LiDAR-based 3D Pose Identification and Physical Workload Estimation of Construction Workers

Yizhi Jia1, Jiawen Zhang1, Mingyu Zhang1, Shuai HAN1,\*, Yinong Hu1, Lei Wang1

1 Department of Building and Real Estate, Hong Kong Polytechnic University, Hong Kong 999077, China.

\* Corresponding author: [shuaihan@polyu.edu.hk](mailto:shuaihan@polyu.edu.hk)

**Abstract.** The high-intensity physical labor of construction workers can easily lead to musculoskeletal disorders (MSDs), posing a threat to their health and construction safety. Traditional physical workload assessment methods suffer from limitations such as subjectivity, invasiveness, or insufficient accuracy in complex construction environments. This study aims to propose an automated physical workload assessment method for construction workers based on LiDAR to overcome the shortcomings of existing technologies. The core of this method involves: capturing 3D posture using LiDAR point cloud data and the VoxelKP network, combining with plantar pressure data collected by smart insoles, and calculating and evaluating joints workload using a bottom-up biomechanical model. The research team recruited several participants at a real construction site and established a synchronous multimodal dataset containing 3D point cloud data and plantar pressure information. Experimental results show that the proposed 3D posture estimation algorithm achieved a mean per joint position error (MPJPE) of 102.94 mm for 15 key human body points. The system can successfully capture the dynamic changes in joint moments during different gait phases of workers' walking, identify the load levels of different joints, and classify risk levels based on the calculated load percentage. In summary, the LiDAR-based automated physical workload assessment method proposed in this study enables non-invasive real-time monitoring of construction workers’ joint loads and effectively identifies potential risks.

**Keywords:** Construction worker; Ergonomic risks; 3D Pose Estimation; Deep learning; LiDAR.

1. Introduction

In the context of rapid global construction industry development, construction safety and health management has become as a critical concern (Akinlolu et al., 2020). For construction workers, the high-intensity physical labor characteristics of construction activities, such as heavy lifting and prolonged standing operations, not only significantly increase the physical burden of workers, but also become one of the major contributing factors of occupational injuries and accidents (Umer et al., 2018).

Repetitive actions and sustained work hour pressure easily lead to multiple chain reactions. Initially, workers face challenges such as short-term distraction and decreased operational precision. As fatigue accumulates, workers’ delayed responses to emergency situations will lead to higher risks of accidents such as falls and collisions (Aryal et al., 2017). Furthermore, it is noteworthy that this chronic fatigue state continuously affects the human body through biomechanical compensation mechanisms, ultimately leading to musculoskeletal disorders.

Musculoskeletal disorders (MSDs) are common in the construction industry across various countries. According to U.S. bureau of labor statistics, there were 19,380 cases of musculoskeletal injuries and illnesses in the private sector construction industry in 2018, with an incidence rate of 28.9%, resulting in an average of 10 days away from work (U.S. Bureau of Labor Statistics, 2020). This problem is also prominent in the Asian region. In 2023, a study conducted in South China found that the incidence rate of WMSDs among 380 construction workers was 57.9% over the past 12 months (Lee et al., 2023). Similar to China, in Korea, the proportion of construction workers with back pain, upper limb pain, and lower limb pain due to chronic fatigue is about 30.7 %, 61.3 %, and 49.2%, respectively (Palikhe et al., 2020). These data indicate that WMSDs have become a common health problem in the global construction industry. Beyond the health threats to workers, fatigue and musculoskeletal disorders often lead to losses in productivity and huge economic burdens ( Anwer et al., 2021; Hamid & Hilmi, 2024).

Workload assessment is a critical approach in monitoring worker states and preventing WMSDs. Currently, approaches to evaluating physical workload can be divided into three main categories. Traditional methods rely on observational assessment tools such as RULA, OCRA, and REBA. These tools enable rapid data collection at a low cost but suffer from subjective bias and a lack of precise quantification. To obtain more objective data, researchers have turned to more precise biomechanical measurement devices, such as Inertial Measurement Units (IMUs) and Electromyography (EMG). While these advanced devices can provide accurate physical workload data, they also present new challenges: their invasive nature, discomfort when worn, and interference with workers’ daily operations significantly limit their practicality and adoption potential in complex and dynamic construction environments. In recent years, computer vision and sensor fusion techniques have provided new solutions for non-contact measurements. However, there are still technical challenges in reconstructing 3D human postures from 2D images accurately in complex construction environments.

