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Fatigue-aware Motion Prediction in Collaborative Assembly

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Abstract

In production environments involving human-robot collaboration, effective management of motion-induced fatigue is critical for optimizing productivity and safeguarding worker well-being. Human movements in collaborative industrial tasks are inherently complex, shaped by repetitive task execution, time constraints, and continuous physical interaction with robotic systems. These characteristics motivate the need for robust methods capable of predicting and mitigating human physical fatigue within dynamic and fast-paced collaborative workflows. Autonomous generation of postural data, independent of body instrumentation and physical data collection setups, offers a compelling alternative for addressing these challenges. This work adopts an integrated approach that combines physics-based simulation with visual pose-based motion analysis to evaluate fatigue in upper-limbs movements during collaborative tasks. CAD-based human and robot models are employed to generate representative motion primitives, onto which fatigue coefficients and temporal decay models are applied to emulate progressive degradation in upper-limb motion performance. The resulting fatigue-modulated motion patterns are encoded using posture-based representation and dynamic movement primitives. The fatigue-induced motion patterns are deployed within a ROS2_RViz simulation environment, where they serve as inputs for robot tracking and adaptive task pacing. By capturing deviations in motion kinematics and timing across repeated task cycles, the proposed framework enables real-time fatigue estimation and supports adaptive adjustment in human-robot task coordination.

Keywords
Human fatigue; pose estimation; task allocation; HRC; virtual simulation.

1. Introduction

The increasing demands for customized products in manufacturing has accelerated the adoption of human-robot collaborative assembly (HRCA) as a means of improving productivity and flexibility (Ajoudani et al., 2018). HRCA systems combines the precision and endurance of robots with the adaptability and cognitive capabilities of the human operator (Villani et al., 2018). However, unlike robotic systems that maintain consistent performance over extended work cycles, human workers are subject to physical limitations, particularly muscle fatigue, which can degrade motion quality, reduce productivity and compromise occupational safety (Ajoudani et al., 2018). This mismatch can lead to reduced coordination, suboptimal task allocation, and inefficiencies in human-robot collaboration (Haddadin and Croft, 2016).

Repetitive industrial tasks, especially those involving sustained upper-limb movements, are known to accelerate fatigue accumulation, increase task completion times, with a higher risk of musculoskeletal disorders (Ajoudani et al., 2018, Villani et al., 2018). In the automotive industry, for instance, workers frequently engage with their upper body in repetitive assembly tasks that involve arm movements, making them particularly susceptible to fatigue. Unlike rigid robotics, repetitive motions of the human limbs result in the accumulation of muscle fatigue (Lorenzini et al., 2019), which induces changes in the motion patterns of the human partner. Collaborative assembly involves close interaction between humans and robots, often requiring real-time task adaptation (Kim et al., 2021).

The complexity of such interactions underscores the growing research on the dynamics of collaborative assembly. Given the complex nature of human movement and its implications for task allocation and pacing in collaborative assembly, the autonomous generation of postural and motion data plays a critical role in enabling scalable modelling and simulation of human-robot collaboration. Effective management of motion-induced becomes necessary not only to improve operational efficiency but also to protect worker health in industrial environments.

Recent reviews on collaborative assembly research highlight the need for non-invasive, fatigue-aware task reallocation strategies that avoid body instrumentation while maintain reliable fatigue assessment (Yonga Chuengwa et al., 2023). In addressing these needs, virtual simulations offer a promising solution by enabling systematic analysis of various collaborative task configurations and human-robot interaction dynamics. It is worth nothing that the accuracy and computational performance of such simulation depend on the fidelity of CAD-based anthropomorphic models and the automated generation of motion data (Thakur et al., 2009). Nevertheless, advancements in model-based simulation have a significant impact on real-world assembly scenarios. In practice, these models enable comprehensive analysis and optimization without reliance on physical experimental setups.

To predict and mitigate motion-induced fatigue in collaborative environments, digital human models (DHMs) can be augmented with fatigue coefficients and decay models to simulate realistic degradation in human motion. Such models help identify ergonomic stress points and fatigue-sensitive motion segments (Maurice, 2015, Vignais et al., 2013). Such simulation-based approaches reduce experimental cost and enhances adaptability (Malik et al., 2020).

