# ESTIMATING CONSTRUCTION WORKERS' PHYSICAL WORKLOAD BY FUSING COMPUTER VISION AND SMART INSOLE TECHNOLOGIES

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**Abstract –**

**Construction workers are commonly subjected to ergonomic risks due to awkward postures and/or excessive manual material handling. Accurate ergonomic assessment will facilitate ergonomic risk identification and the subsequent mitigation. Traditional assessment methods such as visual observation and on-body sensors rely on subjective judgement and are intrusive in nature. To cope up with the limitations of the existing technologies, a computer vision and smart insole-based joint-level ergonomic workload calculation methodology is proposed for construction workers. Accordingly, this method could provide an objective and detailed ergonomic assessment for various construction tasks. Firstly, construction workers' skeleton data is extracted using a smartphone camera with an advanced deep learning algorithm. Secondly, smart insoles are used to quantify the plantar pressures while the worker performs a construction activity. Finally, the gathered data is fed to an inverse dynamic model in order to calculate the joint torques and workloads. The aforementioned approach was tested with experiments comprising simulations of material handling, plastering and rebar. The results reveal that the developed methodology has the potential to provide detailed and accurate ergonomic assessment. Overall, this research contributes to the knowledge of occupational safety and health in construction management by providing a novel approach to assess the risk factors of work-related musculoskeletal disorders (WMSDs).**

**Keywords –**

**Construction worker; Occupational health and safety; Deep learning; Machine learning**

## 1 Introduction

Workplace safety and health is an important issue in construction industry around the globe. One of the main reasons is the highly physical demanding nature of the construction tasks [1]. Repetitive and prolonged working could increase the possibility of fatigue, which in turn could result in decrease in attention and accidents in worst case scenarios [2]. In addition, fatigue might decrease construction workers productivity [3] and develop work-related musculoskeletal disorders (WMSDs) [4]. Considering the significant negative influences of physically demanding workload on construction workers, it is important to provide precise workload assessments for its mitigation. Manual observation is frequently used to estimate construction workers' physical workload based on workers' postures and external loads. However, due to the subjectivity of the observed data and inability to quantify the loads, the assessments appear to be not accurate enough. Additionally, it entails increased requirement of safety management staff on the construction sites. To get more objective and precise quantification of workload, biomechanical measurement devices were introduced to facilitate workload analysis [1]. Although these studies have proven the concept, they are intrusive in nature, requiring multiple sensors to be attached to the body of construction workers. As such, on-body sensors are uncomfortable to wear and could easily instigate irritation.

Considering the limitations of the aforementioned methodologies, this research proposes a blend of computer vision technology and smart insoles for workload assessment of the construction workers. The proposed methodology could provide a novel non-intrusive method to quantify the workload. First, a computer vision-based 3D motion capture algorithm is developed that could model the motion of various body parts while performing construction tasks using a RGB camera. Second, smart insoles equipped with multiple pressure sensors are used to capture workers' plantar pressure distribution. These pressure sensors would register the plantar pressure due to self-weight of the construction workers and other forces while carrying load, operating tools and performing related activities. Together with the 3D joint-model data from the developed motion capture algorithm and pressure data from the insoles, inverse dynamic modelling will be applied to calculate the joint-level torques. Subsequently, these torques will be used to calculate workload and plan ergonomic risks` mitigation strategies.

## 2 Literature Review

The purpose of this review is to provide an understanding of the previous research in this area as well as providing a rationale for the choice of workload assessment and data collection methods used in the present study. We begin with a review of the definitions and influences of workloads; three workload assessment methods, including self-report, observation and biomechanical analysis, are then reviewed and compared; this is followed by a discussion of the behaviour data collection methods used previously in the construction context.

