TReC 2026 - Merged Project Proposal

1. Administrative Data & Project Information

Project Title: From Rich Laboratory Actimetry to Sparse Real-Life Monitoring: Multimodal Learning, Sensor Sparsification and Virtual Patients for Post-Stroke Activity Modelling

Team Leader: Nicolas Bioul (nicolas.bioul@uclouvain.be)

Identified Team Members: Corentin Warzée (UCLouvain), Martin Collot (ULB)

Domain of Application: Healthcare

Scientific Theme: Active & Weakly-supervised Learning

2. Abstract

This project aims to develop multimodal machine-learning methods for modelling physical activity and sedentary behaviour in healthy and post-stroke individuals using wearable actimetry data. It builds on a controlled laboratory dataset collected in the context of Louise Macq's PhD research, including accelerometers, pressure insoles with IMUs, heart-rate monitoring and ergospirometry during standardized rest, walking and upper-limb tasks.

The central scientific challenge is to translate reliable inference from a richly instrumented laboratory protocol to lighter, acceptable and clinically deployable monitoring configurations. Inspired by the rich-to-low multimodal distillation strategy developed in DRESIA, the full laboratory configuration will be used as a high-observability 'teacher' model, while reduced wearable configurations will be trained as 'student' models for future home-based or rehabilitation-centre monitoring. DRESIA explicitly frames this transition as a domain-shift problem between controlled and ecological environments, requiring transfer learning, sensor sparsification and robustness to missing modalities.

The project will therefore investigate which minimal subset of sensors preserves reliable recognition of postures, walking patterns, upper-limb movements and post-stroke-specific motor profiles. It will also explore virtual patient modelling, generating plausible synthetic movement profiles to augment small clinical datasets and test model robustness under sensor loss, noise and altered gait patterns.

3. Background Information & Scientific Rationale

Ageing, neurological impairment, and loss of autonomy create a growing need for reliable technologies that can support people in daily life while limiting the burden on clinicians, caregivers, and families. Current actimetry protocols often rely on multiple wearable devices placed on different body locations. This rich configuration is valuable in laboratory conditions because it provides complementary information on posture, gait, asymmetry, energy expenditure and compensatory upper-limb movements. However, such configurations are burdensome for long-term clinical use: they increase setup complexity, reduce acceptability, create battery and synchronization constraints, and are difficult to deploy in home-based rehabilitation.

This creates a methodological gap: signals acquired in a controlled environment cannot be assumed to transfer directly to ecological settings. We will identify two sources of divergence: domain shift, where signal statistics change between laboratory and real-world conditions, and phenomenological shift, where the nature of the interaction itself changes in ecological contexts. In post-stroke monitoring, the analogous problem is that treadmill walking, standardized rest and controlled upper-limb movements differ from daily-life mobility, where activities are irregular, noisy, interrupted and context-dependent.

The project therefore reframes sensor reduction not only as an engineering simplification, but as a scientific problem of ecological transfer: how can a model trained with rich laboratory observability remain reliable when only sparse, noisy and incomplete real-life signals are available?

4. Project Objectives

The project has five core objectives:

- Develop baseline multimodal models for activity recognition using the full laboratory sensor configuration.
- Perform systematic sensor sparsification, ranking sensor locations and modalities according to predictive value, robustness and practical feasibility.
- Implement a teacher-student learning framework: the full multimodal laboratory model will act as a teacher, while reduced-sensor models will learn to approximate its latent representation and predictions.
- Explore virtual patient modelling, using controlled actimetry patterns to generate plausible post-stroke movement profiles, including altered gait speed, asymmetry, compensatory movements, fatigue and missing-sensor scenarios.
- Define a first roadmap for translation from laboratory actimetry to home-based or rehabilitation-centre monitoring.

5. Project Dataset

The project will rely primarily on a controlled wearable-sensor dataset for post-stroke human activity recognition, provided through Louise Macq's PhD work. It currently includes 18 healthy participants and 18 post-stroke participants, with a planned target of 20 participants per group.

Participants were equipped with six accelerometers positioned on the wrists, hips, and ankles, as well as pressure insoles integrating IMUs and accelerometers. During data collection, participants followed a standardized laboratory protocol including resting phases (lying, sitting, and standing), treadmill walking at different speeds, and upper-limb movements. For healthy participants, walking speeds included 1, 3, and 5 km/h; for post-stroke participants, speeds were adapted to motor capacities, ranging from 0.5 to 5 km/h. Energy-expenditure data were also collected using an ergospirometer and a heart-rate belt.