To overcome the mentioned challenges, this study proposes a novel physical workload assessment method, with its main innovation being the integration of 3D posture recognition and sensor-based physical workload measurement. The method consists of three key components: first, worker’s 3D postures are captured in real-time using LiDAR point cloud data, overcoming the spatial distance and position inaccuracy issues in traditional 2D image recognition; second, smart insoles equipped with 48 pressure sensors are used to collect plantar pressure data; finally, based on the predicted 3D joint coordinates and plantar load data, inverse dynamics modeling is applied to calculate the load on various body joints, enabling comprehensive assessment of workers’ physical workload levels across different construction tasks. This approach significantly improves the accuracy of physical workload assessment by multimodal data fusion, establishing a scientific foundation for developing precise ergonomic interventions and risk prevention strategies at construction sites.

1. Literature Review

To comprehensively understand the current state of research in the workload assessment field, this chapter conducts a systematic review of relevant literature. The literature review includes three primary workload assessment methods: scales for workload assessment, biomechanical analysis methods, and computer vision-based assessment methods, which have their improvements and limitations, respectively.

* 1. Scales for Workload Assessment

The traditional assessment ways for physical workload are primarily perception-based rating methods, such as RULA, OCRA, REBA, NASA-TLX, and Borg RP (Borg, 1982; Hart & Staveland, 1988; McAtamney & Nigel Corlett, 1993; Occhipinti, 1998; Hignett & McAtamney, 2000). These methods face multiple challenges. First, the assessment results are heavily influenced by evaluators’ subjective judgments, with the same working posture potentially receiving different scores; each rating tool has limited applicability, for example, RULA only focuses on upper limbs and cannot achieve whole-body assessment. Second, due to the lack of objective numerical intervals, these methods can only provide relatively crude risk level classifications and rankings, unable to accurately quantify actual workload magnitude (Bolton et al., 2023). Third, observational methods typically only capture static or discontinuous data, failing to continuously monitor dynamic workload changes throughout the work process, making it difficult to fully reflect actual working conditions. More importantly, these assessment tools are primarily designed for repetitive manufacturing operations and struggle to address the diversity and complexity of tasks in the construction industry.

* 1. Wearable Sensor-based Workload Estimation

To overcome the deficiencies of traditional observational methods, researchers have developed various measurement devices based on biomechanical indicators. IMU technology can accurately measure human three-dimensional motion parameters and posture angles, providing objective data for work posture assessment, and is widely applied in preventing work-related musculoskeletal disorders (WMSDs). Khaksar et al. utilized IMUs to record the head, back, and pelvic movements of workers in harsh environments, measuring joint range of motion to prevent high-risk working postures (Khaksar et al., 2022). Rosenhahn et al. used sparse IMU sensors to estimate 3D human postures (Marcard et al., 2017), while the M. Diraneyya team used inertial motion capture systems to predict motion parameters of human joints (Diraneyya et al., 2021). EMG technology is widely applied to measure muscle activity and contraction intensity, assessing workers’ muscle load and fatigue levels by detecting changes in muscle electrical potential (Li et al., 2024). Antwi-Afari et al. utilized Surface electromyography methods to evaluate the effects of different lifting weights and lifting postures on spinal biomechanics (Antwi-Afari et al., 2017).

These devices can directly measure muscle activity, joint angles, and applied forces, providing more precise physical workload data. However, these measurement methods have significant invasiveness issues: the measuring equipment requires direct contact with the skin, is uncomfortable to wear, and can easily cause skin irritation, especially in high-temperature, sweaty construction environments. More importantly, these sensors may interfere with workers’ normal construction activities, reducing work efficiency and even introducing new safety hazards. Therefore, although biomechanical measurements are conceptually feasible in laboratory environments, their application in actual construction sites is severely limited.