### 2.1 Definition of Physical Workload

Workload refers to all of the factors that constitute a challenge which a worker has to surpass in order to perform a task, including physical workload and mental workload [5]. This research focuses on physical workload because: 1) physical workload has been proven to be one of the major risk factors of acute trauma injury and cumulative musculoskeletal disorders [6]; 2) it is more practical to provide a relatively objective and quantitative assessment of physical workload. It should be noted that physical workload can be assessed in two different ways namely biomechanical load and cardiovascular load [7]. Biomechanical load measures the workload as a set of torques applied on a human body resulting from the task which he performs, while cardiovascular workload is defined by the physiological changes in the human body as a response to an external task (e.g. heart rate, breathing frequency, core temperature). Biomechanical workload can be measured with non-intrusive methods such as observation and non-contact sensors (e.g. cameras). Besides, biomechanical load has more clear relation with external load and work postures [8]. Therefore, this research assesses physical workload from the biomechanical perspective.

### 2.2 Previous Workload Assessment Methods

The self-report-based workload assessment method focuses on workers' subjective ergonomic feelings and self-assessment on physical discomfort. For example, NASA-TLX (Task Load Index) scores workload from six aspects such as mental demand and frustration [9]. Borg RPE scale (Borg Rating of Perceived Exertion Scale) was developed to describe perceived work load [10]. Questionnaires and interviews are the main data collection approaches in these methods, making data collection time- and effort- consuming.

Observation-based methods are another kind of widely-used methods. Many workload assessment methods have been developed based on visual assessment of the work being performed and response of the worker to that work (e.g. work posture, external load, repetitive and duration). These methods include but are not limited to OCRA (Occupational Repetitive Actions, RULA (Rapid Upper Limb Assessment), and REBA (Rapid Entire Body Assessment). Although these methods are easy to use and can provide a rough workload assessment, they are prone to subjectivity and requires dedicated safety personnel. Additionally, these methods focus on different aspects of workload constructions (i.e. some of them do not consider work repetition). As a result, assessing the same workload with different methods may lead to different results [11].

Biomechanical analysis has also been applied in various cases to provide workload assessment. [12] applied biomechanical methods to explore the relation between work posture and workload during insertion of pin connectors. [13] determined low back pain risks with biomechanical analysis. Biomechanical methods have also been successfully applied in construction industries to facilitate determination of work-rest schedule using simulations [14].

Theoretically, biomechanics analysis can be applied to all parts of body while examining any work task [11]. Since biomechanical analysis require precise information of orientation of various body parts and their movements, traditional observation-based methods cannot be used. Traditionally, an integrated system of multiple cameras has been used for this purpose under laboratory conditions. As such, this approach could be used for actual construction sites where deployment of such system is not feasible [15,16]. Accordingly, researchers have adopted various other technologies to bridge this gap which are discussed in the following section.

### 2.3 Automatic Data Collection Methods for Workload Assessment

Posture data and biomechanical data are the data foundations of biomechanical analysis. This section reviewed and compared current posture and external load data collection methods.

#### 2.3.1 Automatic Posture Data Collection

One of the widely-used motion capture sensor system is inertial measurement unit (IMU). If attached to key joints, IMU sensors are able to capture the location and acceleration of the joints, and the human body motion data can thus be retrieved [17]. The main disadvantage is the intrusiveness. IMU sensors are required to be tied tightly to human body, but from the view of application, workers may reject wearing sensors so tightly. Such sensors are feasible for short-period track but may instigate irritation if used for long-time [18,19].

With the development of computer vision, various video-based methods are proposed to collect worker's posture data. Compared with sensors, cameras are less intrusive and inexpensive. Several previous studies have applied vision-based methods in construction management, for example, RGBD sensors have been used to recognize workers action [20], whereas depth cameras have been used to capture worker joint angles [21]. The study also found that although depth camera is an efficient tool to collect posture data for ergonomic/biomechanical evaluation but is not appropriate for construction sites because it cannot work under direct sunlight and requires the subject to be in near vicinity. Other researchers extracted posture information based on RGB pictures from ordinary cameras. For example, [14] proposed computer vision-based framework to identify construction activities from 2D image sequences. [17] used ordinary cameras to capture worker's posture. However, the major limitation of these methods is that they can only provide 2D postures of construction workers, which cannot support 3D biomechanical analysis of construction workers.