This paper presents a simulation-driven framework for modelling task pacing in a collaborative assembly while explicitly accounting for human physical fatigue. The proposed approach integrates digital simulations, fatigue-modulated motion primitives, and pose-based motion encoding to generate realistic human movement patterns during collaborative tasks. An autonomous DHM and a virtual robot are deployed in ROS2_RViz environment, where fatigue-induced deviations in human motion are captured and used to adapt robot pacing and coordination in real-time.

The remainder of this paper is organized as follows. Section 2., explores related work on human fatigue management in manufacturing and assembly environments. Section 3., describes the case study and the simulation framework. Section 4 presents and discusses the results and Section 5., concludes the paper, outlining future research directions.

2. Literature Review

Early-stage planning of manufacturing processes plays a critical role in production systems design, with modelling serving as a key decision-support tool. Beyond replicating observed conditions, modelling enables scenario exploration, data extrapolation and evaluation of alternative system configurations. Assembly operations represent a major of manufacturing investment and employ a substantial proportion of the industrial workforce (Abdous et al., 2022, Dalle Mura and Dini, 2021).

In human-involved assembly processes, operational safety and system feasibility are strongly influences by human performance, which directly affects cycle time and quality (Alkan et al., 2016). It is widely accepted that integrating ergonomic considerations during the design phase reduces costly interventions during later production stages (Boothroyd, 1994, Abdous et al., 2022). Despite growing interest in human-robot collaboration, systematic modelling and control approaches that explicitly address collaborative task pacing under human fatigue remain limited. Figure 1., illustrates the sustained growth in HRC research and comparatively smaller contributions of ergonomics-related studies.

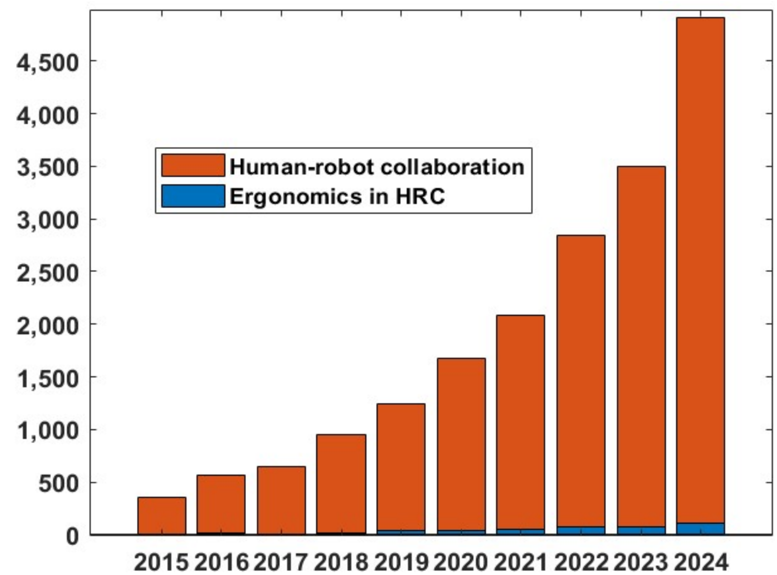

Figure 1: Research publications on human–robot collaboration (2015 - 2024), highlighting the contribution of ergonomics-related studies.

Beyond physical safety, the studying of robots without fatigue to improve workers' fatigue management in the hybrid human-robot assembly cell has not been effectively explored (Cai et al., 2022). Unlike robots, repetitive motions of the human limbs lead to progressive muscle fatigue, resulting in altered kinematics and reduced interaction performance (Lorenzini et al., 2019). Human fatigue levels in collaborative systems depend on factors such as motion speed, posture, task duration, and individual characteristics, which distinguish human capabilities from robotic ones (Dalle Mura and Dini, 2021).

While studies in (Chen et al., 2011)., have demonstrated HRC can reduce assembly time and cost, production planning for shared workspaces introduces additional complexity in task scheduling and line balancing problem (Weckenborg et al., 2020). Consequently, HRC research in manufacturing and assembly has attracted research interest in multiple domains, including task allocation (Atashfeshan et al., 2021, Messeri et al., 2022), collision avoidance and safety (McGhan and Atkins, 2009, De Luca et al., 2006), and the integration of human flexibility with robotic precision (Heydaryan et al., 2018, Boschetti et al., 2022).

