Estimating Knee Joint Contact Forces During Daily Activities Using a Five-IMU Setup

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***Abstract*—The estimation of internal joint loading is critical for assessing musculoskeletal health in daily life. This study proposes a simplified method for estimating knee joint contact forces (JCF) using only five inertial measurement units (IMUs) placed on the pelvis, upper legs, and lower legs. Data were collected from three healthy adults performing activities of daily living (ADL) in a home-like environment. Kinematics and ground reaction forces (GRF) were estimated using segment orientations and accelerations, and the virtual pivot point (VPP) concept. Joint reaction forces were then computed using a musculoskeletal model in OpenSim through static optimization and joint reaction analysis. Results showed strong correlations, larger than 0.79, with a mean Root Mean squared Error (RMSE) of 1.06 body weight (BW), that is about 15% relative to the maximum reference range, compared to a reference full-body system. Some error peaks occurred before toe-off, likely due to kinematic inaccuracies. These findings support the feasibility of accurate JCF estimation with minimal instrumentation, enabling real-world monitoring and potential clinical applications. Future work will address calibration improvements to reduce localized estimation errors.**

***Index Terms*—Knee joint contact force, inertial measurement units, musculoskeletal modeling, ground reaction forces, biomechanics.**

I. Introduction

Estimating internal joint loading is essential for understanding joint mechanics and monitoring musculoskeletal health. Abnormal joint loading has been linked to the development and progression of various conditions, such as osteoarthritis (OA), where elevated or uneven knee joint forces may accelerate cartilage degeneration [1]. Accurate estimation of joint contact forces (JCFs) is therefore important not only in clinical diagnosis but also in rehabilitation and intervention design.

Internal joint loads can be directly measured using instrumented implants, such as those featured in the CAMS-Knee dataset, which provide detailed in vivo force and kinematic data during functional activities [2]. However, this approach is limited to individuals who have undergone total joint replacement surgery, making it unsuitable for the general population. As a non-invasive alternative, lab-based systems estimate joint loads by combining optical motion capture, force plates, and musculoskeletal simulation platforms like OpenSim [3].

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Several studies have evaluated the accuracy of these modeling approaches by comparing predicted knee contact forces against in-vivo measurements. Pelegrinelli et al. [4] compared three generic OpenSim models in gait and sit-to-stand tasks, finding good agreement in peak magnitudes and temporal force patterns. Similarly, Imani Nejadetal. [5] validated OpenSim simulations using the CAMS-Knee datasets and reported strong correlations ($\rho = 0.92$) and acceptable root mean square error (RMSE) of 0.48 times body weight (BW) during gait. These findings support the feasibility of using generic musculoskeletal models to estimate internal knee loading with good accuracy under controlled conditions.

However, these lab-based approaches require extensive equipment, limiting their use in real-world environments. Wearable inertial measurement units (IMUs) offer a portable and cost-effective alternative. Full-body IMU systems, such as the 17-sensor configuration used by Konrathetal. [6], have demonstrated strong agreement with lab-based systems when estimating knee joint contact forces during daily activities. In a clinical cohort of patients with knee osteoarthritis, Di Raimondo et al. [7] demonstrated that IMU-based estimates of peak tibiofemoral contact forces were not significantly different from those obtained via traditional motion-capture methods, highlighting the clinical validity of portable IMU-based load assessment in this patient population. While such full-body systems represent a significant step toward out-of-lab mobility assessment, their relatively bulky setup still poses challenges for routine clinical or home-based applications. As a result, there is growing interest in reducing the number of sensors required while still maintaining sufficient accuracy in estimating internal joint loads. Zangene et al. [8] employed artificial neural networks to estimate knee contact forces for a single leg from 3 IMUs pleced on pelvis, thigh, and shank, demonstrating promising accuracy during level walking. However, this data-driven approach has not yet been generalized to a broader range of daily activities, limiting its current utility in out-of-lab scenarios.