A recent progress in computer vision shed lights on video-based joint level biomechanical assessment. A newly developed computer vision algorithm can estimate 3D human skeleton from 2D video frames, making it possible to collect joint angles just based on videos [22]. By combining the state-of-art computer vision algorithm, this research aims at developing an accurate, real-time, and non-intrusive ergonomic assessment method which is suitable for both indoor and outdoor environments.

#### 2.3.2 Automatic External Load Data Collection

Most of previous methods didn't quantify the external loads and performed ergonomic assessments solely using posture related data. Insole-shaped plantar pressure sensor is an efficient tool to collect external load data, which can quantify the ground reaction forces from both feet non-intrusively [23]. Recently, [24] demonstrated the potential of applying smart insole to collect construction workers' plantar pressure in working status without interfering normal construction activities. Similarly, this research has used smart insoles to continuously collect the ground reaction forces for the calculation of external loads in order to perform biomechanical analysis. By combining computer vision-based posture data and smart insoles-based external workload,

This research provides an automatic workload assessment measurement methodology. Such method could provide relatively accurate and objective workload assessment for construction workers as compared to previously on-site adopted methods, which will help the managers to better understand the ergonomic risks and provide data foundation for ergonomic improvements.

## 3 Methodology

Figure 1 depicts the flowchart of the proposed construction worker's workload evaluation method. The first row in Figure 1 represents the input data, including anthropology information (age, gender, weight and height), RGB video from smart phone camera and plantar pressure data from plantar-shaped pressure sensors. Then joint capacity was calculated based on joint capacity prediction equation. 3D skeletons consisting of the xyz coordinates of key joints are generated from the RGB video frames based on a computer vision algorithm. External loads are calculated based on plantar data. Next, the 3D skeleton data and the external load data are used to calculate joint torques with biomechanical analysis. Finally, the workload is assessed by comparing the joint torques and joint capacity.

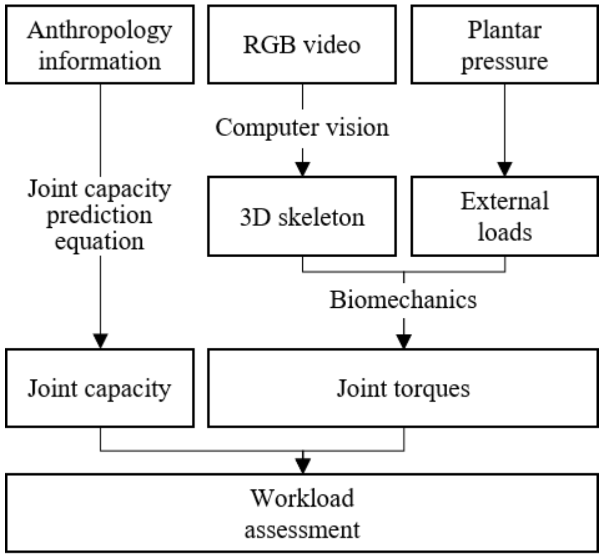


Figure 1. The outline of the automatic workload assessment method

### 3.1 3D Pose Capture from 3D Images

The workflow of the 3D pose estimator is shown in Figure 2. First, RGB images are collected from construction video clips. A deep learning architecture, named hourglass network (Newell et al., 2016) is trained to estimate the 2D coordinates of joints. Then the joint length ratio constrains are used to estimate the 3D coordinates of the various body joints [22].