While manual assembly still suffers from poor synchronisation, instability and frequent physical overload on the human (Dalle Mura and Dini, 2021), limited industrial adoption of HRC has been attributed to stringent safety requirements and the lack of engineering tools for analyzing variable functions within collaborative systems (Saenz et al., 2018, Wang et al., 2019).

2.1 Task allocation

Task allocation is the strategic assignment of operations to available resources based on their capabilities (Messeri et al., 2022). In deterministic HRC settings, human and robot typically execute task sequentially. Emerging studies in (Malik et al., 2020)., emphasize the need to balance cognitive load and physical exertion during task allocation to sustain performance and safety. Human-robot line balancing aims to maximise task allocation efficiency while maintaining precision, speed, and safety in shared workspaces. This requires explicitly considering human factors, particularly worker fatigue, during optimisation. Accordingly, task allocation can be formulated as a multi-objective optimisation problem that seeks to (i) minimise the unexpected task load variability on the human across cycles and (ii) maximise the probability of satisfying task precedence constraints expressed though linear temporal logic (Wu et al., 2017).

2.2 Muscle fatigue estimation

Motion analysis is essential in understanding coordination in HRC, as muscle fatigue alters movement kinematics and reduces functional capacity. In manual material handling, fatigue modelling refers to the experimental attempt to describe the process of fatigue in the muscle of the upper arms (Lorenzini et al., 2019). Such models are typically used to determine the onset of fatigue to optimize manual activities.

Localized muscle fatigue manifests as reduced force generation, discomfort, and impaired motor control (Aquino et al., 2022). Key influencing factors include load intensity, repetition frequency of work, and task duration. Mathematical fatigue models are widely used to describe force decay and recovery dynamics and to simulate the impact of task conditions on joint capabilities. A commonly adopted formulation is expressed as:

$$F_c(t)_i = F_{MVC_i} . \, e^{-\int K_i \frac{F_{Load}(t)}{F_{MVC_i}} dt} \tag{1}$$

where $F_c(t)$ is the force production capacity of muscle i at a time t, F_{MVC_i} is the maximum voluntary contraction, $F_{Load}(t)$ represents the task-induced load, and K_i is a fatigue sensitivity coefficient. The model incorporates biomechanical constraints through generalised human joint coordinates $[X_0^T \;\; \theta_0^T \;\; q_h^T]^T$, enabling simulation of performance degradation during prolonged tasks.

2.3 Simulation of co-manipulated activities considering ergonomics

Human-involved assembly processes are inherently stochastic due to variability in human behavior leading to unpredictable event sequences (Haninger et al., 2022). Incorporating ergonomic factors into collaborative operations is steadily becoming a central research focus (Dalle Mura and Dini, 2019). In such probabilistic environment, the collaborative state must be continuously inferred to allow robot controllers to adapt to planned and unplanned human actions (Ajoudani et al., 2018, Haninger et al., 2022).

Simulation-based approaches provide a cost-effective means of analyzing and optimizing collaborative performance prior to physical deployment. For example, authors (Tsarouchi et al., 2017)., proposed a ROS-based task allocation framework enabling automated motion synchronization, where each resource is represented as a service node. Imitation learning or learning by demonstration enables robots to infer task execution strategies from human demonstrations (Zhang et al., 2022). Kernelized motion primitives have been proposed to preserve properties of demonstrated trajectories while enabling generalization to unseen situations (Huang et al., 2019).

Within this context, Dynamic Movement (DMPs) have emerged as a particularly powerful framework for modelling continuous motion in HRC. Originally proposed in (Ijspeert et al., 2001), DMPs represent movements as stable attractor systems. This formulation enables trajectories learned from human demonstrations to be generalised across goals and time scales while preserving qualitative motion characteristics (Boas et al., 2023).

3. Methodology and implementation

Physics-based modelling integrates biomechanical principles and digital human simulation to estimate joint torques, interaction forces, and fatigue development under near realistic task conditions. Embedding such biomechanical representations within physics engines enables dynamic simulation of human motion across varying interaction scenarios. Figure 2., shows the digital human model (DHM) used for motion and fatigue data generation. The upper limb of the DHM is generally employed to simulate arm dynamics and generate target-directed motion trajectories.