To address this, the present study proposes a simplified approach using only five IMUs placed on the pelvis, thighs, and shanks to estimate internal knee JCF during activities of daily living (ADL).

II. Methods

We conducted the study in the eHealth House at the University of Twente, a home-like environment ideal for simulating daily activities. Three healthy adults (two males; 1.72 ± 0.03 m, 66.1 ± 4.6 kg, 26 ± 2 years) participated, all wearing size 41 (EU) Force Shoes$^{\text{TM}}$. Ethical approval (nr. 241037) was obtained from the EC-CIS committee and informed consent was collected.

The reference system consisted of the Xsens$^{\text{TM}}$ MVN Link motion capture setup (Enschede, The Netherlands) [9], which included sensors on the lower limbs, pelvis, and sternum to provide full-body kinematics and raw inertial data at 240 Hz. Ground reaction forces (GRF) were measured with Xsens Force Shoes$^{\text{TM}}$ [10] (sampled at 100 Hz, mean accuracy 15 ± 2 N), and center of pressure (CoP) was recorded with Moticon$^{\text{TM}}$ (Munich, Germany) Pressure Insoles (PI) at 100 Hz.

The proposed system was composed of five IMUs, placed on the pelvis, upper legs, and lower legs. Calibration of reference system followed standard procedures using MT Manager (v17.4) for Force Shoes$^{\text{TM}}$ and N-Pose and straight-line walking for MVN Link system and a custom sensor to segment calibration for the proposed system detailed in the following sections.

After calibration, participants performed four tasks, each repeated 3 times: (1) Timed Up and Go test (TUG), Free Walking (FW) around the living environment performing some specific tasks such as moving objects in the kitchen, adjusting curtains, opening/closing closet door and turning on and off the water at bathroom sink, and (3) Stairs Ascending/Descending (SAD).

A. Kinematics estimation

To estimate kinematics of the lower limbs, first a calibration procedure is required. During the calibration phase, we aligned the sensor frame (ψ_S) with the body frame (ψ_B) using a sensor-to-segment calibration procedure based on the method described by Bonnet et al. [11]. As presented in Figure 1, the vertical (V) axis was estimated from accelerometer data during a static pose, the mediolateral (ML) axis was identified using Principal Component Analysis (PCA) as the direction of greatest variance during specific movements. For the pelvis, participants performed three bowing movements, while straight-line walking was used for the upper and lower legs. Finally, the anteroposterior (AP) axis was derived as the cross product of the vertical and ML axes. After that we computed joint angles of the hips and knees using segment orientation ($\mathbf{q}$) as follows:

$$\mathbf{q}_{\text{rel}} = \mathbf{q}_{\text{Proximal}}^{-1} \otimes \mathbf{q}_{\text{Distal}} \tag{1}$$

where $\mathbf{q}_{\text{rel}}$ is transformed to Euler angles in the *ZYX* order and the definition of proximal and distal segments is shown in Figure 1. For the ankle joint we decided to lock it (by setting joint angles to zero) as the orientation of the foot is not measured and we observed that the influence of that on the model is not significant, as shown in Figure 2.