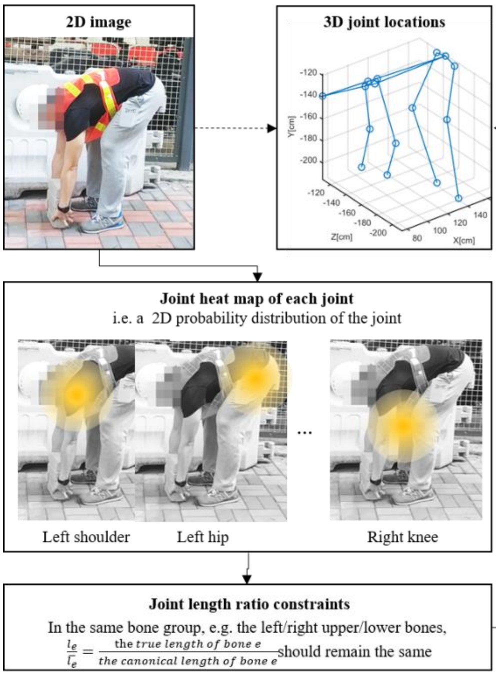


Figure 2. The framework of 3D pose estimator

### 3.2 Automatic External Load Assessment

A novel insole with plantar pressure sensors, named Moticon, is used to measure the total ground reaction force generated during the work task. This includes the worker's self-weight and external burden, as shown in Figure 3. The insole can be used in virtually any shoe. The commercial available smart insoles can transfer data wirelessly through ANT radio service. The size of external loads can thus be calculated by subtracting worker`s self-weight from the total reaction force generated. It is important to note that for most of the construction tasks, the external loads are usually applied at hands, resulting from the tools or equipment which a worker uses to perform the task.

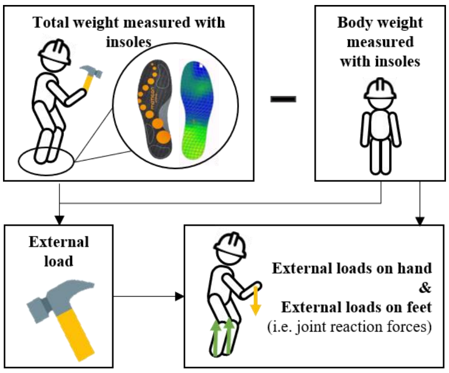


Figure 3. The calculation of external loads with smart insoles

### 3.3 Biomechanical Analysis

Inspired by biomechanics, this research simplifies the human body as a lever system, and then utilizes mechanics principles to analyse the internal load of each joint. The inputs of inverse dynamic model include: 1) a muscle-skeleton model, which simulates the muscles, tendons and skeletons with a lever system connected with hinges and dampers; 2) a motion file containing the time series of three-dimensional coordinates of the joints in muscle-skeletal model; and 3) external load data including the size and direction of ground reaction forces on both feet and the external loads on both hands. Based on the above data, the inverse dynamics model can be written as Equation (1).

$$M(p)\ddot{\boldsymbol{p}} + \boldsymbol{C}(\dot{\boldsymbol{p}}, \ddot{\boldsymbol{p}}) + \boldsymbol{G}(\boldsymbol{p}) = \boldsymbol{\tau} \qquad (1)$$

where $\boldsymbol{p}, \dot{\boldsymbol{p}}, \ddot{\boldsymbol{p}} \in \boldsymbol{R}^N$ are the vectors of joint positions, velocities and accelerations, respectively ; $N$ is the number of the degrees of freedom; $M(p) \in \boldsymbol{R}^{N\times N}$ refers to the mass of different body parts; $\boldsymbol{C}(\boldsymbol{p}, \dot{\boldsymbol{p}}) \in \boldsymbol{R}^N$ is the vector of centrifugal forces; $\boldsymbol{G}(\boldsymbol{p}) \in \boldsymbol{R}^N$ is the vector of gravitation forces; and $\boldsymbol{\tau} \in \boldsymbol{R}^N$ is the vector of generalized forces. 3DSSPP (Michigan University), a human body motion simulation software was used here to solve Eq.1.