* 1. Vision-based Workload Estimation

In recent years, computer vision technology has provided new ideas for physical workload assessment. The physical workload of the human body can be measured using a non-intrusive, non-contact solution that minimizes interference with workers ( Mehrizi et al., 2018; Mehrizi et al., 2019; Yu, Li, Umer, et al., 2019; Yu, Li, Yang, et al., 2019Aghazadeh et al., 2020; Wang et al., 2021). The Yu team combines computer vision technology with sensor fusion, calculating physical workload through biomechanical models by using cameras to compute workers’ joint coordinate information, integrating physical sensor data (such as load insoles) and environmental physical data (Yu, Li, Umer, et al., 2019; Yu, Li, Yang, et al., 2019). These non-contact measurements avoid the invasiveness issues of traditional sensors while continuously monitoring large work areas. However, image-based human posture recognition methods still face technical challenges: mainly the difficulty of accurately reconstructing 3D human postures from 3D images, especially in construction environments with complex lighting conditions and severe occlusions (Jang et al., 2023).

Besides optical cameras, depth cameras have also been attempted for physical load estimation. Ning et al. proposed a depth camera-based spinal load assessment method, where depth cameras can collect 3D motion postures to predict human loads (Ning & Guo, 2012). Seo et al. utilized RGB-D cameras to collect data from real construction workers, then used virtual human modeling to simulate and generate human motion training datasets for posture risk assessment (Seo & Lee, 2021). However, due to structured light with limited detection depth, depth cameras scan are only suitable for indoor or outdoor environments with good weather conditions and cannot adapt to the complex environmental conditions of the construction industry (Lee & Park, 2024).

In summary, with the rapid development of computer vision and various non-contact sensors in recent years, there is enormous potential for optimizing real-time physical workload monitoring. However, numerous challenges still exist regarding data collection accuracy and applicability in various environments.

1. Methodology

The overarching aim of this research is to facilitate the automatic and non-contact assessment of physical workload for construction personnel utilizing LiDAR point cloud data. Fig. 1 illustrates the main workflow of this assessment method. The methodology is structured into three primary modules: (1) Data collection, (2) LiDAR-based 3D Human Key points Estimation, (3) Biomechanics-based Workload Assessment.

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**Fig. 1.** The Main framework of the pose estimation-based workload assessment method

* 1. LiDAR-based 3D Body Key Joints Estimation Model

### Objective and Input. This module focuses on the accurate and automated determination of 3D coordinates for crucial skeletal joints from individual LiDAR scan frames. The precise localization of these key points (including head, shoulders, elbows, wrists, hips, knees, and ankles) is fundamental for the subsequent biomechanical analysis and workload evaluation. The input consists of the raw 3D point cloud acquired by the LiDAR sensor, where N denotes the point count and C represents the feature dimensions per point.

### VoxelKP Network. To fulfill this objective, we utilizes VoxelKP (Shi & Wonka, 2023), an advanced, fully sparse neural network architecture engineered for 3D human key points estimation specifically from LiDAR data. The selection of VoxelKP is motivated by its proficiency in managing the inherent sparsity of LiDAR point clouds while adeptly capturing the fine-grained local details essential for key points localization. The operational flow and principal techniques are outlined below:

#### Data Preprocessing: Sparse Voxelization. The initial point cloud undergoes discretization into a 3D voxel grid. Only voxels populated with point data, along with their associated features, are preserved, creating a sparse voxel representation. This approach markedly curtails data dimensionality and computational overhead while retaining vital spatial information.

#### Feature Extraction Backbone. The resulting sparse voxel data is processed through a multi-stage, entirely sparse convolutional network designed for hierarchical feature extraction. The VoxelKP backbone integrates several novel components to augment feature representation capabilities:

* Hybrid Feature Learning: Within multiple network stages, feature extraction occurs concurrently through a sparse convolutional path (capturing neighborhood spatial characteristics) and a parallel MLP path (processing features within individual voxels). The outputs from these paths are combined using element-wise summation, synergizing local geometric structural data with detailed point-level information.
* Sparse Selective Kernel (SSK) Module: This component dynamically aggregates spatial context across multiple scales. It operates by concurrently using sparse 3D submanifold convolutional kernels of differing receptive fields (e.g., 3×3×3, 5×5×5) and employing a channel-focused attention mechanism to selectively weight and merge features from these varying scales. This empowers the network to adaptively emphasize the most pertinent feature scale at any given location, which is vital for addressing variations in human distance and posture.
* Sparse Box-Attention Module: To precisely delineate the spatial relationships among key points clustered in localized areas, this module divides the voxel space into distinct local "boxes." Self-attention mechanisms are then applied within the confines of each box, concentrating on modeling the dependencies among voxel features in that specific vicinity to derive fine-grained, distinguishing characteristics.