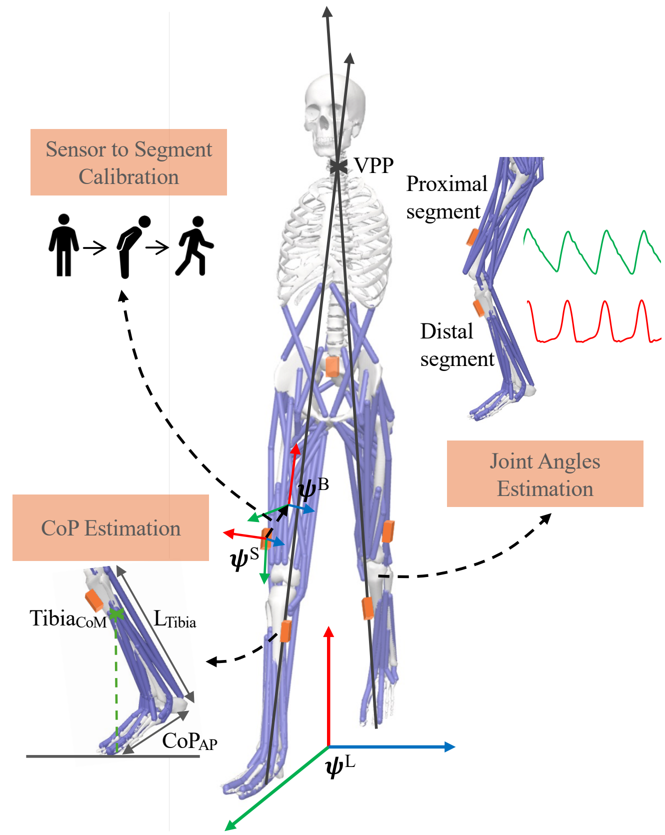

Fig. 1. Experimental setup and data processing pipeline. The figure illustrates the wearable sensor configuration used in the study, the sensor-to-segment calibration procedure, center of pressure (CoP) and joint angle estimation, and the conceptual representation of the Virtual Pivot Point (VPP) used to estimate Ground Reaction Forces (GRF).

B. Kinetics Estimation – GRF and CoP

To estimate the total GRF, we applied Newton's second law by multiplying the subject's mass with the acceleration of the body's center of mass. The overall body acceleration was approximated as a weighted average of the accelerations of the pelvis and lower limb segments, with the shank and foot considered as a single combined segment. Then, to split total GRF between feet during double support, we employed the method of our previous work [12]. The Virtual Pivot Point (VPP) concept distributes the estimated total GRF across the feet using the full lower-body kinematic chain comprising the pelvis, upper legs, lower legs, feet and pressure insoles. However, our recent work [13] demonstrated that comparable accuracy can be achieved by limiting the kinematic input to only the segments from pelvis to ankles. So, segment orientation is used to express relative position between pelvis and ankles and apply the VPP distribution method. As a remark, for TUG, the sit-to-stand task was not included in the analysis because of the limitation in [13] to estimate GRF as other forces are acting on the body and the Center of Mass (CoM) lays outside the body. For the CoP estimation, we adopted the method introduced in [14], which computes the