### 3.4 Workload Analysis

The joint capacity in this paper is defined as Maximal isometric strength (MVIC) of each individual. MVIC can predicted with anthropology information including age, gender, weight and height [26]. Then workload equals to the ratio of joint torque to the joint capacity.

## 4 Experiment

Three main construction activities, including material handling, rebar, and plastering, were conducted during the experiment, as shown in Figure 4. The subjects wore smart insoles to capture the self-weight and any external load. A smart phone camera fixed on a tripod recorded the whole process. At the same time, a set of IMU sensors tied to the subject's main joints also recorded the location of the joints. The IMU sensor has an accuracy of up to 1 degree [27]. Experiments were enacted in both indoor and outdoor environments to demonstrate the feasibility of the proposed method.

Figure 4. The example frames during material handling, plastering and rebar

## 4.1 Experiment Data

Table 1 provides the raw data. The video data frequency is 25 fps (frames per second). The IMU data frequency is 30 fps. The insole pressure data is 50 fps. The 3D joint coordinates, ground reaction forces, and hand loads were calculated and synchronized.

Table 1 The information of experiment data

| Activity | | Material handling | Plaster | Rebar | Total |
|---|---|---|---|---|---|
| Duration [sec.] | | 22 | 19 | 114 | 155 |
| Video data | No. of frames | 550 | 475 | 2853 | 3878 |
| | No. of joints | 16 | 16 | 16 | - |
| IMU data | No. of frames | 660 | 570 | 3424 | 4654 |
| | No. of joints | 13 | 13 | 13 | - |
| Insole data | No. of frames | 1100 | 950 | 5706 | 7756 |
| | No. of sensors | 26 | 26 | 26 | - |

### 4.1.1 Posture Data

The video clips were first separated to frames at the rate of 1 fps (frame per second). Then the 3D pose estimator was applied on each frame to get the 3D coordinates of each joint. Figure 5 provides an example of the frame during material handling. Given a picture (Figure 5(a)), the 3D posture estimator estimates the 3D coordinate of 16 key joints. Figure 5(b) visualizes the 3D pose estimation results.

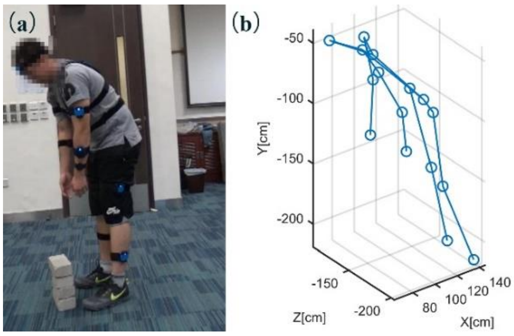


Figure 5. An example of the 3D pose estimation result

IMU sensors were used as the ground-truth to test the accuracy of the pose estimator. Figure 6 shows joint average of the estimation error of each frame. The results indicate that the average error of each joint was 4.10 cm.

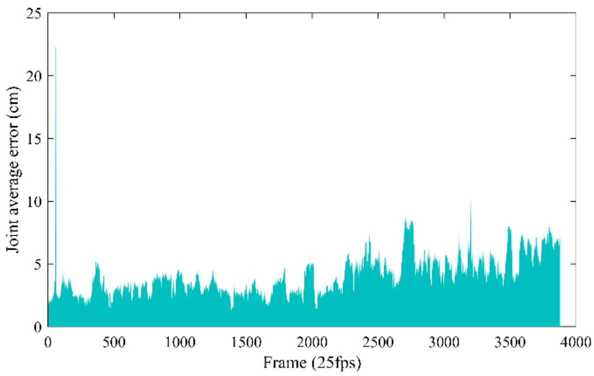


Figure 6. The error of 3D pose estimation

### 4.1.2 External Load Data

External load was estimated with the pressure data from the smart insoles. During the material handling experiment, the subjects were required to lift 0,1,2,3 or 4 bricks and hold them for 10 seconds. Each brick weights 2 kg, which equals to an external load of 19.6 N when g=9.8 $m/s^2$. The estimated external load resulting from the bricks was calculated as the difference between the ground reaction forces of consecutive liftings, as shown in Figure 7. The relative error is 5.99% by comparing the differences between the estimated external load and the ground truth external load.