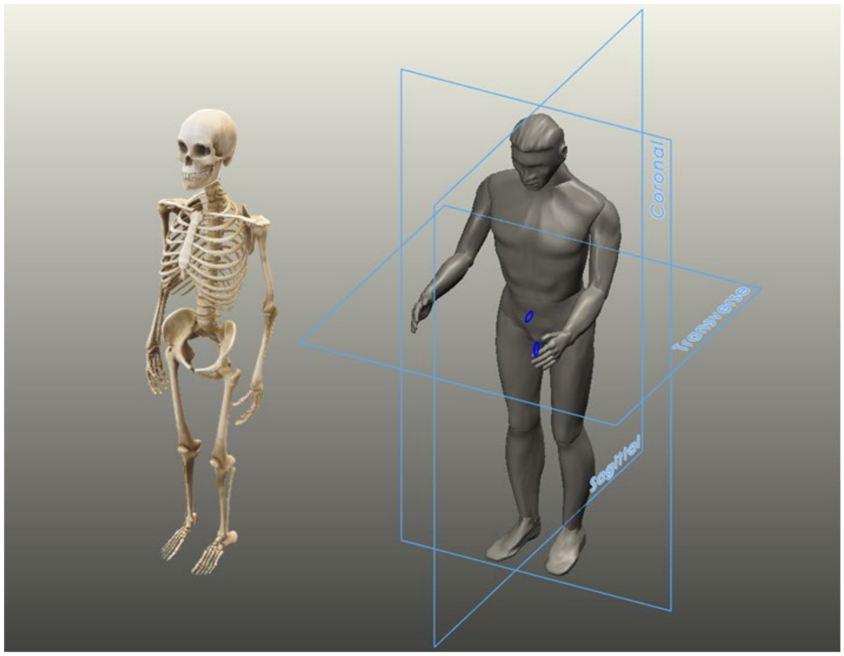

Figure 2: Digital human model illustrating structure and anatomical reference planes (sagittal, coronal, and transverse) used for physics-based simulation.

3.1 Human motion analysis

Human motion analysis predicts joint kinematics required for the end-effector to reach a target in Cartesian space while accounting for external loads and fatigue progression. The task represents the motion to be performed by the upper arm model, which can either be the execution of a specific operation or the motion required to reach a target. Figure 3., presents a simplified 7-DOF human arm model in the sagittal plane. The end effector (hand) must reach the target point, with the motion being constrained by the increasing fatigue in the arm. Human posture is assumed to govern task performance, with joint torques expressed using Euler-Lagrange formulation.

$$M_i = I_i\ddot{\theta}_i + C_i\theta_i + G_i + W_i r_i \qquad (2)$$

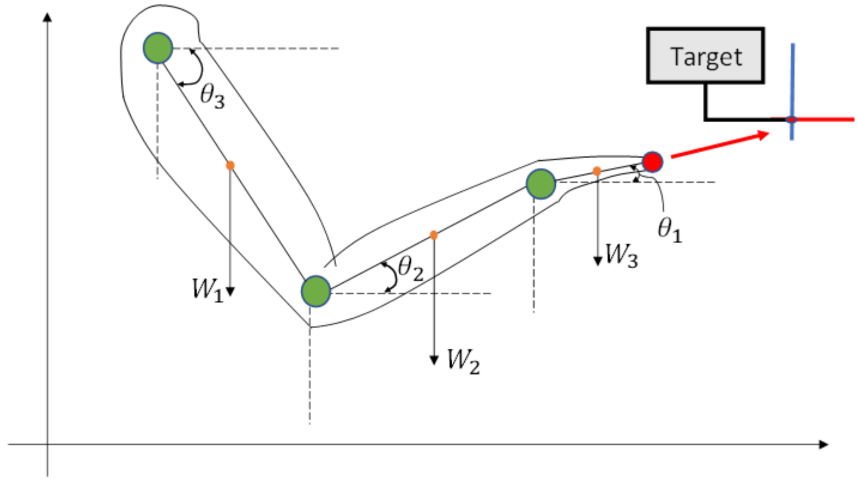

Figure 3: Posture prediction of a human arm reaching a target point under dynamic constraints.