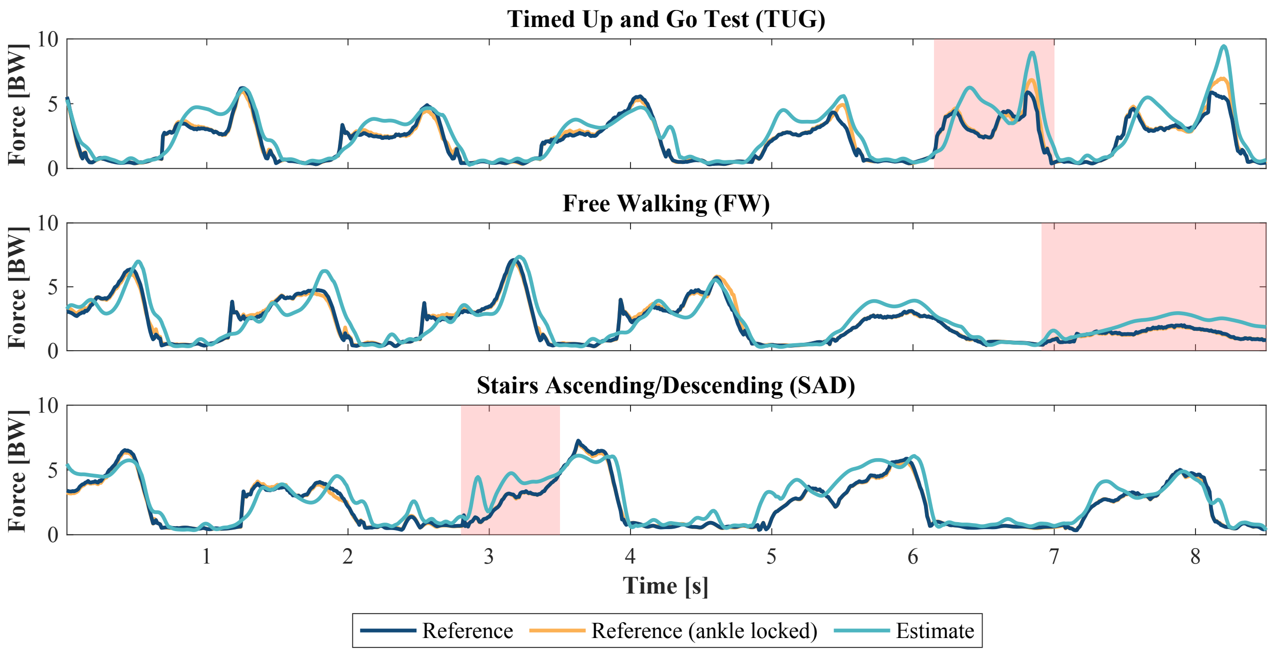

Fig. 2. Knee JCF Estimation of Timed Up and Go test (TUG), Free Walking (FW), and Stairs Ascending/Descending (SAD) trial for Subject 3: A 8.5-second snapshot overview. The dark blue curve depicts the outcomes of the reference, the light blue curve represents the estimate, and the orange curve represents the estimate with the ankle joint unlocked. The red shaded areas illustrate the inaccuracies due to kinematics estimation.

anteroposterior (AP) component of the CoP in the foot frame using the orientation of the shank IMU and the known shank length. Specifically, the CoP position in the foot frame is as follows:

$$\mathrm{CoP}^{\mathrm{F}}_{\mathrm{AP}} = \sin(\theta_{\mathrm{shank}}) \cdot l_{\mathrm{shank}} \cdot r_{\mathrm{CoM}} + \frac{l_{\mathrm{PI}}}{2}, \tag{2}$$

where $\mathrm{CoP}^{\mathrm{F}}_{\mathrm{AP}}$ is the CoP in the AP direction expressed in the foot frame, θ_{shank} is the shank rotation around the mediolateral axis, $l_{\mathrm{shank}} = 0.246 \cdot \mathrm{BH}$ is the shank length expressed as a fraction of body height (BH) [15], $r_{\mathrm{CoM}} = 0.57$ is the normalized location of the center of mass along the tibia, and l_{PI} is the length of the PI, used to express CoP in the foot frame defined in Opensim. This formulation estimates the AP direction of the CoP. We set the ML component to zero due to its relatively small magnitude, as an assumption to simplify the model.

C. Joint reaction analysis

Once we estimated the kinematics and kinetics, our objective was to compute the internal knee joint loading. For this analysis, we used OpenSim and we transformed the inputs to the OpenSim ground frame. We employed the Rajagopal2015 [16] musculoskeletal model and performed scaling manually using scale factors based on the subjects' BH [15]. Next, we ran the static optimization tool to estimate muscle forces, which we then used as input for the joint reaction analysis tool to compute the superior force acting on the knee joint, expressed in the tibial reference frame. To reduce noise in the estimated JCF, we applied a Savitzky-Golay filter (order 4, frame length 21) as a post-processing step. While this filtering helps smooth the signal and attenuate high-frequency fluctuations, it does not fully compensate for underlying inaccuracies introduced by kinematic estimation errors. We further discuss these limitations and their impact on force estimation in the Discussion section.

D. Metrics for data analysis

We detected contact events using the vertical force measured by the Force Shoes™ with a threshold of 30 N. The knee JCF was normalized to BW. To assess accuracy, we calculated both Pearson's correlation coefficient (ρ) and the RMSE. Correlation strength was categorized as follows: negligible ($0 \leq \rho \leq 0.3$), weak ($0.3 < \rho \leq 0.5$), moderate ($0.5 < \rho \leq 0.8$), and strong ($\rho \geq 0.8$) [17]. For each trial, the full signal was analyzed, and results were reported as the mean and standard deviation across participants for both RMSE and ρ.