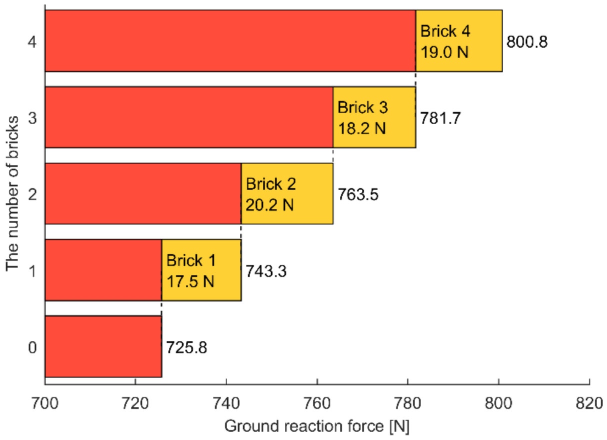


Figure 7. The measurements of external loads

## 4.2 Workload Assessment

Inverse dynamic modelling was applied to calculate the torque at each joint based on the posture data and ground reaction force data 3DSSPP was applied to facilitate the biomechanical calculations. The joint capacity was estimated according to the equations as suggested by The National Isometric Muscle Strength (NIMS) Database and the participant`s anthropometric information (age, gender, weight and height). Then, the workload was calculated as the percentage of maximum joint torque. Figure 8 delineates the joints` capacities, joints torques and resulting workload at each joint, which helps to assess the workload by illustrating the various body joints with different colors depending upon the workload percentage.

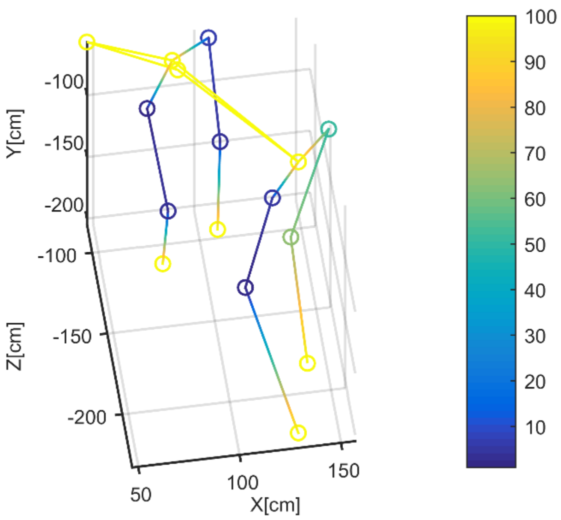


Figure 8. The visualization and calculation result of workload

Figure 9 shows the joint workload distributions during typical postures of the three construction activities involved. By comparing the join workloads of three construction activities, material handling was more likely to result in high joint workload than plaster and rebar. In all of the three activities, left hip and left knee had higher workload than other joints. The result suggested that the subject may need to reduce the workload of left legs by balancing the workload of both legs.