#### Spatially Aware Multi-Scale Bird’s Eye View (BEV) Fusion. To effectively leverage the extracted 3D features for downstream detection tasks while preventing the loss of critical height information often associated with conventional BEV transformations, VoxelKP implements a unique fusion technique. It transforms multi-scale 3D feature maps from the backbone’s later stages into enriched 2D BEV feature maps. This is achieved using convolutional operations designed to encode vertical information (e.g., employing a (1,1,h) kernel, where h represents height) and by expanding the number of feature channels. Through specific alignment protocols and weighted fusion, essential 3D spatial details, particularly height, are maintained, which is crucial for the accurate prediction of 3D key points coordinates.

#### Prediction Heads. The finally consolidated multi-scale BEV feature map is directed to several parallel prediction heads. These heads perform regression to determine the center position, dimensions, orientation, and critically, the 3D coordinates of all K key points, along with their visibility status, for every identified human figure.

### Output. The concluding output from this module comprises a collection of 3D key points coordinates corresponding to each identified construction worker *i*, where . This high-fidelity 3D pose information serves as the input for the subsequent phase of biomechanical analysis.

* 1. Biomechanics-based Workload Assessment

The function of Workload assessment is to calculate every joint torques for workload assessment. This part is consisted by three steps, a) Plantar pressure data collection; b) Joints workload calculation; c) workload assessment.

### Plantar Pressure Data Collection. This step utilizes a pair of smart insoles featuring high-precision pressure sensor arrays to measure the plantar contact pressure distribution. Fig. 2 shows that each insole is embedded with a 12x4 matrix of pressure sensors, yielding 48 sensing points across the entire sole, with each point capable of measuring up to 50kg. The spatial arrangement of these sensors is designed based on established human plantar pressure distribution patterns, enabling focused monitoring of the forefoot, midfoot, and hindfoot regions. The integrated data acquisition system operates at a maximum sampling frequency of 20Hz and employs low-energy Bluetooth for real-time wireless data transmission. The complete system weighs under 50 grams, minimizing interference with the worker’s mobility, and is powered by a battery providing over five hours of continuous operation.



**Fig. 2.** Smart Insoles and Accessories

### Joint Workload Calculation. An inverse dynamics methodology is employed to calculate the joint workload of construction workers, based on the acquired 3D joint coordinates. This approach models the human body as a multi-segment rigid body system. By integrating the 3D human key points information with data on the total body load (including self-weight and external loads), the torque acting on various joints are computed for specific working postures. Particular attention is directed towards quantifying the biomechanical loading on the lower extremity joint.

The computational process relies on two primary assumptions: a) the total weight of the worker and any external loads are ultimately transferred to the ground via the feet; and b) the worker is assumed to maintain a quasi-static state during the measurement intervals. Different computational models may be utilized depending on the specific posture, and data streams from the load measurement system and the 3D pose estimation system are time-synchronized using low-latency wireless transmission to ensure temporal alignment for the analysis.

The biomechanical model incorporates anthropometric data derived from human mass distribution studies. The specific segmental mass percentages for the male population, taken from this source, are detailed in Table 1. Table 1 also provides the relative location of the center of mass (CoM) for each segment, typically expressed as a percentage of the segment’s length from the proximal joint. The absolute 3D position of each segmental CoM, denoted as *PCoM*​, is calculated using linear interpolation between the proximal and distal joint centers of the segment, based on the relative CoM location percentage. The calculation is performed using the following equation:

(1)

where ​represents the 3D coordinate vector of the segment’s proximal joint center, ​ represents the 3D coordinate vector of the segment’s distal joint center, c is the dimensionless ratio representing the location of the CoM along the segment length, measured from the proximal joint. This value (e.g., 10.08 for 10.08%) is sourced from the anthropometric data presented in Table 1.