To account for fatigue-induced degradation of force-generation capacity, joint torques are modulated by a fatigue coefficient $F_i(t)$, which reduces the ability to generate torque over time. The resulting moment becomes Equation 3. Human tasks are translated into kinematic constraints, and forward kinematics using Denavit-Hartenberg (D-H) parameters to predict posture evolution while adapting motion to fatigue progression.

$$M_i^{fatigue} = F_i(t) \cdot \left(I_i\ddot{\theta}_i + C_i\theta_i + G_i + W_i r_i\right) \qquad (3)$$

3.2 Human ergonomics data generation

For progressive reaching and interaction analysis, the upper limb is modelled as a planar 3-DOF kinematic chain (shoulder-elbow-wrist), where joints trajectories are defined as time-parameterized functions: $\boldsymbol{\theta_i(t) = f_i(t)}$ **(4).** These time-parameterized curves are then propagated through forward kinematics to obtain the evolving hand path, as illustrated in Figure 4. Joint torques are computed using rigid-body dynamics in Equation 5. These quantities form the basis for ergonomics assessment, fatigue estimation, and motion prediction

$$\tau_i(t) = I_i\ddot{\theta}_i(t) + C_i(\dot{\theta}) + G_i(\theta) + F_i \qquad (5)$$

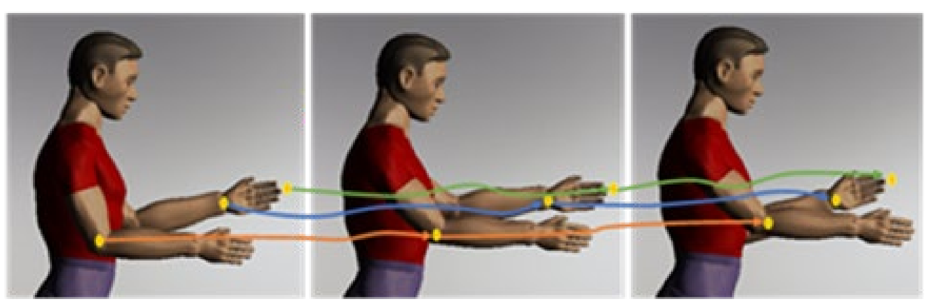

Figure 4: Spatiotemporal evolution of upper-limb joint motion during a reaching task.

3.2 Robot parameterization

Robot behavior is parameterized to account for fatigue and joint overload, extending the approach of authors (Kim et al., 2021). The robot predicts human exerted force f_h and adapts its motion to minimize human joint torque while maintaining task feasibility. Figure 5., summarizes the fatigue-aware interaction loop. The robot predicts this load and compensates by shifting the task dynamics, modifying its own movement, and providing support in a way that minimizes the human's exerted force.

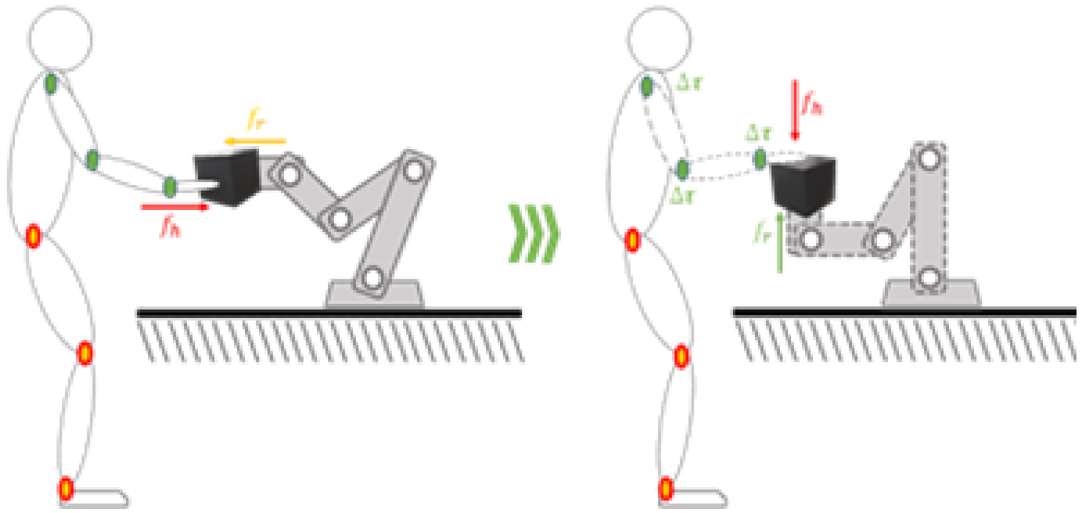

Figure 5: The procedure for fatigue estimation and overload joint torque reduction in human-robot collaboration

The collaborative task is formulated as a multi-objective optimization problem (MOOP) that minimizes (i) human joint overload and fatigue accumulation and (ii) deviation from task timing and precedence constraints. The resulting optimal human motion trajectories serve as inputs to the DMP-based formulation in Section 4,, ensuring consistency between ergonomics optimization and motion generation.

