LIGHTEN THE LOAD: HARNESSING MACHINE LEARNING AND WEARABLE SENSORS TO ESTIMATE JOINT LOADING DURING INDUSTRY-RELEVANT TASKS

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Introduction:
Lower-limb joint injuries remain prevalent in manual labor tasks on construction sites and warehouses where tasks involve moving heavy loads with awkward postures. Modifications to workers' kinematic patterns have not yet resolved the problem, so companies have sought out wearable devices to assist users and offload daily bodily wear and tear. However, such equipment can be costly to distribute to an entire company's workforce; therefore, there is a need to find inexpensive, portable, and reliable wearable sensing systems to provide 'real-time' monitoring of joint loads in the work environment. For this, we can look to IMUs and pressure insoles to measure segment positioning and ground reaction forces, respectively [1]. Wearable sensors have shown promise for estimating risk of injury [2], joint moments [3] and joint contact forces (JCFs) [4], but the minimal sensor inputs needed to build a reliable biological joint loading estimation tool are unknown. We hypothesized that combining IMU and insole data as input to a deep learning model would provide the best performance ($R^2 > 0.7$) at estimating both biological joint moments and JCFs at the knee and back during industrial lifting tasks.

Methods: In this study, we assessed the performance (R^2) of a temporal convolutional network (TCN) trained for estimation of participant-dependent biological joint moments and internal joint contact forces using simulated wearable sensors: IMUs and insoles (Fig. 1A). Our N=9 'ground truth' dataset consisted of moments and contact forces at the L5/S1 and knee joint (Fig 1A). Each participant performed 24 combinations of lifting conditions, with varying lifting turn symmetries (0°, 90°, 180°) and start-end heights (knee-to-waist (KW), waist-to-knee (WK), shoulder-to-waist (SW), waist-to-shoulder (WS), and waist-to-waist (WW)). On this dataset, we utilized the TCN to estimate L5/S1 and knee joint contact forces and biological moments with variation in wearable sensing inputs 1) IMUs and insoles, 2) IMUs *only*, and 3) insoles *only*. IMU data were simulated from inverse kinematics and transformed into the reference frame of sensor-segment locations and insole data were transformed from force plates. Joint moments and contact forces were computed using OpenSim 4. The machine learning models were executed via Python scripts and their R^2 values were evaluated with MATLAB scripts using the *fitlm* function.

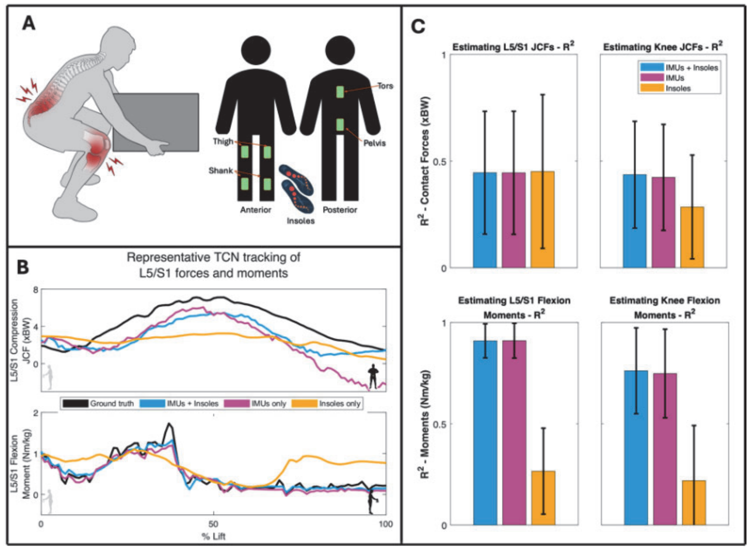

Figure 1: (A) We targeted our estimates of 'ground truth' biomechanical outputs at the L5/S1 and knee joint (left) using simulated IMUs (green) and insoles as inputs (right). (B) A representative time series of L5/S1 compression joint contact force (JCF) and biological L5/S1 flexion moment estimates compared to ground truth (black) using IMUs + insoles (blue), IMUs *only*, (pink), and insoles *only* (gold) during asymmetric lifting. (C) Group averages of each model's performance in estimating contact forces and biological moments at the L5/S1 and knee across all lifting tasks.

Results & Discussion: We found that utilizing IMUs *only* as input to a TCN model had comparable performance to utilizing both IMUs + insoles in estimating joint contact forces (Fig. 1C, top). This contradicted the notion that ground reaction forces would provide useful additional information when added to motion data – especially for internal states like joint contact forces (JCFs). Overall, the TCN estimated joint moments (average $R^2 = 0.64$) better than JCFs (average $R^2 = 0.42$). For JCFs, L5/S1 compression estimates using IMUs + insoles, IMUs *only*, and insoles *only* ($R^2 = 0.45, 0.45, 0.45$) showed negligible differences - whereas estimates of knee compression forces using IMUs + insoles ($R^2 = 0.44$), and IMUs *only* ($R^2 = 0.42$) showed an improvement of 53% and 49%, respectively, compared to using insoles *only*. Estimates of L5/S1 flexion moments using IMUs + insoles ($R^2 = 0.91$), and IMUs *only* ($R^2 = 0.91$) provided a 242.0% and 242.4% improvement versus insoles *only* ($R^2 = 0.27$). Similarly, knee flexion moment estimation using IMUs + insoles ($R^2 = 0.76$), and IMUs *only* ($R^2 = 0.75$) provided a 248% and 242% improvement compared to insoles *only* ($R^2 = 0.22$). Overall, using IMUs as the lone input to a TCN-based joint kinetic estimator may be effective for monitoring external states (e.g. joint moments), but falls short of providing accurate estimates for more indirect states like joint contact forces (JCFs) – even when insole data are incorporated. Because JCFs depend primarily on forces from muscles surrounding the joint – it may be necessary to incorporate sensors that indicate muscle force/activation (e.g., EMG, or bioimpedance).

Significance: Our findings highlight the potential to employ a consolidated set of wearable sensors and machine learning tools for estimating joint kinetic variables related to injury risk 'in the field'. More work is needed to find the optimal set of sensor types and locations to improve estimates further. Long-term, we hope to realize lean, wearable technology capable of warning people doing demanding physical work when they are using hazardous postures – so they can modify their behaviours and reduce injury risk.

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References: [1] Manupibul et al., 2023. [2] Nurse et al., 2023. [3] Molinaro et al., 2022. [4] Giarmatzis et al., 2020.