**Table 1.** Comparison of average mass ratio and centers of mass of body segments

|  |  |  |
| --- | --- | --- |
| Body Segment | Average Mass Ratio (%) | Segmental Centers of Mass (%) |
| Head | 10.08 | 39.4 |
| Upper Torso | 19.17 | 59.4 |
| Middle Torso | 12.72 | 49.3 |
| Lower Torso | 10.07 | 42.9 |
| Thigh | 12.13 | 34.8 |
| Shank | 5.4 | 45.0 |
| Foot | 1.49 | 43.2 |
| Upper Arm | 2.44 | 45.0 |
| Forearm | 1.57 | 43.2 |
| Hand | 0.59 | 35.8 |

### Calculation of Moments at Body Joints. Taking the Left Knee Joint as an example, its moment calculation process is as follows. Under the assumption of static or quasi-static equilibrium, the net internal moment generated at the knee joint must balance the sum of external moments produced by the gravitational forces acting on its distal limbs (shank and foot) and the net reaction force transmitted from the ankle joint. Specifically, the net moment of the knee joint, *MLKnee*​, is obtained by algebraically summing the moment MWL​Calf​ generated by the shank’s own weight *WLCalf*​ (calculated via mass *mLCalf*​) acting at its center of mass *PLCalfCOM*​, and the moment *MFL​Ankle*​ generated by the net vertical force *FNetL​Ankle*​ acting at the ankle joint *PLAnkle*​ (equal to the vertical component of the ground reaction force *FGRFz​​* minus the foot’s weight *WLFoot*​, calculated via mass *mLFoot*​).

The main formulas involved in the calculation are as follows:

(2)

(3)

(4)

where *MLKnee*​ = net left knee joint moment (N/m); *MWL​Calf​*= moment from left shank weight (N/m); and *MFL​Ankle*​ = moment from net vertical force at left ankle (N/m). The masses *mLcalf​* (left shank) and *mLfoot*​ (left foot) in kg are from anthropometric models; g = gravitational acceleration (9.81 m/s2); *FGRFz*​​ = vertical Ground Reaction Force (GRF) on the foot (N); *PLknee*​, *PLankle*​, and *PLCalfCOM*​ = 3D coordinates for left knee center, left ankle center, and left shank CoM, respectively; −*k* = downward vertical vector; +*k* = upward vertical vector; and *r*(⋅) = function for moment arm magnitude (m), being the perpendicular distance from joint to force’s line of action.

Through this calculation, the biomechanical load experienced by the knee joint under specific postures or actions can be quantitatively assessed. The same bottom-up analysis method can be applied to calculate moments at other key joints, such as the hip and lumbar spine.

### Workload Assessment. The maximum tolerable moment (Mmax​) for each joint is estimated based on a regression model proposed by The National Isometric Muscle Strength Database Consortium(The National Isometric Muscle Strength Database, 1996). This model comprehensively considers individual physiological parameters, and its calculation formula is as follows:

(5)

where *Mmax*​ represents the maximum theoretical tolerable moment for a specific joint (Nm); Age is the worker’s age (years); Gender is the worker’s sex (typically defined as male=1, female=0); BW is the worker’s body weight (kg); H is the worker’s height (m), thus represents the Body Mass Index (BMI, kg/m2); *Lbone*​ is the length of the bone segment associated with the joint (m); *a, b, c, d* are specific regression coefficients for different joint, which are typically derived from existing anthropometric and biomechanical research databases, shown in Table 2.

After calculating the joint moment (*Mjoint​*) and the maximum tolerable moment (*Mmax*​) for that joint, the joint workload (*WLjoint*​) is defined as the percentage ratio between these two, calculated as:

(6)

For risk warning and intervention, joint load is categorized into four risk levels based on the calculated workload percentage: Low risk (<30%), medium risk (30-50%), high risk (50-70%) and very high risk (>70%).

**Table 2.** Joint capability regression coefficients

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
| Joint | *a* | *b* | *c* | *d* |
| Right shoulder | 0.17 | 16.26 | 0.17 | 23.35 |
| Left shoulder | 0.18 | 14.64 | 0.29 | 19.59 |
| Right elbow | 0.13 | 11.24 | 0.07 | 22.78 |
| Left elbow | 0.11 | 10.63 | 0.05 | 19.66 |
| Right hip | 0.33 | 19.19 | 0.66 | 34.44 |
| Left hip | 0.29 | 18.75 | 0.47 | 36.05 |
| Right knee | 0.16 | 8.78 | 0.08 | 22.47 |
| Left knee | 0.17 | 7.67 | 0.14 | 21.10 |

1. Experiment
   1. Dataset

This study established an innovative multimodal dataset, synchronously integrating 3D point cloud data with plantar pressure information, to assess the workload of construction workers. Data acquisition equipment was deployed on actual construction sites, and 20 participants with diverse physiological characteristics were recruited. These participants wore custom-made smart insoles while performing routine work tasks.

