-9.0]	[3.5-4.9]	[13.0-36.4]

3.4.2 Train-mode implementation

Data segmentation. In contrast to the Teach-mode, Trainmode operation requires online period estimation and subsequent performance analysis. A sliding window was used to segment the incoming data stream. The sliding window size was set to cover two average repetitions based on the parameters estimated in the Teach-mode ($2m_d$) with an overlap of 75% between consecutive windows. The overlap ensures timely feedback during a newly detected repetition.

Period estimation. The hill-climbing algorithm was applied in the sliding windows, configured according to the Teachmode. Due to the overlap in sliding windows, duplicate peak detections had to be corrected by matching the peak locations across the sliding windows.

3.4.3 Exercise performance class estimation

Based on the peak detection, repetitions could be counted. To provide timely feedback, i.e. before the trainee starts a subsequent repetition, the first half of a repetition was evaluated to estimate duration and range of motion estimates. In preliminary tests, we observed that the error incurred by considering only half of a repetition was negligible. The derived duration d_i and range of motion r_i estimates were used to compare with the parameters estimated in the Teach-mode, i.e. m_d, σ_d, m_r and σ_r. For duration and range of motion, each repetition performance is estimated based on a Gaussian distribution $N(m_d; \sigma_d)$ and $N(m_r; \sigma_r)$. The performance of each exercise is classified into 3 class types: in-between, under and above the ranges: $[m_d - 2\sigma_d, m_d + 2\sigma_d]$ and $[m_r - 2\sigma_r, m_r + 2\sigma_r]$. In total, there are then nine different classes to which each performed exercise repetition could be associated. While we aimed here at a generic system that can deal with various exercises, some of them may not benefit from all performance classes. For the exercise Steps up, only three performance classes (Correct, Too fast, Too slow) were expected, since step height was fixed by the stairs used, thus range of motion was not relevant for this exercise. After the performance class corresponding to the ongoing repetition was evaluated, an audio feedback was provided to the trainee, to notify if a repetition was erroneously performed. The nine performance classes and feedback are listed in Table III.