4. Results and discussion

Human-like trajectories are generated using the minimum-jerk principle [36], during point-to-point movement. Polynomial trajectory fitting estimates coefficients from previous and current motion data [37], enabling smooth, fatigue-aware motion synthesis compatible to DMP modulation. From the simulated motion data (Figure 6a), deviations in end positions at contact points under fatigue conditions are quantified. To integrate fatigue effects into human motion generation, the DMP formulation is modified in two ways: (i) decay of temporal scaling and (ii) modulation of forcing term.

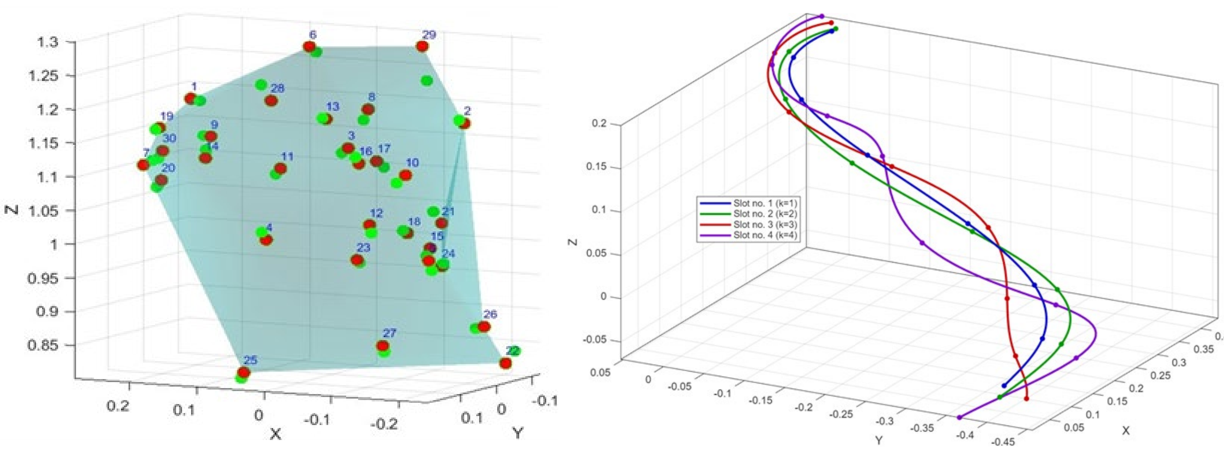

Figure 6: a) comparison of nominal (green) vs fatigue-affected (red) contact points; b) Comparison of the baseline and fatigue-affected elbow trajectories. The blue curve represents the baseline (non-fatigued) motion, while the others progressively show the fatigue-affected conditions.

Fatigue-dependent constraints are imposed on initial velocity and acceleration to improve robustness under variable fatigue conditions. Specifically, fatigue-dependent weights modulate the forcing term $f(x)$, while the temporal scaling τ decays over successive task cycles (Equation 6 and 7). The coupled fatigue parameters result in trajectories that gradually deviate from their nominal paths, reflecting accumulated fatigue. These deviations become prominent at critical interaction points such as handover and alignment locations (Figure 6b).