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**Fig. 3.** Example of cloud points view

The acquisition equipment included a Robosense LiDAR system, robust enough to withstand the harsh conditions of a construction environment, featuring a 120° horizontal scanning range and a ±12.5° vertical field of view. The scanner was mounted on a movable tripod to ensure comprehensive coverage of the work area. Fig. 3 show the Robosense M1 and one of the cloud points views in our datasets. Each worker was equipped with a smart insole system embedded with 26 strategically distributed pressure sensors. This system transmitted real-time plantar pressure data to a data integration platform via low-latency wireless technology. The two systems (LiDAR and insoles) were precisely synchronized using a millisecond-level timestamping mechanism, providing spatiotemporally consistent input parameters for subsequent biomechanical modeling.

Data collection spanned various construction phases across multiple projects, encompassing diverse work conditions such as foundation treatment, frame erection, and interior decoration, thereby ensuring sample diversity in environmental context and task type. The collection process adhered to non-intervention principles, with workers maintaining their natural working states, exhibiting realistic postural changes and load distributions. All personally identifiable information was filtered out during the data processing stage using specialized algorithms to strictly protect participant privacy.

Worker postures were categorized into three types: standing/walking, forward bending/stooping, and squatting, forming a comprehensive posture library totaling 3,478 records. Each record includes precisely annotated 3D bounding boxes, documenting the worker’s spatial position, body dimensions, and orientation angles, while also correlating with the plantar pressure distribution map at the corresponding moment. Through this multi-dimensional data fusion, we can establish a mapping relationship between workers’ postural characteristics and lower limb joint loads, providing an empirical basis for workload assessment.

The in-depth analysis of standing postures also was focused specifically, not only due to their prevalence in construction work but also because they provide a stable baseline reference for biomechanical models. Standing posture samples constituted 37% of the total records, with feature distances ranging from 5 to 35 meters, and point cloud densities varying from 25 to 1300 points depending on the distance.

The unique value of this innovative dataset lies in its pioneering achievement of synchronously capturing human 3D posture and real-time force-bearing states within a construction site environment, offering a novel analytical perspective for studying biomechanical loads during construction activities.

* 1. Results

### 3D Joints Estimation Results. The 3D pose estimation model of a construction worker demonstrated satisfactory performance in a real site environment. Fig. 4 and Fig. 5 show a predicted worker body skeleton and joints coordinates, which is a 13 × 3 matrix.

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**Fig. 4.** Example of the predicted skeleton

**Fig. 5.** Example of 3D joint predicted coordinates

Through the evaluation of the test dataset, the model has a mean joint position error (MPJPE) of 102.94 mm at 15 key points of the human body, as shown in Table 3.

**Table 3.** Average MPJPE of predicted joints

|  |  |
| --- | --- |
| MPJPE | Mean (mm) |
| Head | 60.61 |
| Left Shoulder | 97.55 |
| Right Shoulder | 75.86 |
| Mid Shoulder | 69.13 |
| Left Elbow | 95.12 |
| Right Elbow | 76.66 |
| Left Hand | 219.41 |
| Right Hand | 134.80 |
| Left Hip | 103.20 |
| Right Hip | 66.92 |
| Mid Hip | 80.44 |
| Left Knee | 91.68 |
| Right Knee | 87.40 |
| Left Foot | 140.06 |
| Right Foot | 145.20 |
| Average | 102.94 |

The joint estimation accuracy exhibited distinct hierarchical characteristics, with the core trunk region demonstrating optimal performance: the mean errors for the right hip (66.92mm), mid hip (80.44mm), left hip were all below 110mm, providing a reliable foundation for the accurate estimation of lower limb loads. Key points in the upper trunk, including the left shoulder (97.55mm), right shoulder (75.86mm), and head (60.61mm), also maintained a high level of recognition accuracy.

