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Development of Wearable Technologies to Titrate Rehabilitation Interventions for Individuals with Knee Osteoarthritis

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2025

* This dissertation is presented in partial fulfillment of the requirements for **Ph.D. degree** in the Graduate School of Politecnico di Torino (ScuDo).

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Benito Lorenzo Pugliese

Knee osteoarthritis (OA) is a degenerative joint disease characterized by pain, reduced mobility, and inflammation, affecting daily activities. While exercise can mitigate disease progression, excessive activity may worsen symptoms. Current tools for guiding rehabilitation rely on retrospective self-reports, lacking the real-time precision needed to titrate interventions. Wearable technologies offer a promising approach to capture biomechanical and physiological parameters that may inform such decisions.

This thesis presents two wearable systems aimed at enhancing OA rehabilitation: one for estimating knee flexion-extension during walking, and one for detecting exercise-induced changes in knee skin temperature distribution.

The first system integrates five polymer optical fiber sensors within a sleeve and employs a Long Short-Term Memory network to estimate knee joint angular displacements during walking. Monitoring knee flexion-extension is clinically relevant in OA, where reduced range of motion has been associated with disease progression and symptom severity. Data were collected from 31 healthy participants at multiple walking speeds, using a camera-based motion capture system for validation. Sensor configurations from one to five were tested. The best performance was achieved with three sensors, yielding a median root mean square error (RMSE) of 3.41° (IQR: 2.50° – 5.19°). This configuration demonstrated consistent performance across the gait cycle and was able to detect gait adaptations associated with walking speed. While additional sensors improved robustness, data from sub-optimally placed sensors degraded performance. The system supports accurate, real-world monitoring of knee flexion-extension and may assist in developing personalized walking programs and proactive symptom management. Future work should address signal calibration and dataset expansion to account for variability in sleeve fit.

The second system comprises an array of 12 thermistors with a graphical interface for real-time visualization and recording of knee skin temperature. Prior studies have linked the spatial variance of temperature, quantified by the Heat Distribution

Index (HDI), to inflammatory activity in OA. In this study, data from 10 healthy participants were collected at baseline and during recovery after treadmill running, with thermal camera images used as reference. The system detected significant HDI changes between pre- and post-exercise conditions and captured recovery trends consistent with thermal imaging data. Simulations with virtual thermistors evaluated the influence of number of sensors, placement, and misplacement on HDI estimation accuracy. Bias remained negligible; variance decreased with increasing sensor count, reaching a standard deviation of approximately 0.25°C with 12 sensors. Distributed placement outperformed peripheral layouts ($R^2 = 0.44$, $p < 0.001$), and landmark-based placement performed comparably to optimized configurations. Minor displacements had minimal effects, except in outlier cases. These results support the feasibility of a wearable thermistor array to detect exercise-induced HDI changes, offering a potential tool for tracking inflammation in knee OA. Enhancing sensor contact while allowing for skin perspiration may improve reliability.

Together, these systems demonstrate the feasibility of wearable technologies to capture biomechanical and thermal responses relevant to OA rehabilitation. Simulation results offer design guidelines for sensor count and placement, informing future system iterations. Collectively, these findings lay the groundwork for real-time, data-driven rehabilitation strategies tailored to individuals with knee OA.

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