Department of Instrumentation and Applied Physics Seminar Series

From Biomechanical Priors to Probabilistic Models: Explainable Learning-Based Motion Anomaly Detection for Rehabilitation

Date: 4th Feb 2026 **Time:** 3PM **Venue:** ONLINE

Abstract: Reliable detection of anomalous motion is critical in many medical applications, particularly in neurorehabilitation, where compensatory movement strategies may enable task completion while undermining long-term recovery. Despite growing interest in learning-based approaches, most existing methods rely on dense, expert annotations and task-specific models, limiting scalability, generalization, and clinical adoption.

In this talk, I present a sequence of learning-based methods we developed for anomalous motion detection that progressively reduce annotation requirements while improving interpretability and task generality. I begin with an approach that integrates biomechanical priors through energy-based features and linear classifiers to detect anomalous, compensatory movement and to identify contributing joints without requiring time-resolved compensation labels. This work demonstrates that embedding domain knowledge can yield strong performance and interpretability even with simple models.

I then introduce an unsupervised anomaly detection framework that models distributions of healthy movement using probabilistic movement primitives. Deviations from these normative models are used to detect anomalous motion in stroke patients, while the explicit probabilistic structure enables localization of anomaly sources and differentiation between compensatory and inhibited degrees of freedom. Validation on clinical datasets shows high detection accuracy and robust source identification, particularly under high inter-rater agreement.

Finally, I present a task-agnostic probabilistic formulation that models normative joint configurations conditioned on end-effector pose, motivated by evidence that anomalous motor behavior often manifests as atypical joint postures despite preserved task outcomes. Using conditional normalizing flows, this approach enables likelihood-based anomaly detection and joint-level interpretability without reliance on task-specific models or dense expert annotations.

Together, these works illustrate a progression from biomechanically informed feature-based models to fully probabilistic, learning-based frameworks for anomalous motion detection that are interpretable, annotation-efficient, and well suited to real-world medical applications.

MS. NEHA DAS

DOCTORAL CANDIDATE AT THE TECHNICAL UNIVERSITY OF MUNICH

About the Speaker

Ms.Neha Das is a doctoral candidate at the Chair of Information-Oriented Control at the Technical University of Munich. Previously, she received a Master’s degree in Informatics from Technical University of Munich, Germany, and a Bachelor’s degree in Software Engineering from Delhi Technological University, Delhi, India.

Her research interests are at the intersection between healthcare, machine learning, and control. She is interested in modeling dynamical systems representing human biomechanics, learning representations of healthy human motor behavior, and data-driven anomaly detection and correction of motor behavior. Additionally, she is interested in learning-based control using human feedback.