The hip and knee joints, which are of particular focus in this study, demonstrated excellent recognition accuracy. The average error for the hip joints was approximately 85.06mm, and the average error for the knee joints was 87.54mm (left: 91.68mm, right: 87.40mm). These joints are critical nodes for force transmission and core calculation points for lower limb workload assessment. In practical applications, this error range constitutes only 8% to 9% of the standard lower limb length of an adult worker, ensuring sufficient reliability for moment arm length calculations based on pose. The foot error was approximately 142.63mm (left: 140.06mm, right: 145.20mm), which still allows for the formation of a complete lower limb load transmission chain.

Upper limb joint errors increased with distance from the trunk. The average error for the elbows was 85.89mm (left: 95.12mm, right: 75.66mm), while the hands exhibited the largest errors, reaching 177.11mm (left hand: 219.41mm, right hand: 134.80mm). This error distribution pattern aligns with fundamental principles of 3D pose estimation: core body parts, due to their larger volume and smaller range of motion, yield higher recognition accuracy, whereas distal joints, characterized by high flexibility and susceptibility to occlusion, exhibit relatively larger localization errors. Notably, the recognition accuracy of the load-bearing lower limb joints was superior to that of the upper limbs, providing robust support for studying the workload of standing workers.

Compared to pose estimation in controlled indoor environments, the accuracy achieved by our model in complex construction environments is encouraging. Although slightly lower than optimal results under laboratory conditions (typically MPJPE < 100mm), considering the challenging conditions of construction sites, including complex backgrounds, sparse point clouds, and partial occlusions, this level of accuracy meets the demands of practical engineering applications.

#### Workload assessment results. Based on 3D human key points recognition technology, we have successfully achieved the calculation and assessment of construction workers’ workload. The system can accurately capture the dynamic changes in joint moments during different gait phases of workers’ walking and provide corresponding risk ratings, as shown in Table 4 and Fig. 6.

**Table 4.** Moment of knee and hip in three gait phase

|  |  |  |  |
| --- | --- | --- | --- |
| Joints | Average Joints Moment in Different Gait Phase (N/m) | | |
| Step left | Gait transition | Step right |
| Left knee | 7.99 | 26.24 | 26.70 |
| Right knee | 26.83 | 21.43 | 17.22 |
| Left hip | 62.46 | 36.72 | 3.45 |
| Right hip | 9.37 | 7.74 | 54.08 |



**Fig. 6.** Workload assessments of joints in different step states

According to gait cycle analysis, our system can effectively identify and assess biomechanical loads under the following typical walking states:

* Completion of Left Step State. When a worker completes a left step and the center of gravity shifts to the left leg, the system accurately captures a relatively low left knee moment (range: 6-11N/m, load: 7%-11%), while the left hip joint load significantly increases (range: 57-74N/m, load: 26%-33%). Particularly in certain postures, the left hip load can exceed 33%, and the system automatically classifies it as "Medium Risk." Simultaneously, the right knee joint of the swing leg maintains a higher moment (range: 24-26N/m, load: 23%-25%), preparing for the next step.
* Gait Transition Phase. During the transition phase of a step, the system successfully captures a unique load distribution pattern: the supporting leg’s knee joint moment increases (average approx. 26Nm, 27% load) to support body weight, while the swing leg’s knee joint maintains a moderate moment (average approx. 21 N/m, 22% load) to control the impending step. The hip joint moment presents a transitional characteristic between the support and propulsion phases (average approx. 37 N/m, 17% load). This complex workload distribution validates the system’s high sensitivity to subtle changes in gait.
* Completion of Right Step State. When the center of gravity shifts to the right leg, the system effectively identifies an increased load on the right hip joint (range: 52-56N/m, load: 23%-25%), which is responsible for stabilizing the body. Concurrently, a significant increase in the left knee moment is captured (range: 23-30 N/m, load: 24%-31%). When the load exceeds the 30% threshold, the system accurately issues a "Medium Risk" warning. The biomechanical pattern in this state exhibits a mirror symmetry to that after a left step, validating the system’s consistent recognition capability across the gait cycle.