$$\tau\dot{v} = K\,(g - y) - Dv + Kf(x) \tag{6}$$

$$\tau\dot{y} = v \tag{7}$$

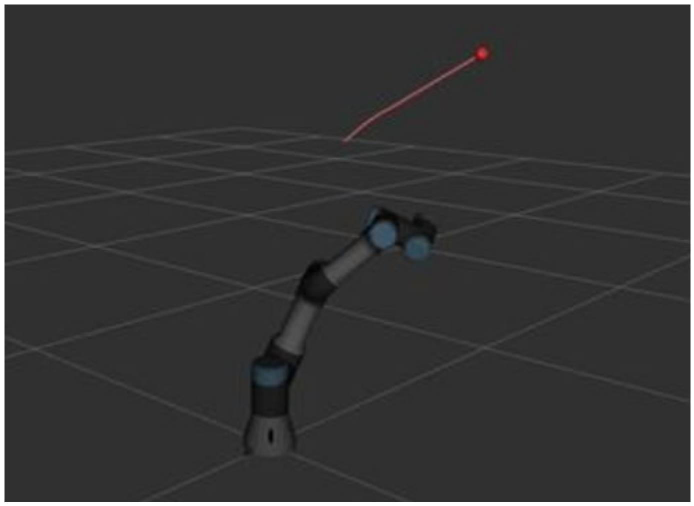

Figure 7: Visualization in RViz of a robot tracking a human elbow joint (red dot) trajectory under fatigue

To validate real-time applicability, fatigue-affected trajectories are deployed ROS2_RViz environment, where a UR3 tracks the predicted human fatigue-induced elbow motion (Figure 7).

6. Conclusion

The results demonstrate that human fatigue induces measurables deviations in upper-limb trajectories and contact point during collaborative tasks. By modulating both the temporal and forcing terms of the DMP formulation, fatigue-affected motion is realistically reproduced in simulation. The integration of fatigue aware DMP trajectories into a ROS2_RViz environment enables real-time robot adaptation without reliance on body instrumentation.

Combining pose-based estimation methods with behavior-level motion prediction establishes a scalable framework for foundation models in fatigue-aware HRC systems. Future work will leverage vision-based pose estimation and multi-frame temporal analysis to enhance autonomous robot adaptation to human physical fatigue.

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Biographies

Mr Yonga Chuengwa is a Doctor-Engineering Candidate with a focus on Human–Robot Collaboration. His current work explores fatigue-aware human motion adaptation. In addition, he has interest in engineering education, particularly in the use of project-based learning (PBL) and technology-enhanced teaching approaches. His experience includes facilitating and supporting learning environments that promote critical thinking, problem-solving, and practical application of engineering concepts. Yonga Chuengwa holds a master's degree in technology management from Tshwane University of Technology, a B-Tech in Mechanical Engineering from University of South Africa and a National Diploma in Mechatronics Engineering from Tshwane University of Technology

Dr. Mukondeleli Kanakana -Katumba is a distinguished academic leader and Industrial Engineer with over 18 years of strategic experience in higher education. Currently serving as the Deputy Vice-Chancellor for Teaching, Learning, and Student Affairs at the Vaal University of Technology, she has previously held senior leadership roles at the Tshwane University of Technology and the University of South Africa. Her leadership has shaped policy and innovation across engineering and built environment disciplines, particularly in teaching, research, transformation, and community engagement. Dr. Kanakana-Katumba holds a DPhil in Engineering Management from the University of Johannesburg, an MBA from Nelson Mandela Metropolitan University, and a master's in systems engineering from George Washington University.

Prof. Jan Adriaan Swanepoel is an Associate Professor in the Department of Industrial Engineering at the Tshwane University of Technology (TUT). His expertise spans industrial engineering, engineering management, and strategic operations. He is noted for his research on technological organizational design for Industry 4.0, and engineering data analysis. He previously served as Acting Chief Engineer and Section Head at the Department of Water and Sanitation (2017), managing large capital infrastructure projects.

Prof. Anish Mathew Kurien received his DTech in Electrical Engineering with specialization in Telecommunication Technology from the Tshwane University of Technology (TUT), Pretoria, South Africa in 2012, and his PhD in Computer Science (Joint Degree) from the University of Paris-Est, Champs-sur-Marne, France in 2012. Since 2010, he has been the Node Director of the French South African Institute of Technology (F'SATI) at TUT. He has been the Telkom Centre of Excellence Head at TUT since 2010. In 2022, he was appointed as TETA Research Chair focusing on the development of an Agile and Open Transport Industry. Since June 2023, he has been appointed as the Acting Director of the TUT Hub of the Artificial Intelligence Institute of South Africa (AI-ISA). Prof Kurien has 25 years of experience in the Higher Education sector, has supervised and co-supervised over 39 postgraduate students since 2006, contributed to over 100 publications in journals, peer-reviewed conference proceedings, book chapters, one book, and a patent. His research interests include feature extraction and pattern recognition, mobile and wireless networks, and application of AI & ML approaches to various sectors of industry