This dataset is labeled, controlled, and multimodal, making it perfectly suited for supervised human activity recognition, gait/activity analysis, sensor-reduction experiments, and teacher-student distillation.

6. Team Composition & Work Plan

Expected Team Roles (6 people):

- Person 1 (Project coordinator / clinical interpretation): Defines clinical questions, validates post-stroke relevance, interprets gait and rehabilitation markers.
- Person 2 (Data preprocessing lead): Synchronizes signals, cleans data, segments windows, aligns labels.
- Person 3 (Machine-learning lead): Builds baseline activity-recognition models and evaluates performance.
- Person 4 (Sensor sparsification lead): Runs ablation studies (ankles only, wrists only, hips only, insoles only, HR only, combined minimal sets).
- Person 5 (Teacher-student / transfer learning lead): Implements rich-to-low distillation from full multimodal teacher to sparse student models.
- Person 6 (Virtual patient / simulation lead): Generates synthetic profiles, missing-sensor scenarios and augmented sequences.

Concrete Deliverables:

- D1 - Clean synchronized multimodal dataset: Segmented activity windows, aligned labels, quality-control report.
- D2 - Baseline multimodal activity-recognition benchmark: Performance of classical models and lightweight neural models using the full sensor setup.
- D3 - Sensor sparsification matrix: Ranking of sensor combinations according to accuracy, F1-score, robustness, comfort and deployment feasibility.
- D4 - Rich-to-low distillation prototype: Teacher model trained on full laboratory actimetry; student models trained on reduced sensor subsets.
- D5 - Virtual post-stroke patient generator: Synthetic or perturbed movement profiles modelling gait asymmetry, slower walking, fatigue, compensatory upper-limb activity and missing sensors.
- D6 - Final dashboard / notebook: Interactive visualization of activity recognition, sensor trade-offs, patient profiles and real-versus-simulated sequences.
- D7 - Short scientific report: A 6-8 page report structured as a workshop paper, including methodology, results, limitations and future clinical translation.

7. Multidisciplinarity: Bridging STEM & SSH

The project is strongly multidisciplinary, combining STEM methods with SSH perspectives to address a healthcare problem that is both technical and human.

On the STEM side, the project involves machine learning, time-series analysis, wearable sensing, human activity recognition, and sensor-reduction methods (rich-to-low distillation). Participants will work with multimodal data from accelerometers, IMUs, pressure insoles, and heart-rate monitoring.

On the SSH side, the project addresses how these technologies are interpreted, trusted, and used by clinicians, caregivers, and post-stroke individuals in ecological settings. The goal of sensor sparsification is directly linked to patient comfort, acceptability, and autonomy. Furthermore, testing robustness against real-world noise ensures that detected activities or anomalies are meaningful in real care contexts, limiting the risk of alarm fatigue. The project asks how machine-learning outputs can become understandable and actionable for real users, ensuring the development of trustworthy AI systems that are technically robust, clinically relevant, and socially acceptable.

8. Bibliographic References

- Lara OD, Labrador MA. A Survey on Human Activity Recognition using Wearable Sensors. IEEE Communications Surveys & Tutorials, 2013.
- Hammerla NY et al. Deep, Convolutional, and Recurrent Models for Human Activity Recognition using Wearables. IJCAI, 2016.
- Roggen D. et al. Collecting complex activity datasets in highly rich networked sensor environments. INSS, 2010.
- Wang J. et al. Deep Learning for Sensor-based Activity Recognition: A Survey. Pattern Recognition Letters, 2019.
- Haresamudram H. et al. Assessing the Need for Wearable Sensors in Human Activity Recognition. IEEE PerCom Workshops, 2020.
- Reiss A., Stricker D. Introducing a New Benchmarked Dataset for Activity Monitoring. ISWC, 2012.
- Ward, J. A., et al. Activity recognition of assembly tasks using body-worn microphones and accelerometers. IEEE PAMI, 2006.
- Gupta S. et al. Cross Modal Distillation for Supervision Transfer. CVPR, 2016.
- Ma M. et al. Learning with Missing Modalities for Multimodal Activity Recognition. IEEE Transactions on Multimedia, 2021.
- Bioul, N., et al. A novel approach in testing life-monitoring technologies for ageing in place: A focus on fall detection and behavioural alerts. ICT4AWE, 2024.