In all types of gait states, the upper limb joints consistently maintain low load levels. The elbow joint moment ranges from 0.5-1.5N/m (0.8%-2.1%), and the shoulder joint moment ranges from 2.0-3.4N/m (2.4%-3.4%). This is consistent with the physiological characteristic that upper limbs are primarily used for balance rather than load bearing during walking, reflecting the system’s accuracy in whole-body load assessment.

Risk assessment results indicate that during normal walking, workers’ joint loads are mostly at a low-risk level (Safe load, sustainable work). However, the system can precisely identify key risk points in the gait cycle, such as when hip joint load exceeds 33% or knee joint load exceeds 30%, automatically flagging them as "Medium Risk" and advising "Moderate load, recommend regular breaks." This risk classification mechanism provides an important basis for preventing cumulative injuries.

The experimental results demonstrate that the workload assessment system we developed can effectively capture and analyze changes in joint loads of construction workers under various gaits. The system’s assessment results are highly consistent with human biomechanical principles, showcasing the scientific validity and practicality of this method in actual engineering applications. This technology can be further applied to more complex construction work scenarios, providing data support for reducing the risk of musculoskeletal injuries to workers and optimizing work processes.

1. Discussion

This study proposed a LiDAR-based workload assessment method, aiming to achieve automated, non-invasive, and accurate evaluation of construction workers’ workload through 3D human key points estimation technology and biomechanical analysis. According to the experimental results, the system can effectively capture changes in joint moments at different stages of the human gait cycle, such as significant variations in hip joint load during left and right stepping states. Even in low-intensity activities like normal walking, the system successfully identified higher instantaneous loads on certain joints at specific gait phases, suggesting that the risk of cumulative damage may exist in daily activities. The differentiated analysis of load distribution between upper and lower limb joints provides a scientific basis for targeted intervention measures.

The primary advantage of this method lies in its non-invasive nature. Unlike traditional wearable devices, the system does not require workers to wear any equipment, thereby not interfering with normal work processes and enhancing the ecological validity of the assessment. The 3D human key points estimation technology avoids measurement errors caused by a limited field of view inherent in 2D methods, making the system more suitable for evaluating complex movements in construction environments. The customized biomechanical model, established by considering individual worker parameters, improves the accuracy of moment calculation and load assessment.

It is particularly noteworthy that we created a 3D construction worker dataset, providing an important foundation for human pose estimation in specific scenarios. The visualized results generated by the system make complex biomechanical data easy to understand, offering intuitive support for management decisions. Compared to traditional ergonomic scales, this method not only considers working postures but also quantifies the ratio of joint moment to capacity, making it more suitable for assessing complex and dynamic construction activities.

Despite these positive outcomes, the method still has some limitations. The accuracy of point cloud scanning needs further improvement; the current MPJPE for each joint in complex construction environments is approximately 102 mm. Although this accuracy supports basic load assessment, there is still a gap compared to the latest 3D pose estimation algorithms (MPJPE < 100 mm). The coverage of posture types is limited; the system has mainly been validated for walking and standing postures, while high-risk postures common in construction work, such as squatting and bending, have not yet been fully integrated. When workers are in a squatting posture, line-of-sight obstruction may lead to inaccurate key points estimation, affecting the reliability of the assessment results.

1. Conclusion

In this study, a novel automated workload assessment method is proposed based on LiDAR point cloud, 3D human pose estimation and biomechanical analysis. The main contributions of this system include the development of a non-invasive workload assessment technique, the creation of the first 3D point cloud dataset of construction workers, and the establishment of a risk classification framework based on joint moment percentage. By employing 3D estimation instead of traditional 2D methods, the method effectively overcomes measurement errors caused by view limitations.

Experiment results indicate that this method can estimate human joint positions and calculate joint moments in real-time, with an average joint estimation error of 102mm, and has successfully captured the dynamic changes in joint loads during the gait cycle. Specifically, lower body joints bear significantly greater loads (up to 33% maximum) than upper limbs (<5%). Furthermore, the loads on the left and right knee and hip joints continuously change with gait variations. The system’s response time is approximately 0.5 seconds, fully meeting real-time assessment requirements.

Although current limitations exist in point cloud scanning accuracy, posture type coverage, and tool recognition capabilities, the system has shown potential for application in ergonomic risk management within the construction industry. Future research will focus on improving point cloud scanning accuracy, expanding recognition to high-risk postures, establishing a long-term cumulative risk assessment framework.

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