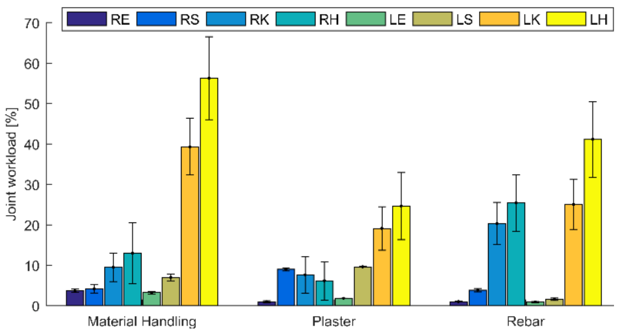


Figure 9. Joint workload assessment results

# 5 Discussion

Construction workers faced with high ergonomic risks, resulting in a negative influence on the workers' wellbeing and productivity. It is important, therefore, to assess the workers' ergonomic risk accurately. Observations, sensors, and depth cameras are three main posture data collecting methods, but are faced with challenges of low accuracy, uncomfortableness, and unsuitability to outdoor environments. This research intends to solve the issues by blending a video-based 3D pose estimation algorithm with smart insoles. The experiment results suggest that the method could 1) accurately collect construction workers posture and external load data, 2) automatically provide workload assessments without intrusiveness, 3) work well in both indoor and outdoor environments.

The methodology, however, has the following shortcomings and deserves further improvements.

First, the 3D motion estimation accuracy should be improved. Figure 10 provides two failure cases of the 3D posture estimation in an on-site experiment. The reason lies in visual obstacles. In Figure 10, the worker was squatting, and most of the body parts was invisible. The 3D pose estimation could be improved by adding more pictures with obstructions to the training dataset, so that the blocked body segment could be inferred.

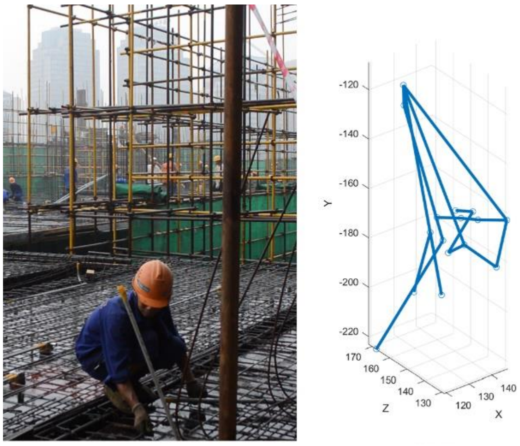


Figure 10. Failure examples of 3D pose estimation

Secondly, the current methodology can only be applied on frames containing only one worker. However, in most of the case, one supervision camera can record the activities of several workers. If the methodology could recognize all the workers within one frame, the efficiency could be increased a lot.

Thirdly, the pressure sensor data is not stable. Figure 11 shows the data from one sensor in the insole. It can be found that there exists sharp fluctuation in the first several frames. The reason might be workers' quick movements, which could lead to the unstable connections between pressure sensors and data receiver in the insole.

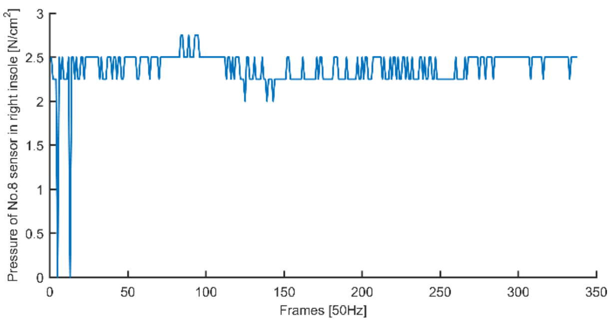


Figure 11. The data from one pressure sensor in the right insole

Finally, the methodology needs to be further demonstrated with real construction site data. Though the experiment demonstrates the feasibility of the methodology, the on-site experiment only records a ten-minute video for each worker. For data-based ergonomic improvement suggestions, it is necessary to take longer-period video records for more construction workers.

## 6 Conclusions

The research proposed a non-intrusive workload assessment approach for construction workers by merging computer vision, pressure sensors and biomechanics. The experiment results demonstrated the feasibility and accuracy of the approach. Development of such a system could equip the industry with a non-invasive tool for workload monitoring. Also, the approach provides detailed information about the posture and external load and associated patterns which could help understanding the relations between construction activities and workloads, which could serve as the data foundation for ergonomic improvements such as work-rest schedule and workstation design.

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