III. Results

In this section, results for right knee JCF are reported as the study includes only healthy subjects and there were no gait asymmetries. Figure 2 reports a comparison between the JCF computed with the reference and the estimation systems for all the movements included in the study. Moreover, Table I summarizes mean and standard deviation across movements for every subject for ρ and RMSE.

IV. Discussion

The results of this study demonstrate that knee JCF can be estimated with good accuracy using a minimal setup of five IMUs. Across a range of ADL, the proposed method achieved

TABLE I
PERFORMANCE METRICS FOR EACH SUBJECT

	ρ	RMSE [BW]
Subject 1	0.79 ± 0.05	1.05 ± 0.05
Subject 2	0.83 ± 0.02	1.08 ± 0.1
Subject 3	0.85 ± 0.02	1.06 ± 0.05

strong correlations ($\rho > 0.79$) and a consistent RMSE of approximately 1.06 BW, that is about 15% of the maximum reference range, supporting its potential for joint loading estimation using wearable sensors for real-word applications.

Compared to previous studies utilizing more extensive sensor configurations, the method proposed in this study achieves comparable accuracy with a simplified sensor setup. Konrath et al. [6] used a full-body configuration with 17 IMUs, reporting strong correlations ($\rho = 0.86$) and RMSE of approximately 0.9BW for SAD. Similarly, Di Raimondo et al. [7] reported a coefficient of determination of $R^2 = 0.68$ with RMSE values of 0.40BW in a clinical cohort of knee OA patients during gait. Zangene et al. [8] demonstrated high intra-subject correlations ($\rho = 0.89$) and Normalized RMSE of $NRMSE = 15.6\%$ for gait using three IMUs for single leg estimation. In comparison, our setup achieves competitive accuracy with a considerably lower sensor count for a wider range of ADL.

The slightly higher RMSE in this study is mainly due to residual kinematic errors that propagate through the OpenSim pipeline, affecting joint force estimates. This is most evident in Figure 2 during the TUG and SAD tasks (red shaded areas), where larger joint angle errors occur. In the TUG task specifically, some peaks can be attributed to errors introduced by the assumption of a locked ankle joint. A similar pattern appears in the FW tasks, where joint force profiles align in shape but exhibit an offset, increasing RMSE despite high correlation. This offset likely stems from differences in joint angle estimation, influenced by varying calibration methods. Soft tissue artifacts may further contribute by adding noise to segment pose estimation. Future work should aim to refine calibration and compensate for soft tissue motion to reduce these discrepancies.

In this study, contact events were identified using force shoes, providing high accuracy. However, future work should focus on integrating shank-mounted IMUs for contact detection, as they are more suitable for real-world applications. Importantly, this approach must achieve sufficient accuracy to reliably detect double support phases, which are essential for the application of the virtual pivot point (VPP) concept. Additionally, CoP estimation can be extended to the ML direction by projecting the tibia's center of mass position along that axis. Finally, the generalizability of this study is limited by its small and homogeneous sample, consisting exclusively of healthy individuals. Future research should include larger and more diverse cohorts, especially individuals with pathological gait patterns such as those associated with knee OA, to assess the robustness and clinical relevance of the proposed approach.

Despite these limitations, the five-IMU setup achieves JCF estimation performance that is comparable to more complex sensor systems, while offering better portability and ease of use. These characteristics highlight its potential as an effective solution for monitoring knee joint loading in real-world scenarios.

V. CONCLUSION

This study presents a simplified method to estimate knee JCF using only five IMUs. Despite the reduced sensor count, the approach achieves good accuracy in various ADL. Although some limitations remain, mostly due to segment kinematics estimation, the five-IMU setup shows strong potential for estimating knee joint loading in real-world applications.

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